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Adaptive water waste processing strategy at floating barriers using computer vision, route finding, and Monte Carlo simulation

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ABSTRACT

Floating barriers installed along the riverbanks block floating debris (water trash) from contaminating marine environments. Regular removal of accumulated trash before reaching weight capacity is crucial to maintain structural integrity and prevent trash overflow. However, research on the costs of collecting floating debris in water infrastructure has been insufficient. To fill this knowledge gap, this study investigates the costs of processing water trash at multiple floating barriers and presents a novel water trash processing framework comprised of trash detection, valuation, and collection planning. The proposed framework (1) detects the types and mass of collected trashes using computer vision, (2) evaluates the process cost of the water trashes, and (3) derives an optimal garbage collection path planning. Monte Carlo Simulation is employed to simulate water trash collection and processing scenarios for estimating the total associated costs. Experimental results showed that the proposed framework achieved a 10% to 30% cost reduction compared to conventional time-based collection methods. The proposed water trash processing framework and the findings will contribute to our understanding on the costs of processing water trash at floating barriers to prevent ocean pollution, thereby facilitating the implementation of such infrastructure and planning the budgets required for their operation and maintenance.

1. Introduction

Marine debris in the ocean and coastal areas around the world pollutes marine environment and eventually gives detrimental effects to human beings via the trophic transfer phenomenon (Agamuthu et al., 2019). The negative impact of marine debris is becoming more serious, drawing global attention and posing a threat to the sustainability of humanity (Sharma et al., 2024). Plastic, one of the main components of marine debris, was produced at around 390 million tons in 2022, which is much higher than the 230 million tons produced in 2009(Plastics Europe, 2019, 2022). Most plastic-based products are disposed of as landfill or recycling. Each year, however, an increasing number of plastics are flowing into the ocean due to illegal dumping, littering, or insufficient waste management infrastructure (Hopewell et al., 2009; Barnes et al., 2009; Lee et al., 2013). Moreover, other types of marine debris such as wood, bottles, papers, styrofoam, and vinyl are also increasing.

Rivers, streams, and tributaries are major pathways for land-based debris, which account for 80% of the total marine debris (Jambeck et al., 2015). Rivers transport 5.8 million tons of plastic waste annually, with 1000 small urban rivers responsible for 80% of ocean-bound plastic pollution (UNEP, 2025). While 19–23 million tons of plastic enter aquatic environments each year, much of it remains trapped in river systems (UNEP, 2025). Floating barriers can intercept trash from rivers, stopping it before it reaches the ocean. By collecting debris early, these barriers make removal less costly and more efficient than if the trash were to drift further downstream or into the ocean. To block the most of floating marine debris, floating barriers can be installed at riversides or tributaries. Floating marine debris is collected at the upstream side of a floating barrier before it is collected and processed by a responsible governmental agency. An important issue to manage the water infrastructure is to monitor the quantity of collected floating debris, as the barrier could break due to the excessive load. Therefore, it is crucial to empty the floating barrier in a timely manner. However, it is not trivial to timely monitor and collect floating debris as floating barriers are widely distributed along the streams of rivers. Therefore, it entails a lot

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of costs and time to manage floating barriers and process the collected water trash. There have been attempts to create a systematic strategy for collecting urban waste on land. However, to the best of the authors' knowledge, there has been no research on developing an appropriate framework for collecting water trash over a wide area, such as along the streams of rivers. Moreover, no cost-benefit analysis has been conducted on the collection of water trash from widely spread floating barriers in previous research. Consequently, the current administrators of floating barriers rely solely on their personal experience to determine the collection plan, which could be costly and inefficient. This is a critical knowledge gap that hinders the implementation of floating barriers to prevent ocean pollution.

To fill this knowledge gap, this experiment proposes a cost-efficient framework for processing water trash accumulated at floating barriers and assesses its economic advantages compared to conventional time-based collection methods. The proposed framework consists of three key components: trash detection, trash valuation, and trash processing cost estimation. Firstly, the trash detection step utilizes an object detection model, YOLOv7, to identify each type of piece of trash in images. Second, the trash process cost valuation step calculates the cost of collection the trash on the floating barriers through a quantity-weight conversion process based on statistical data about marine debris in South Korea. Lastly, the trash processing cost estimation step simulates the total cost by finding an optimal path to collect trash through combining dynamic programming and heuristic approaches. The primary research question of this study is: Does the proposed framework offer a greater economic advantage than the conventional time-based collection method, and to what extent does it improve cost efficiency? The experimental results demonstrate the effectiveness of the proposed method compared to the traditional approach. The main contributions of this study are as follows:

- Presenting a novel cost estimation framework for processing water trash using trash valuation with Monte Carlo Simulation.
- Providing cost estimations for processing trash at floating barriers under different conditions and strategies.
- Presenting a novel water trash processing strategy integrating water trash detection and path finding to process accumulated water trash at floating barriers, using vision-based object detection and optimization methods.
- Demonstrating the benefits of the novel water trash processing strategy to reduce the total costs for operating and maintaining floating barriers compared with the current practice.

The initial idea of this research was presented in our previous publications (Kim et al., 2024a; Kim et al., 2024b). Compared to those publications, this paper significantly enhances the content, proposes more advanced methodologies, conducts rigorous experiments and simulations, and provides a thorough discussion for academic rigor.

2. Related work

2.1. Water trash monitoring

Trash classification plays a crucial role in vision-based trash monitoring because it helps to identify different types and sources of trash, prioritize cleanup efforts, and monitor the effectiveness of trash management strategies. In the field of construction site monitoring, Davis et al. (2021) utilized a deep convolutional neural network to classify construction site trash into seven categories. Similarly, in the context of water trash, Marin et al. (2021) identified six categories of water trash in the Adriatic Sea, including rubber, plastic, metal, glass, other trash, and no trash. Similarly, Wolf et al. (2020) employed image analysis techniques to classify six types of floating debris as water, vegetation, sand, litter-high, litter-low, and others. Jang et al. (2014) used six categories of water waste, such as hard plastic, film, fiber (fabric), styrofoam, other foamed, and other polymer. Panwar et al. (2020) employed a deep learning model to automate the detection of waste in water bodies and classify them into four categories such as glass, metal, paper, and plastic. Likewise, the previous studies defined different numbers of water trash categories for monitoring. Considering the types of water trash commonly found in the target monitoring area, this study defines six categories of floating trash: plastic, vinyl, styrofoam, paper, bottles, and wood.

2.2. Object detection

Object detection algorithms are widely used for localizing and categorizing objects of interest in the form of bounding boxes in images, with the YOLO series being the most popular models in civil engineering (Marin et al., 2021; Wolf et al., 2020; Jang et al., 2014; Panwar et al., 2020; Chern et al., 2023). For instance, YOLOv5 has been adapted to detect personal protective equipment like hooks and helmets in the context of worker safety at construction sites (Chern et al., 2023). Additionally, YOLOv5 has been used to enhance the sorting accuracy of recycling at construction sites in China (Zhou et al., 2023). YOLOv7 which is more advanced architecture than YOLOv5 (Wang et al., 2023) is a novel one-stage object detection algorithm and is now being actively applied to various applications and research. For example, YOLOv7 has been used to rebuild 3D shapes of buildings by detecting and classifying their rooflines from 2D maps with satellite images (Barranquero et al., 2023). It has also been used to detect potholes on roads using a smartphone, providing useful information for road maintenance (Reddy and V, 2022). These studies demonstrate the benefits of applying novel object detection models in the civil infrastructure domain. Inspired by the previous studies, this study also adopts YOLO models to detect water trash by each category in images.

2.3. Remote weight estimation

Accurately estimating the weight of each type of accumulated water trash on floating barriers is essential for calculating processing costs, identifying benefits of recycling, and optimizing the collection pathway to minimize these costs. However, estimating the weight of each type of trash can be challenging due to the following reasons. First, the composition of floating trash can vary, with different types of waste having different densities and water absorption properties. Second, the location of floating barriers and the waterway can be remote, making it challenging to access and carry out weight measurements. Third, manual weight measurements can be costly and time-consuming, particularly if the collection site is remote and requires specialized equipment for weight measurements.

Previous studies suggested non-contact weight measurement methods which can address the challenges in the weight estimation. For instance, Ly et al. (2020) proposed a non-contact approach to estimate human body weight by measuring volume and multiplying it by the average density factor. Yu et al. (2022) developed a non-contact weight estimation system using instance segmentation based on a computer vision algorithm that recognizes the perimeter of fishes and estimates their weight. These studies use statistical relationships between appearance and weight to enable non-contact weight estimation techniques. Inspired by the previous approaches, this study estimates the weight of water trash by recognizing the regions of water trash in images, counting the number of each trash units, and multiplying weight conversion factors.

2.4. Multi-dimensional scaling

A transportation cost for collecting water trash is significant considering the large number of floating barriers and their locations. To estimate it, one cycle of collecting water trash with a collection vehicle should be predicted based on the selected nodes (locations of floating barriers and a water trash processing facility) to be visited. Nodes are selected based on their proximity and accumulated trash amounts to minimize the traveling cost. Euclidean distance between original nodes' coordinates is unrealistic as it does not consider actual road networks. To consider existing road networks to reflect realistic proximity between nodes, Multi-Dimensional Scaling (MDS) techniques can be employed to represent nodes based on the actual proximity considering existing road networks and select nodes to visit using clustering algorithms.

MDS is a mathematical technique for representing high-dimensional data in two dimensions, which is primarily used for visualizing complex data (Torgerson, 1958). MDS is largely divided into Metric MDS which uses Euclidean distance as a measure of similarity between data (Martinez et al., 2017), and Nonmetric MDS which uses non-Euclidean distance measures. That is, Metric MDS can measure Euclidean distance between floating barriers in actual road networks. It is primarily used for tasks that involve adjusting the locations of nodes based on the actual proximity, which are dimensionally complex (Kruskal and Wish, 1978).

Utilizing Metric MDS simplifies clustering among adjacent nodes, even in scenarios such as pathfinding problems where there are differences between the straight-line distance and the actual path distance between nodes. Shang and Ruml (2004) proposed the Multi-Dimensional Scaling MAPping using Patch (MDS-MAP(P)) technique for determining locations using signals instead of Global Positioning System (GPS) when the distance between any two signal devices is nonlinear. Similarly, Wang et al. (2019) adopted the MDS method to determine the installation locations of sensors in wireless sensor networks, considering network shadow areas. Both calculated the 2D locations of sensors from distance matrices, such as signal strength information between wireless sensors, which are not straight-line distances.

In most cases, the locations of floating barriers and water trash processing facilities (nodes) are connected by road networks that are not straight. Therefore, this study adopts Metric MDS to represent the locations of nodes considering the actual path distances. Clustering is conducted on this adjusted node distribution to calculate the traveling cost of a processing vehicle.

2.5. Vehicle routing

Finding an optimal trash collection route is important to efficiently process water trash at floating barriers. To this end, vehicle routing algorithms can be utilized. Previous studies proposed various approaches to find the optimal routes for their problem. For example, the traveling salesman problem (TSP) (Jünger et al., 1995)—which is a well-known optimization problem that seeks to find the shortest possible route that a salesman can take to visit a given set of cities exactly once and return to the starting node—is particularly relevant to the context of water trash collection. Since TSP is a well-known NP-hard combinatorial optimization problem, alternative approaches were proposed to solve the problem in finite time (Razali and Geraghty, 2011).

Cheikhrouhou and Khoufi (2021) argued that the routing approaches should vary by the types of vehicles (e.g., ground vehicles or unmanned aerial vehicles). For ground vehicles, there are three main ways to solve vehicle routing such as (1) deterministic, (2) metaheuristic-based, and (3) market-based approaches. Deterministic approaches in vehicle routing optimization offer several advantages, including guaranteed solution quality, faster computation times, deterministic convergence, easier implementation and interpretation, and reduced computational complexity. For example, Vali and Salimifard (2017) proposed a routing method using constraint programming, a subtype of deterministic approaches, which took over two hours to yield an optimal visit route between 51 cities with three salesmen. Metaheuristic-based approaches are optimization methods that use high-level strategies to find approximate solutions to complex optimization problems. The metaheuristic-based approaches mostly consist of a genetic algorithm and swarm intelligence such as ant colony optimization, particle swarm optimization, and artificial bee colony algorithm. While these techniques do not guarantee a true global optimized solution, many studies have shown that the results are reasonable to use (Venkatesh and Singh, 2015; Lu and Yue, 2019; Xu et al., 2008; Wei et al., 2020; Zhou et al., 2018). Market-based approaches in vehicle routing involve the use of market mechanisms to allocate transportation resources such as vehicles and routes to customers, with the goal of optimizing overall system efficiency and reducing transportation costs (Sariel et al., 2007). That is, it involves modeling vehicles as buyers and collection sites as sellers, assigning a cost to each site, and having vehicles choose the sites with the lowest cost to visit first. Duan et al. (2021) proposed an optimal vessel route using a hybrid heuristic approach for debris vessels operating in the ocean and achieved a 6.38% cost reduction.

In this study, the optimal route for water trash collection is predicted by combining dynamic programming (Bouman et al., 2018) and 2-opt (Croes, 1958). Dynamic programming is categorized as a deterministic approach, while 2-opt is classified as a heuristic approach that falls under the category of local search methods, which are considered non-deterministic. Using dynamic programming and 2-opt in water trash collection vehicle routing can provide benefits such as obtaining an optimal solution, faster computation, and robustness. Dynamic programming can ensure the best possible solution, while 2-opt can iteratively reduce the overall distance. Dynamic programming involves breaking down a problem into smaller subproblems and solving them in a recursive manner to obtain the optimal solution, while 2-opt is a local search algorithm that iteratively improves a given solution by swapping two edges to reduce the overall distance. The integration of dynamic programming and 2-opt requires fewer iterations, and is less computationally intensive.

2.6. Monte Carlo simulation

There are various factors related to costs of processing water trashes, such as a distance between a floating barrier to a disposal site, a trash accumulation speed, amounts of water trash, and etc. Each variable is not a constant, rather a value determined by probabilistic distributions. Therefore, it is not a trivial task to estimate the water trash processing cost in a deterministic way. Monte Carlo Simulation (MCS) is a widely used computational technique to simulate the randomness of variables that arise from uncertainties. Due to the complexity of calculating the probability of an event in a real-world system, researchers have employed simulations using random sampling of variables based on probability density functions during the MCS process to draw reliable conclusions (Harrison, 2010).

To name a few studies, Lin et al. (2021) used the MCS to generate sample datasets with a normal distribution to address the uncertainties of soil property data collected from an excavation site. Similarly, Xie et al. (2022) considered the randomness of soil properties, such as cohesion and sensed data from Random Field (RF) sensors attached to the soil wall, to determine the maximum ground surface settlement and wall deflection at a subway station excavation field using the MCS. Shi et al. (2020) proposed a novel construction planning scheme that utilized the Monte-Carlo Tree Search algorithm to divide a rectangular floor. Rausch et al. (2019) developed a tolerance simulation system for prefabrication and offsite construction using the MCS to account for the manufacturing error of each member as a repeated random variable, which could induce assembly problems. These studies demonstrate the applicability of MCS in construction fields with acceptable reliability. Furthermore, Xu et al. (2020) used the MCS to perform an adaptive optimal energy demand limiting strategy, considering the exploration-exploitation tradeoff, which is related to the information acceptance rate between predicted and actual loads. Arnold and Yildiz (2015) and Naderpour et al. (2019) analyzed the economic feasibility of infrastructure construction projects using the MCS approach to consider the risk derived from financial uncertainty. These studies highlight the

Fig. 1. A floating barrier on the river to collect plastic waste and debris, preventing pollution from spreading downstream.

scalability of the MCS approach, making it a valuable tool for a wide range of applications, simulating and analyzing complex systems with inherent randomness and uncertainty. However, there have been no attempt to utilize MCS or similar approaches to estimate water trash processing costs. This lack of knowledge hinders a decision on the implementation of floating barriers, as the cost projection is critical for establishing viable budget plans for municipalities.

2.7. Knowledge gap

While the previous studies have made significant strides in water trash monitoring, object detection, remote weight estimation, vehicle routing for trash collection, and optimization with MCS, a knowledge gap still exists in estimating water trash processing costs and the integration of these methodologies for automated water trash collection and processing. Most existing work has focused on detecting floating trash on the water rather than on floating barriers, where trash actually accumulates. Additionally, current detection models have not been fully incorporated into the maintenance workflows of these barriers, limiting practical applicability. Furthermore, little attention has been paid to the financial feasibility of trash collection in river tributaries, leaving a significant void in the literature regarding cost assessment. Critically, no prior research has proposed a comprehensive end-to-end framework that seamlessly connects trash detection, valuation, route optimization, and overall collection. As a result, current administrators of floating barriers depend on their personal experiences, leading to suboptimal decisions in the collection and processing of water trash.

This knowledge gap emphasizes the significance of the research problem to be addressed in this study, which is to develop an integrated framework that automates water trash detection, valuation, and collection planning in water infrastructure. In addition, the framework estimates the expected costs associated with collection routes. This study represents the first attempt to analyze the anticipated economic benefits of applying state-of-the-art deep learning techniques to the maintenance of floating barriers. By bridging this gap, the study aims to provide a systematic and data-driven approach to improve the overall efficiency of water trash management in water infrastructure. Fig. 1

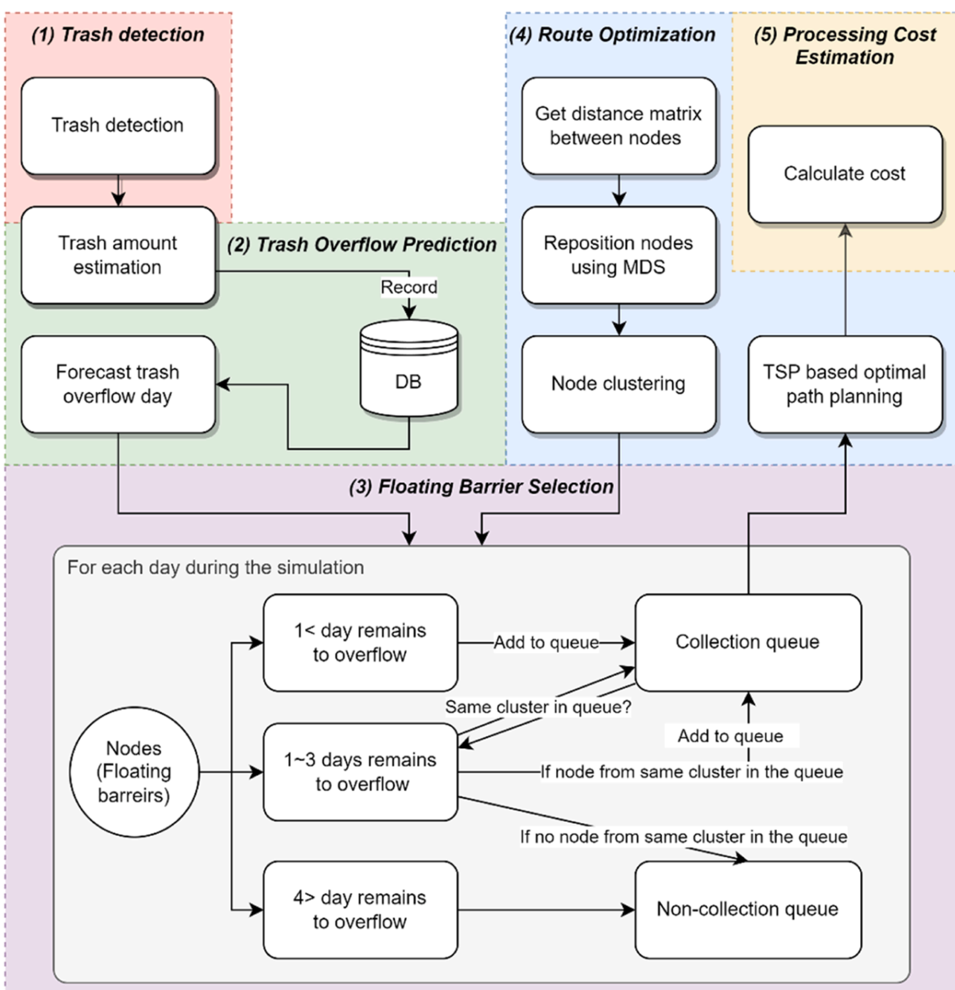

Fig. 2. Overview of the adaptive water trash collection strategy.

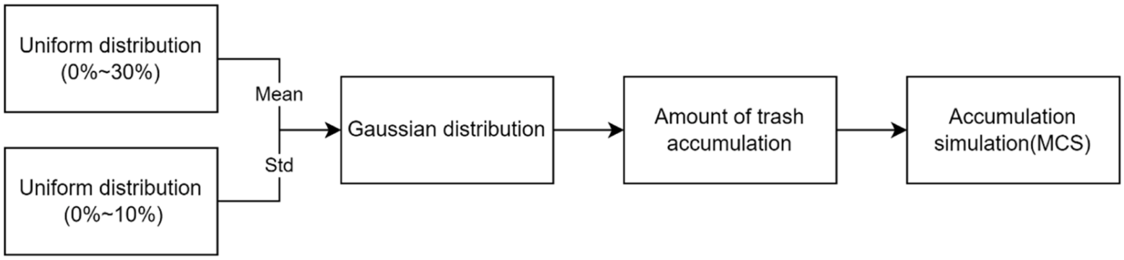

Fig. 3. Prediction process of a trash accumulation speed at a floating barrier using MCS. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3. Adaptive water trash collection strategy

The proposed adaptive water trash collection strategy optimizes the allocation of collection vehicles to floating barriers based on real-time trash accumulation, as illustrated in Fig. 2. Unlike traditional methods that rely on pre-determined time intervals or civil complaints to dispatch collection vehicles, this strategy dynamically responds to actual trash accumulation levels. By ensuring timely collection, the proposed approach minimizes water trash processing costs and protects the functionality of floating barriers by preventing excessive accumulation. This strategy consists of five key steps that enable adaptive collection and cost estimation:

- Trash Detection – Detects accumulated water trash at floating barriers and estimates its volume.
- Trash Overflow Prediction – Predicts when the trash will exceed a floating barrier's capacity based on the current accumulation rate.
- Floating Barrier Selection – Identifies which floating barriers should be prioritized for collection, considering actual travel distances.
- Route Optimization – Determines the most efficient collection route by clustering selected floating barriers to minimize travel distance.
- Processing Cost Estimation – Calculates total processing costs based on travel distance and the rental cost of the collection vehicle.

By integrating these steps, the proposed method optimizes collection efficiency, reduces operational costs, and prevents floating barriers from becoming overloaded, ensuring their sustained effectiveness in water trash management.

3.1. Trash detection

Water trash detection is a crucial step for the automated management of floating barriers, to identify water trash by its type, such as plastic, vinyl, styrofoam, paper, bottles, and wood in images. The detection results are used to estimate the amount of water trash in each category. To achieve this purpose, a deep learning-based computer vision model, YOLOv7, is employed. YOLOv7 (You Only Look Once version 7) (Wang et al., 2023) is one of the most advanced real-time object detection models available today, exhibiting impressive accuracy in localizing and classifying objects within images.

Many variants of YOLOv7 exist with different hyperparameters, which result in different performance and computational efficiency. Generally, an increase in the depth of layers in deep learning models typically boosts performance but also increases computational demands, often slowing processing speed. YOLOv7, however, strategically navigates this trade-off. While YOLOv7 employs a complex structure during training to identify intricate patterns in images, its 'Bags of freebies' technique during inference ensures both high performance and rapid processing speed. This distinctive approach optimizes the balance between model complexity and computational efficiency, making YOLOv7 an ideal choice for real-world applications requiring both precision and speed. For this reason, the YOLOv7x model was finally selected for water trash detection.

3.2. Trash overflow prediction

It is assumed that trash accumulates daily at each floating barrier, and this daily accumulation is modeled with a Gaussian distribution. The accumulation rate differs for each barrier because it is significantly affected by site-specific upstream conditions, resulting in unique accumulation characteristics at each barrier. To reflect these variations, the mean and standard deviation of the Gaussian distribution are not fixed to all the floating barriers as same; instead, they are drawn as random values following uniform distributions within a specified range that captures the typical conditions of each floating barrier's location.

MCS is used to account for the multi-level variability and uncertainty in trash accumulation rates due to different barrier locations and temporal environmental changes, as illustrated in Fig. 3. In this two-step

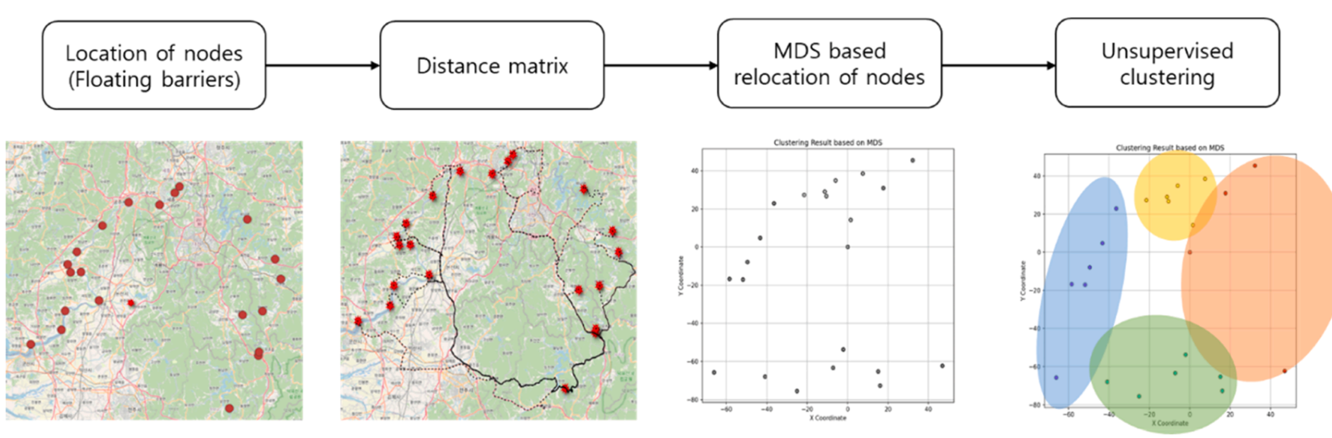

Fig. 4. Floating barrier (node) selection and clustering with Multi-Dimensional Scaling (MDS).

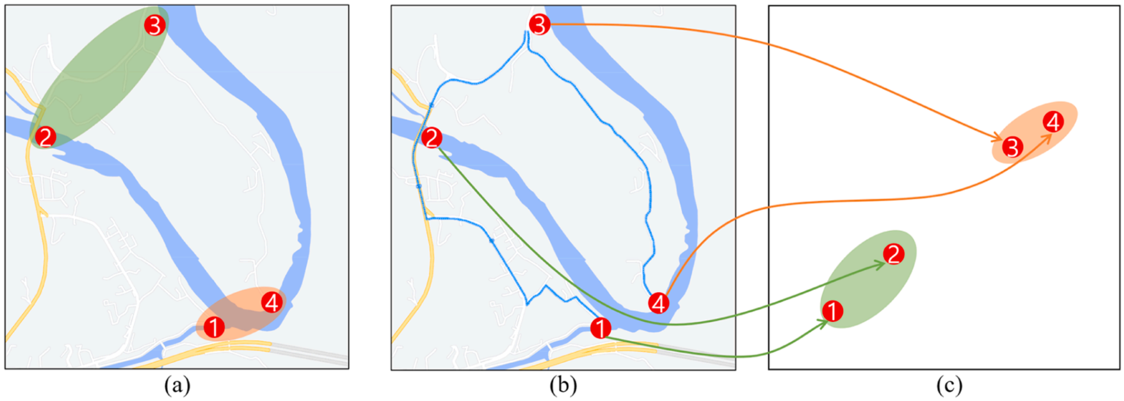

Fig. 5. Visualization of MDS process. (a) Euclidian clustered nodes. (b) Actual road network with blue line. (c) Node repositioning with MDS and clustered nodes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

approach, the mean and standard deviation of the Gaussian distribution for each barrier are sampled from uniform distributions to represent the barrier-specific and relatively constant upstream influences. Then, using these sampled parameters, daily fluctuations in trash accumulation are simulated multiple times for each barrier, producing possible daily accumulation patterns.

Each node (a floating barrier) has a recorded history of trash accumulation, and this information is utilized to predict the trash overflow (saturation) timing using linear regression. The trash overflow timing, when the accumulated trash reaches a full capacity of a floating barrier ($y = 100\%$), is predicted based on a trash accumulation speed that is derived from the past three days. After the trash collection, a trash accumulation amount, y, is set to 0.

3.4. Floating barrier selection

Generally, a crane truck for trash collection can visit a limited number of floating barriers in a day due to its loading capacity and traveling time. Therefore, it is efficient to visit adjacent floating barriers that need to be emptied to reduce the processing cost. The floating barrier selection and clustering process is illustrated in Fig. 4. Firstly, the locations of floating barriers and a trash processing facility are determined to be represented as nodes. The nodes are stored as a shapefile of a geographic information system program such as Q-GIS.

3.4.1. Determination of a distance matrix with node-to-node path finding

For route optimization, a distance matrix, which has traveling distances between nodes, should be prepared. In this study, the traveling distances between nodes are obtained using Naver Maps API (NAVERCLOUD PLATFORM, 2023). The distance matrix for MDS requires the traveling distance between two locations. The optimal routes of traveling from node A to B and from node B to A could be different depending on traffics conditions or road networks. Therefore, an average of the round-trip distance is used as the traveling distance.

3.4.2. Node repositioning with MDS

To group adjacent floating barriers into a single cluster, their node locations are rearranged using a MDS algorithm. The reason for conducting MDS is that the Euclidean distance between the nodes is frequently not same as the actual traveling distance, leading to unrealistic situations such as an example shown in Fig. 5. Circles labeled as 1, 2, 3, and 4 represent nodes (floating barrier or a trash processing facility). Due to the obstacles, the distance between nodes 1 and 4 is the farthest. However, if the Euclidean distance is used, nodes 1 and 4 could be clustered together due to the mis-calculated Euclidean distance without considering the obstacles as shown in Fig. 5. (a, b). After MDS, the node arrangement would look like Fig. 5. (c). As a result, nodes 1 and

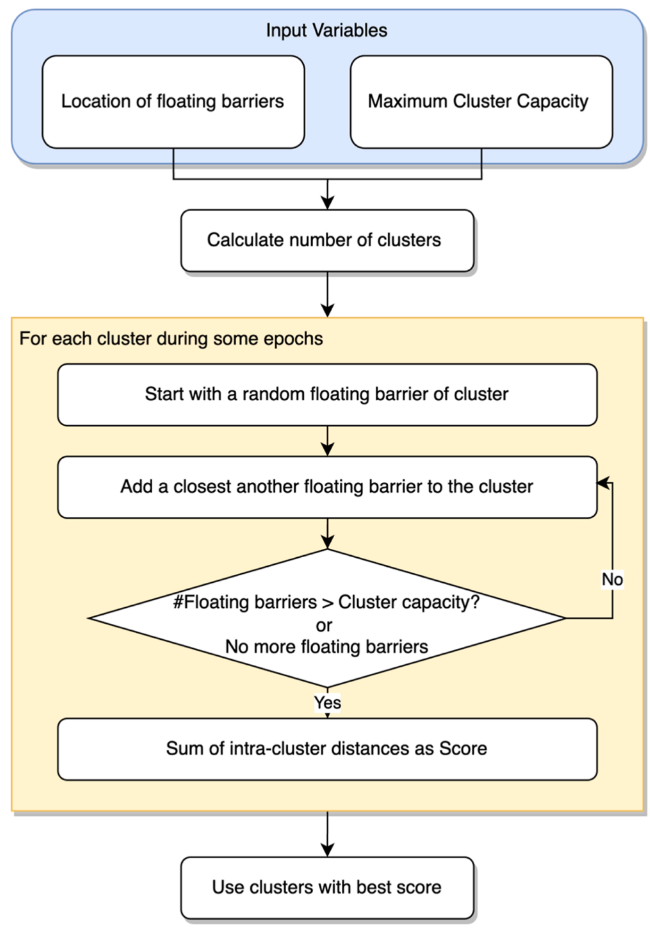

Fig. 6. Greedy clustering flowchart for floating barriers to be emptied.

4 would not be grouped together. In this way, clustering can consider an actual road network topology.

3.4.3. Greedy clustering for floating barriers

A greedy clustering algorithm is a method for grouping floating barriers, with the process comprising initialization, cluster formation, repetition, and termination. It operates by iteratively adding floating barriers to a cluster based on a similarity measure until no further floating barrier meet the specified criterion, thereafter, proceeding to form new clusters with the remaining floating barriers. As shown in Fig. 6, the greedy clustering technique starts with a random floating

Table 1
Variables for cost calculation.

	Variable	Value
Crane truck with 2 workers	Gas fee (Diesel)	1.5$/litter
	Fuel efficiency of a crane truck	2 km/litter
	Average speed of a crane truck	30 km/hour
	Operation cost	60$/hour
25t dump truck	Rental cost of 25-ton capacity dump truck	600$/EA

barrier and make it an initial cluster center. Then, the closest another floating barrier to the initial floating barrier is added to that clusters, and this repeats until either the pre-set maximum cluster size is reached or there are no remaining floating barriers. Once the addition of floating barriers for each cluster is complete, the distances between floating barriers within the cluster are measured. This measurement serves as a quantitative metric for the cluster. Depending on a pre-determined number of iterations, this clustering process is continuously repeated. The clustering result with the smallest score is finally used.

3.5. Route optimization

As the cost of collecting water trash at floating barriers can be large according to the number of floating barriers and traveling distances, it is crucial to find the optimal traveling path of a processing machine such as a crane truck. This study explores path optimization algorithms, specifically focusing on dynamic programming and the 2-opt technique. Dynamic programming is a method for efficiently solving a broad range of search and optimization problems which exhibit the property of overlapping subproblems. It systematically breaks the problem into smaller, more manageable subproblems, solves each subproblem just once, and stores its solution for future reference. On the other hand, the 2-opt algorithm is a simple and effective local search method for solving the traveling salesman problem and related network optimization issues; it works by iteratively removing two edges from the tour and reconnecting the paths in a different way to yield a shorter tour. In the context of this study, which aims to develop a shortest path for collecting water trash at floating barriers, dynamic programming is employed when the number of locations of these barriers is less than 17. However, considering the computational burden associated with dynamic programming—which grows exponentially with the number of locations—the 2-opt algorithm is used when the number of barrier locations is equal to or greater than 17.

3.6. Processing cost calculation

The standard practice in South Korea for collecting floating trash from water surfaces involves a crane truck with two workers(KOEM, 2023). This study calculates the total processing cost by estimating both equipment rental and labor costs. It assumes the use of a typical dump truck with a dump capacity of 25 tons and a truck-mounted crane capable of lifting 2 tons(KOEM, 2023). A single crane truck can process approximately six floating barriers per day, based on the data from (KOEM, 2023)and considering the labor hours (with a maximum of 52 working hours per week in South Korea). Assuming each floating barrier accumulates 12.5 tons of trash, it is estimated to take about an hour to collect water trash at a floating barrier. Additionally, if the average travel distance and time to each barrier are estimated to be around 30 min, a single crane truck can service up to six barriers in a day.

Fig. 7. Locations of floating barriers (dots) in the Geum River and a trash processing facility (a red star). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

The price for cost calculation is shown in the Table 1. The crane truck costs about $60(USD) per hour, including labor, and renting a 25-ton truck costs about $600 per day, according to 2023 market survey by this research team in South Korea. The cost for operating a crane truck was determined using standard price data from the Korea Hydraulic Machinery Association(Ganacranes Rental Rates, 2023). These prices may vary by on-site access conditions, location, and the task's difficulty level at each site. A 2-ton crane truck has a monthly rental fee of 12 million KRW, which translates to 400,000 KRW (approximately $307 per day. Given six collection trips per day, the cost per trip is 66,000 KRW (approximately $50). Factoring in additional operational costs (labor, maintenance), this rounds off to $60 per trip. The cost for renting a 25-ton truck was referenced from the Korean Specialty Construction Association's 2023 first half standard labor rate and construction machinery hourly usage fee(Korea Specialty Contractors Association Jeju Special Self-Governing Province Chapter, 2023). A 25-ton dump truck costs 139,543 KRW (approximately $103) per hour, totaling approximately 1116,344 KRW (approximately $827) for an 8-hour day. However, considering it takes about 5–6 h, including breaks, to collect waste from 2 to 3 barriers and transport it back to the waste processing facility, the rental price for one truck was set at $600 per day.

The travel costs are calculated using Eq. (1). The diesel price is set at $1.5 per liter (as of March 4th week of 2024), reflecting the average price of South Korea and Germany(Find Cheap Gas Stations Opinet, 2023). For a maintenance vehicle, typically a truck with a 2-ton capacity, the assumed fuel efficiency is 2 kilometers per liter. The total cost is subsequently determined using Eq. (2)

$$\textit{Traveling cost} = \frac{\textit{Gas fee}(USD)}{\textit{Fuel efficiency of a maintenance car}(USD/km)} \tag{1}$$

$$\begin{aligned} &\textit{Totalcost} = \\ &(\textit{NumberofNodesVisited}(EA)) * (\textit{CraneOperatingCostperHour}(\textit{USD per hour})) * (\textit{CraneOperatingEfficient}(\textit{Hours per EA})) \\ &+(\textit{TotalTravelDistance}(km)) * (\textit{TruckOperatingCostperDistance}(\textit{USD per km})) \\ &+ (\textit{Required Number of Dump Trucks}(EA)) \ * \ (\textit{Dump Truck Rental Cost}(\textit{USD per EA per day})) \end{aligned} \tag{2}$$

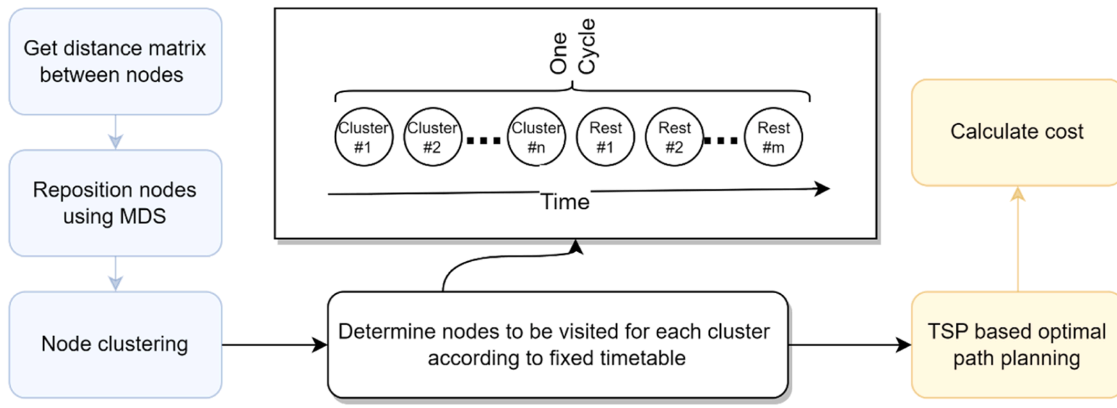

Fig. 8. Flowchart of traditional time-based route planning for water trash collection.

4. Case study: water trash processing cost simulation

In a case study, two collection strategies—the adaptive water trash collection strategy and the traditional time-based water trash collection strategy—were compared. This study considers a virtual scenario that the Geum River has floating barriers for cost simulation. MCS was employed to make an accurate comparison between the collection strategies. This allows for a more objective comparison between the two strategies by considering uncertainties using probability distributions, such as different trash accumulation rates at each floating barrier.

4.1. Case study region

The proposed strategy was applied to the Geum River basin, located in North Jeolla Province in South Korea. The Geum River is one of the six major national rivers in Korea. When combining all the river systems in the Geum River basin, it spans 3739.59 km, with the main course being 397.79 km long, and it encompasses a massive river system with 468 tributaries (Korea River Association, 2023). For the cost simulation, this study selected locations where the river width is less than 50 m, suitable for the installation of floating barriers, as illustrated in Fig. 7.

4.2. Case study settings

All simulations were conducted using a desktop equipped with an AMD Ryzen 7 5800X processor, 64GB of RAM, and an NVIDIA GeForce RTX 3090 GPU operated on Ubuntu 18.04 LTS. All algorithms ran in Python, utilizing libraries including NumPy, SciPy, Matplotlib, PyTorch, and Sklearn. Variables such as fuel costs, travel distances, fuel efficiencies, amounts of collected water trash, rental costs of trash collection vehicles, hourly crane rental costs, and the average travel speed were considered as independent variables of MCS to estimate the total cost of water trash processing.

4.3. Control group: time-based water trash collection route planning

The traditional method of water trash collection route planning operates on a fixed time schedule as illustrated in Fig. 8. Firstly, floating

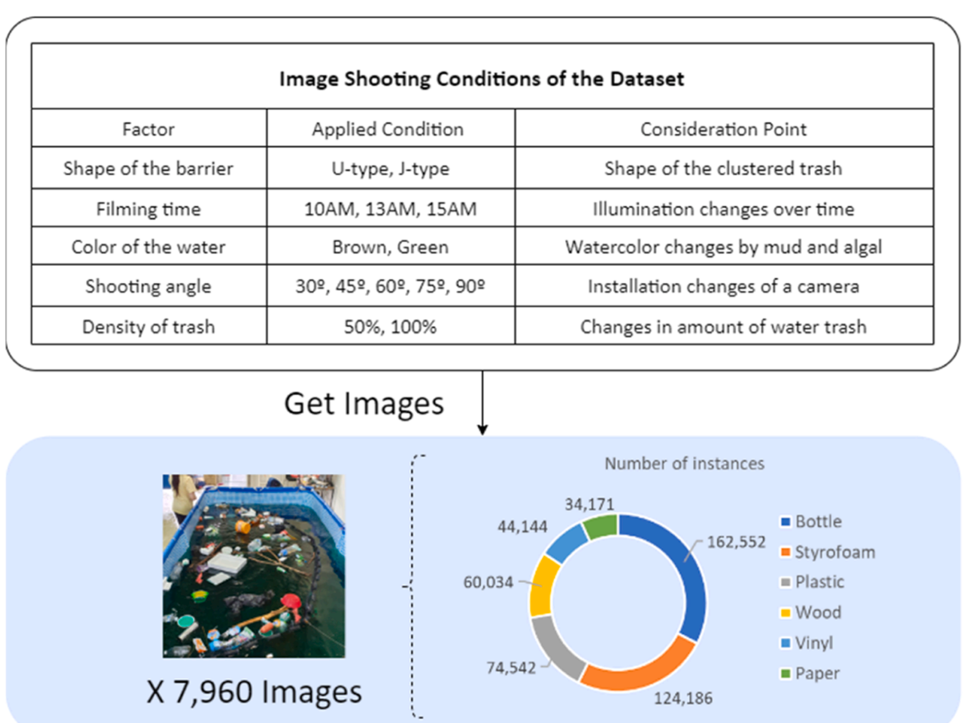
Image Shooting Conditions of the Dataset

Factor	Applied Condition	Consideration Point
Shape of the barrier	U-type, J-type	Shape of the clustered trash
Filming time	10AM, 13AM, 15AM	Illumination changes over time
Color of the water	Brown, Green	Watercolor changes by mud and algal
Shooting angle	30º, 45º, 60º, 75º, 90º	Installation changes of a camera
Density of trash	50%, 100%	Changes in amount of water trash

Fig. 9. Imaging conditions to construct a water trash dataset and the instance statistics.

Table 2
Applied augmentation techniques and hyperparameters.

Image Augmentation Parameters		Hyperparameter for Training	
Types	Value	Variables	Value
Hue	0.015	Initial learning rate	0.01
Saturation	0.7	Final learning rate	0.001
Value	0.4	Momentum	0.937
Degrees	5.0	Weight decay	0.0005
Flip up-down	0.3	Focal loss gamma	1.5
Flip left-right	0.5	Warmup epochs	3
Mosaic	1.0	IoU threshold	0.2
Paste in	0.15	Anchor threshold	4.0

barriers to be visited are determined as nodes and the distances between these nodes are calculated. A route-finding API by Naver was utilized to create the distance matrix which contains distance information between nodes (NAVERCLOUD PLATFORM, 2023). The locations of the nodes are adjusted using MDS considering the actual path distance between them. Subsequently, nodes are clustered using the greedy clustering method based on their distances, grouping nearby nodes together. Once clustered, groups are visited sequentially according to a predetermined timetable for collection which contains the garbage collection scheduling information. Each cycle includes a sequence of group visits and rest days. If there are n groups and m rest days, a cycle takes $m + n$ days, and one group is visited per day. Thus, a floating barrier visits once every $m + n$ days. This interval is referred to as the 'cycle'. For instance, if the cycle is 5 days, it means the trash is collected once every 5 days. Once the visiting group order is determined, the shortest path is calculated using the TSP method. Floating trash is collected following this path, and costs are calculated accordingly. The cost calculation is conducted using Eq. (2).

4.4. Water trash image dataset

Since no public dataset currently exists for detecting floating water trash in rivers and streams, a new water trash dataset was collected from an experimental floating barrier site in Incheon, South Korea to test the feasibility of employing deep learning-based object detection models. The dataset was introduced in details in the authors' previous conference paper (Kim et al., 2024a). Images were captured under 120 different environmental conditions reflecting five factors: the shape of the floating barrier, filming time, water color, shooting angle, and trash density. (see Fig. 9 for details). The images were captured in the RGB format with a resolution of 3024 by 3024 pixels. The dataset consists of 7960 images labeled with six classification categories (plastic, vinyl, styrofoam, paper, bottle, and wood) in the form of bounding boxes to train the YOLOv7x algorithm. In total, the dataset contains 162,552 bottles, 124,186 styrofoam items, 74,542 pieces of plastic, 60,034 items of wood, 44,144 vinyl items, and 34,171 pieces of paper.

4.5. Training detection model

The dataset was divided into training, validation, and testing sets with an 8:1:1 ratio. During the training process, the stochastic gradient descent (SGD) algorithm was used as the optimizer and a cosine annealing strategy was used as the learning rate scheduler. In addition, the model was pre-trained with the MS COCO dataset and transfer learning was applied to fine-tune all weights in the model for ensuring high performance and generalization capability, along with a fast convergence rate. A set of image augmentation techniques and the hyperparameters of YOLOv7x used in the experiments are listed in Table 2.

4.6. Evaluation metrics for the water trash detection model and the trash overflow date prediction model

The mean Average Precision (mAP) was used as a detection performance indicator in identifying floating trash. To compute the Average Precision (AP) score for each class, precision and recall values were calculated at various confidence thresholds, and the area under the precision-recall curve was determined. The true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were determined based on the Intersection over Union (IoU) between the ground truth and predicted bounding boxes for each classification category. The IoU threshold was varied from 0.5 to 0.95 with a step size of 0.05. A detection result was considered as TP if the intersection over union between a predicted bounding box and a ground truth bounding box was greater than the threshold. Recall and precision were then calculated using Eq. (3) and Eq. (4) respectively.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Linear regression was used to predict the trash overflow date. The accuracy of linear regression is typically evaluated by the Mean Square Error (MSE), therefore, it was used as the loss function to train the prediction model. Additionally, R^2, the coefficient of determination, was employed to assess the model's ability to explain the variance in the data. A higher R^2 indicates that the model can better account for the variability observed in the data.

Once the trash overflow date was predicted using the linear regression model, this paper employed a quantitative metric that uses the time difference between the predicted date and the actual trash overflow date, to measure the error. For instance, if the prediction was in 1.3 days and the actual overflow date was in 1 day, the prediction error is calculated as $|1.3–1.0| = 0.3$. If the actual overflow occurred in 2 days, the error is calculated as $|1.3–2.0| = 0.7$.

4.7. Quantity-Weight conversion matrix

It is necessary to estimate the weight of detected water trash as it can be used to estimate the water trash overflow and the timing of floating barrier collapse. Therefore, quantity-weight conversion factors for water trash categories are required. This study referenced these factors for Styrofoam(Appendix 1), wood(Appendix 2), and paper(Appendix 3), and from a national costal trash(National Coastal Trash, Marine Environment Information Portal, 2023). This dataset encompasses water trash related information collected from 2009 to 2017, detailing the count, weight, and volume of marine litter surveyed six times annually. Averages of these metrics (count, weight, volume) were used for analysis. For the remaining categories – plastic(Appendix 4), bottle (Appendix 5), and vinyl(Appendix 6), from Korea standard specifications and design criteria for marine debris cleaning projects(KOEM, 2023) was referenced.

4.8. MCS for water trash processing cost estimation

To compare the adaptive water trash collection strategy and the time-based water trash collection strategy, MCS was utilized. The simulation environment incorporates several assumptions due to a lack of real data and to prevent the simulation from becoming overly complex, focusing solely on comparing the collection strategies. The assumptions were as follows:

EnclosedCircle1 The maximum capacity of a floating barrier is assumed to be 12.5 tons. There are no established references that define a universal maximum capacity for floating

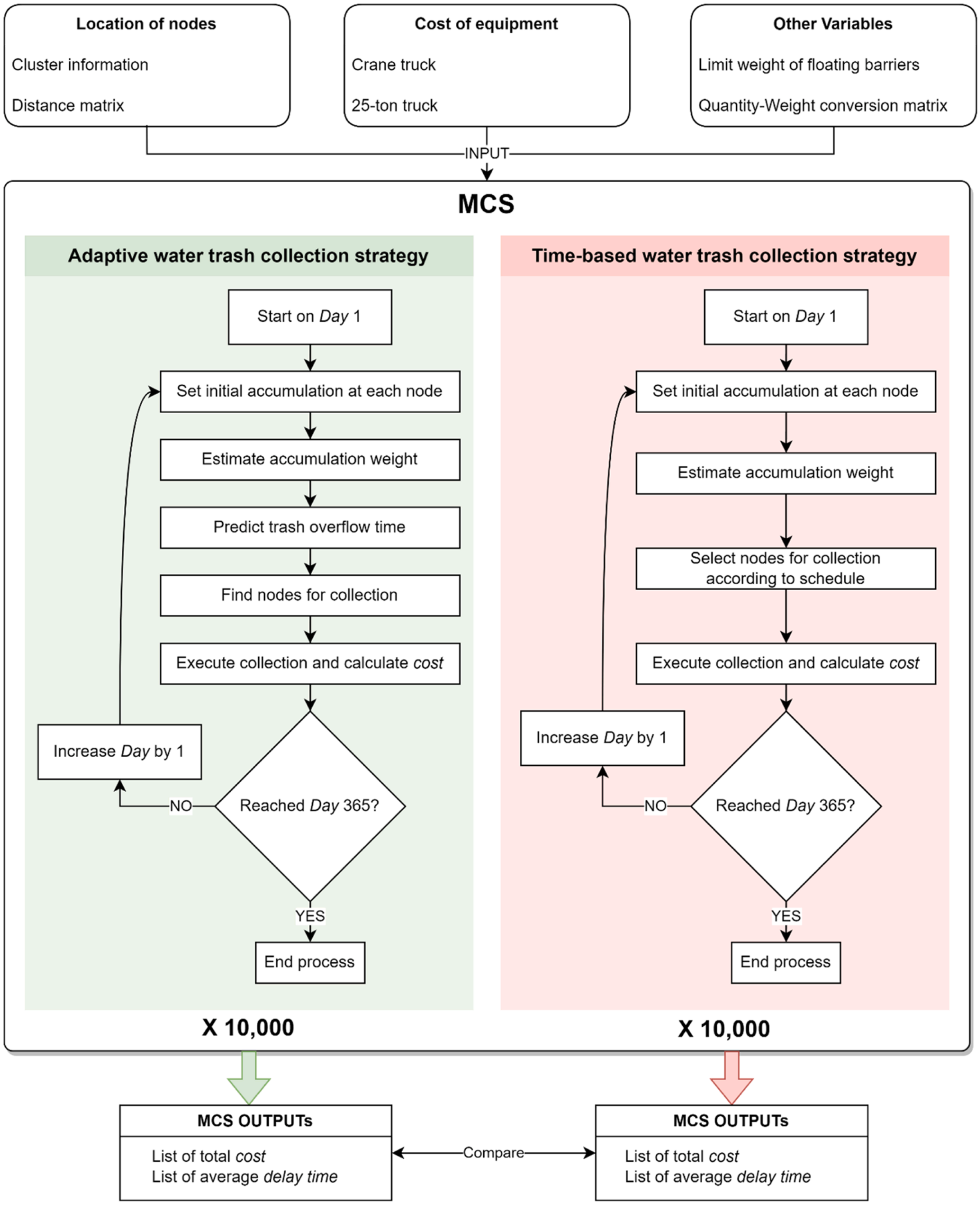

Fig. 10. Flow chart of MCS to compare water trash collection strategies.

barriers. In this study, 12.5 tons is adopted because it represents half the load of a 25-ton truck, thereby allowing efficient single-trip operations. While this serves as a practical starting point for our simulations and cost analyses, the actual capacity may vary depending on the floating barrier's material, design, and environmental conditions.

EnclosedCircle2 A single crane truck can service up to six waste barriers in one day. It is assumed that collecting water trash at a single location requires approximately one hour, with an average travel time of 20 min between locations. Factoring in typical labor law constraints, a single crane truck can service a maximum of six barriers in one day. This assumption is for research purposes and may differ from real-world operating conditions.

EnclosedCircle3 The locations of nodes remain constant throughout the simulation. Each floating barrier is physically fixed at its installation site, so its coordinates do not change during operation.

EnclosedCircle4 The barriers reached the maximum trash accumulation amount must be emptied within one day. Once a barrier is at full capacity, there is one additional day to service it. This approach assumes that most barriers can tolerate a short-term overflow, although the actual safety margin may depend on the specific design.

Table 3
Location of floating barriers in the simulation.

List of Geum River Tributaries	Longitude	Latitude
Guryongcheon	127.5148	35.82777
Jeoksangcheon	127.6269	35.99291
Namdaecheon	127.6287	36.0045
Bonghwangcheon	127.5652	36.1195
Hotancheon	127.6418	36.13175
Chogangcheon	127.7132	36.23188
Bocheongcheon	127.6906	36.29407
Gasancheon	127.5842	36.41819
Samseongcheon	127.3029	36.50041
Daegyocheon	127.2444	36.46253
Jeongancheon	127.1252	36.47102
Eocheon	127.0233	36.3977
Jicheon	126.9251	36.3163
Eunsancheon	126.8899	36.27734
Geumcheon	126.8999	36.2525
Yeomchangcheon	126.9405	36.25381
Nonsancheon	127.01	36.16488
Gilsancheon	126.7462	36.02841
Wonsancheon	126.865	36.07354
Impocheon	126.88	36.1325
Mihocheon	127.3212	36.5201

EnclosedCircle5 Removing water trash at a floating barrier is charged at a fixed rate - 60$/hour.
EnclosedCircle6 The cost calculation follows Eq. (2), excluding other expenses that might incur during the trash processing.
EnclosedCircle7 The amount of trash increases daily at a floating barrier.

If the assumptions change, the collection cycle, collection time, and overall costs would also change, which may lead to different results. For instance, increasing the floating barrier's capacity could reduce how often collections are needed, thereby decreasing operational frequency and cost. Similarly, any changes in labor or equipment rental costs would alter per-hour or per-trip charges, influencing the total cost.

Based on these assumptions, the structure of MCS was defined as illustrated in Fig. 10. Essential inputs for the MCS encompass the geographical locations of nodes, clustering information, a distance matrix, equipment rental costs, the designed capacity of the floating barriers, and the probabilities such as uniform and gaussian distribution (described in Section 3.2) that dictate the rate at which floating water trash accumulates at each node. These input variables were established before executing the simulation to ensure a realistic simulation of water waste collection and processing. The simulation outputs two key metrics: the total cost and the delay in water trash collection.

The locations of the floating barriers are listed in Table 3. These locations were chosen to derive the distance matrix and clustering results. The exact locations of the floating barriers are specified by their longitudinal and latitudinal coordinates. The unit costs associated with processing vehicles are listed in Table 1.

Each simulation in the MCS was set to run over a period of 365 days. During these 365 days, trash accumulated daily followed the probabilities illustrated in Fig. 3. The cost incurred in the process of collecting water trash was summed up as the output of the simulation. During the simulation, delay time was measured. The delay time refers to the time gap between the moment when the floating barrier becomes filled with trash and the actual emptying of the trash. It is calculated and recorded for each simulation to indicate the timeliness of the trash collection strategy in dealing with floating trash at the barriers. This simulation was repeated 10,000 times to obtain 10,000 individual sets of costs and delay times. A frequency analysis was followed among the obtained data.

5. Case study results and discussion

5.1. Water trash detection results

The training process of the detection model was monitored by 10 learning curves in Fig. 11. Each graph shared a common x-axis denoting the number of epochs and a distinct y-axis quantifying various metrics. The curve 'Box' means the box loss, which quantifies the error in the predicted bounding boxes compared to the ground truth. The curve 'Objectness' measured the objectness loss, which evaluates the performance of the model to distinguish between the presence of an object versus background or no object. The curve 'Classification' depicts classification loss, representing the model's errors in categorizing the objects within the bounding boxes.

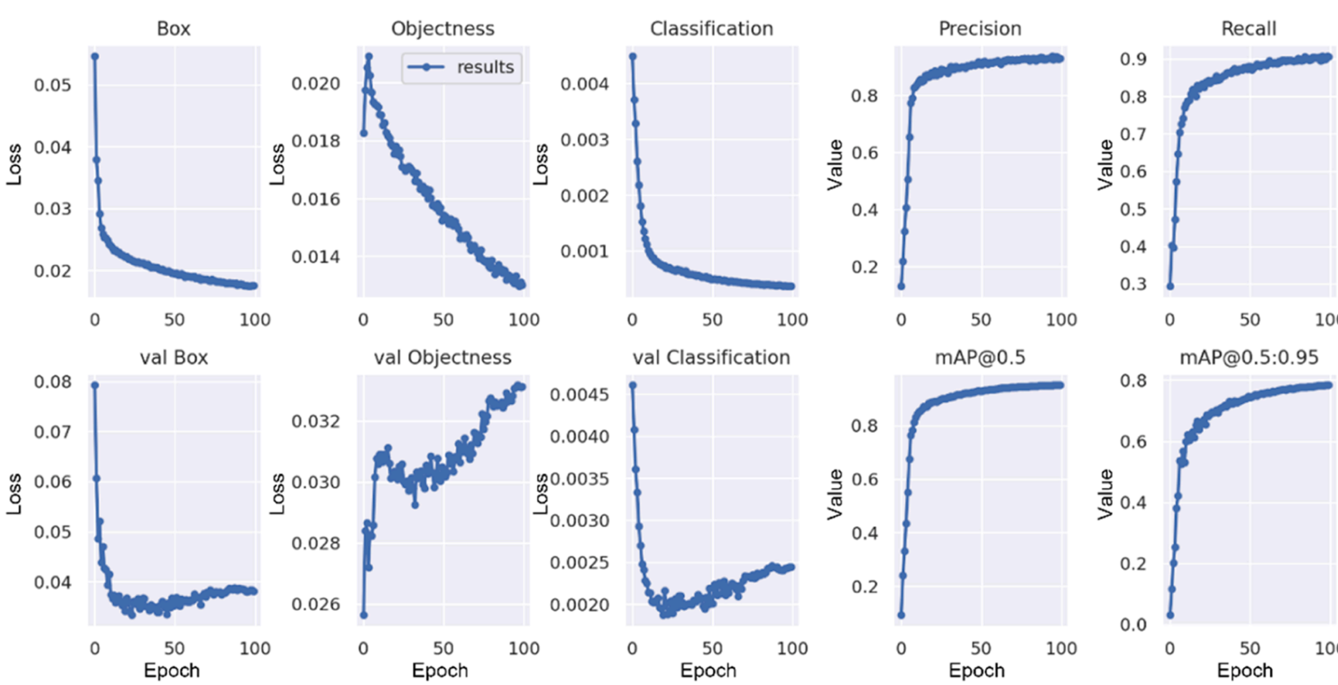

Fig. 11. Learning curves of YOLOv7x during the training process.

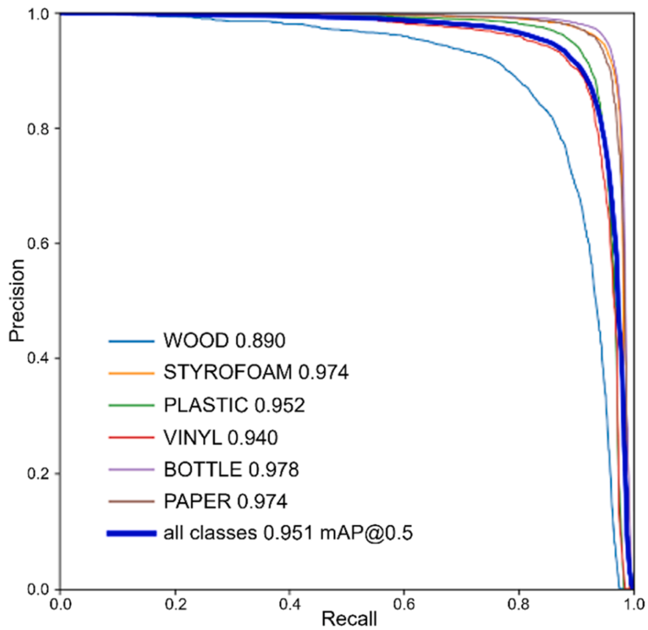

Fig. 12. Precision-Recall curves and mAP scores for water trash.

For the training dataset, a steady decrease of the Box, Objectness, and Classification losses was observed over time, while the Precision, Recall, and mAP values consistently increased throughout the training process. These results indicate that there were continuous learning and improvement of the model during the training process. For the validation dataset, the Box, Objectless, and Classification losses initially decreased similar to the trend observed in the training dataset. However, after 40 epochs, these loss values started to increase, which was a sign of overfitting. Therefore, the model parameters at epochs 40 was selected as optimal for the detection model to maximize the detection performance on unseen data while mitigating the risk of overfitting.

Following the optimal parameter selection, the model's performance, mAP at IoU threshold of 0.5, on different categories of water trash was recorded. As shown in Fig. 12, the model demonstrated impressive results across all categories. For the 'Wood' category, the mAP was 0.9, while for 'styrofoam', it was 0.974. 'Plastic' and 'vinyl' were mAP of 0.952 and 0.940 respectively. For 'bottle' and 'paper', the

Table 4
Quantity-Weight conversion matrix.

Category	Weight(kg)/EA
Wood	0.8037
Paper	0.0829
Styrofoam	0.2794
Plastic	0.2881
Vinyl	0.0102
Bottle	0.2421

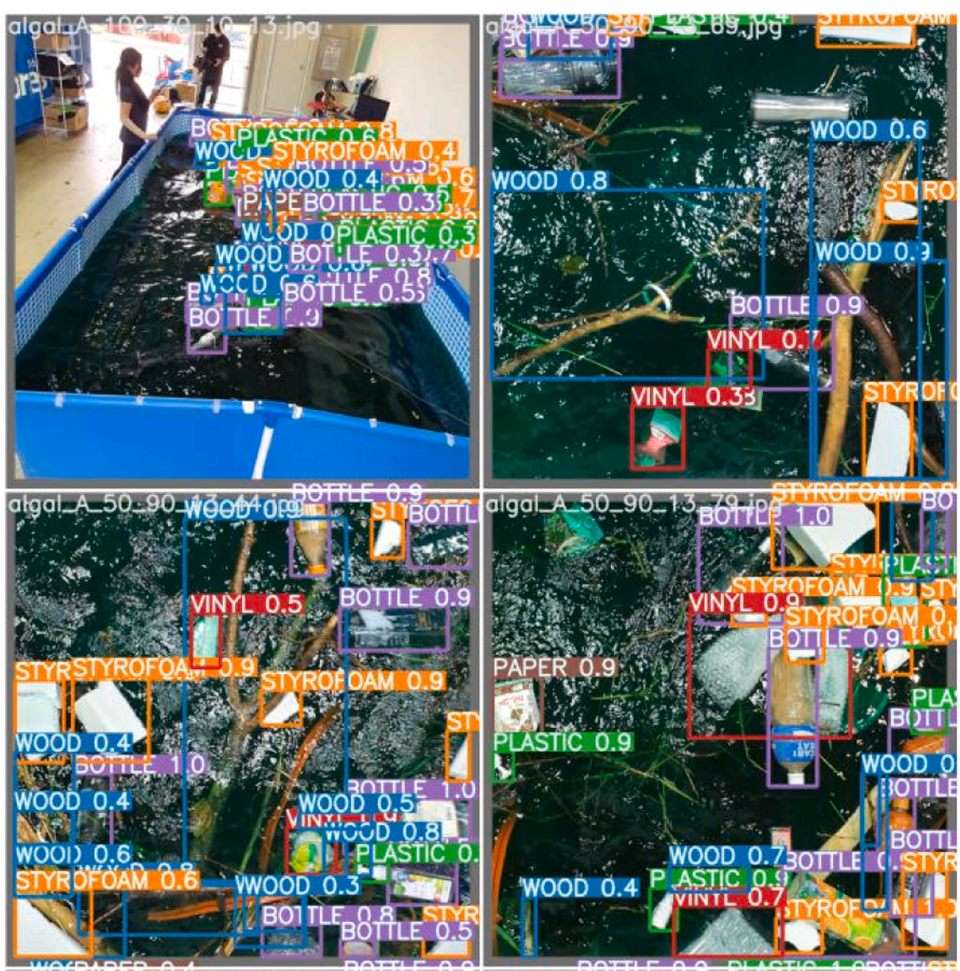

Fig. 13. Examples of detection results on test data.

Fig. 14. Visualization of water trash weight(g) estimation results.

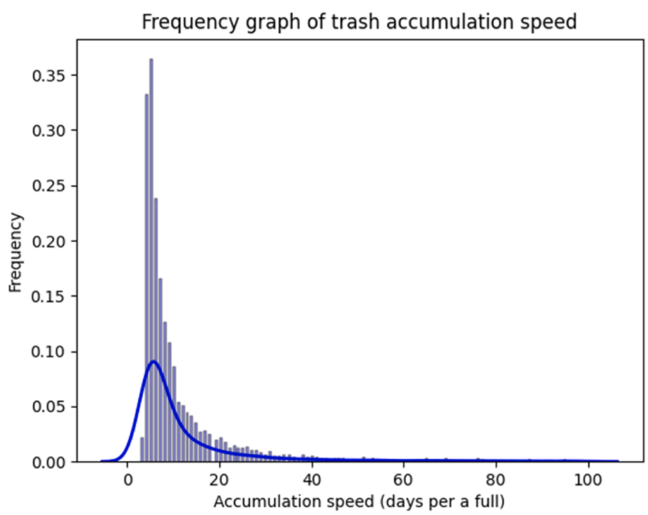

Fig. 15. MCS result of trash accumulation.

Table 5
Evaluation of the linear regression model's performance in predicting overflow day for floating barriers.

Days ahead of overflow	MSE		R^2		Errors in prediction	
	Mean	Stds	Mean	Std	Mean	Std
1	2.09	4.84	0.93	0.16	0.41	4.63
2	9.09	11.72	0.78	0.29	−0.03	16.91
3	14.48	12.79	0.68	0.27	0.19	5.93
4	7.45	11.15	0.83	0.25	1.28	10.71

model achieved a higher mAP of 0.978 and 0.974, respectively. The overall mAP was 0.951, indicating that water trash can be identified with high accuracy using a state-of-the-art object detection model across different types of waste materials. Fig. 13 shows its effectiveness not just in theoretical terms, but also in practical, real-world scenarios. This highlights the model's potential utility in an adaptive water trash processing system, capable of reliably identifying and categorizing various types of floating water trash.

5.2. Integration of trash detection and weight estimation

Table 4 presents a conversion matrix used for quantity-to-weight conversion. This conversion matrix was used to estimate the weight of water trash based on quantity identified by the object detection model. The trash detection model was successfully integrated with the quantity-weight conversion matrix, creating a seamless pipeline. Floating trash estimation results were simultaneously derived with the trash detection as shown at the top left of Fig. 14.

5.3. Results of water trash accumulation speed estimation

Fig. 15 shows the MCS simulation results. The results suggest that it takes an average of about 5 days for the floating barriers to reach its full capacity from an empty state. Subsequent frequencies indicate that 4 days and then 6 days are the next common durations for accumulation, with most trash collection occurring within 20 days.

5.4. Performance of the trash overflow prediction model

The regression model's performance in predicting the water trash overflow day was evaluated at different days before the expected overflow, with the results summarized in Table 5. It is evident that the model shows a high degree of accuracy, particularly when predictions were made one day before the expected overflow, as indicated by the high R^2 mean value of 0.93. This implies that the model can reliably forecast the overflow day with minimal deviation from the actual day. However, as the prediction window increases (2 to 4 days before overflow), the model's accuracy, as indicated by the R^2 value, shows a gradual decline. This is particularly noticeable in the increase in MSE and the decrease in R^2 values. For instance, the MSE mean increases from 2.09 to 14.48, and the R^2 mean decreases from 0.93 to 0.68 as we move from a 1-day to a 3-day prediction window. This demonstrates the potential of using overflow prediction models for effective management of floating barriers. Future work could focus on refining the model to improve its predictive power over longer time for more dynamic and responsive trash management strategies.

5.5. MCS results of comparing trash collection strategies

Fig. 16 and Table 6 presents a comparative analysis in terms of costs and delay time for an adaptive trash collection strategy versus a time-based strategy over various collection cycles (4 to 10 days). The adaptive approach reveals a mean cost of $493,284 with a standard deviation (Std) of $44,385, suggesting a relatively lower variability in costs. The time-based strategy exhibits a gradual decrease in the average cost from $640,578 to $465,494 as the cycle lengthens from 4 to 10 days. The associated standard deviations range from $49,067 to $43,416, suggesting a somewhat consistent variance across different cycle lengths.

Regarding delay time metrics, the adaptive strategy maintains a lower mean of 0.938 days with a standard deviation of 0.133, implying a quicker response to the risk of overflowing barriers. The time-based strategy shows an increasing trend in the average delay time from 0.185 to 3.285 as the cycle length extends, with corresponding standard deviations increasing from 0.073 to 0.575. This indicates that the longer the cycle, the higher the likelihood of delays in trash collection, which could result in barrier collapse. Therefore, cycles more than 6 days, where the mean delay time exceeds 1, are considered impractical.

As shown in Fig. 16(a), if the collection cycle in the time-based strategy exceeds six days, a severe delay occurs. When the collection cycle is six days or less, the adaptive strategy is more cost-effective than the time-based strategy. Compared with the adaptive strategy, the four-day cycle in the time-based approach results in a 30% increase in costs, and extending the cycle to six days results in an additional 10% cost increment. These findings highlight the inefficiencies of the time-based approach. Although the cost can be reduced with the increase in the cycle length, it is not desirable due to the risk of a structural failure leading to higher costs of reconstruction and adverse environmental effects. The adaptive strategy, tailored specifically to real-time trash

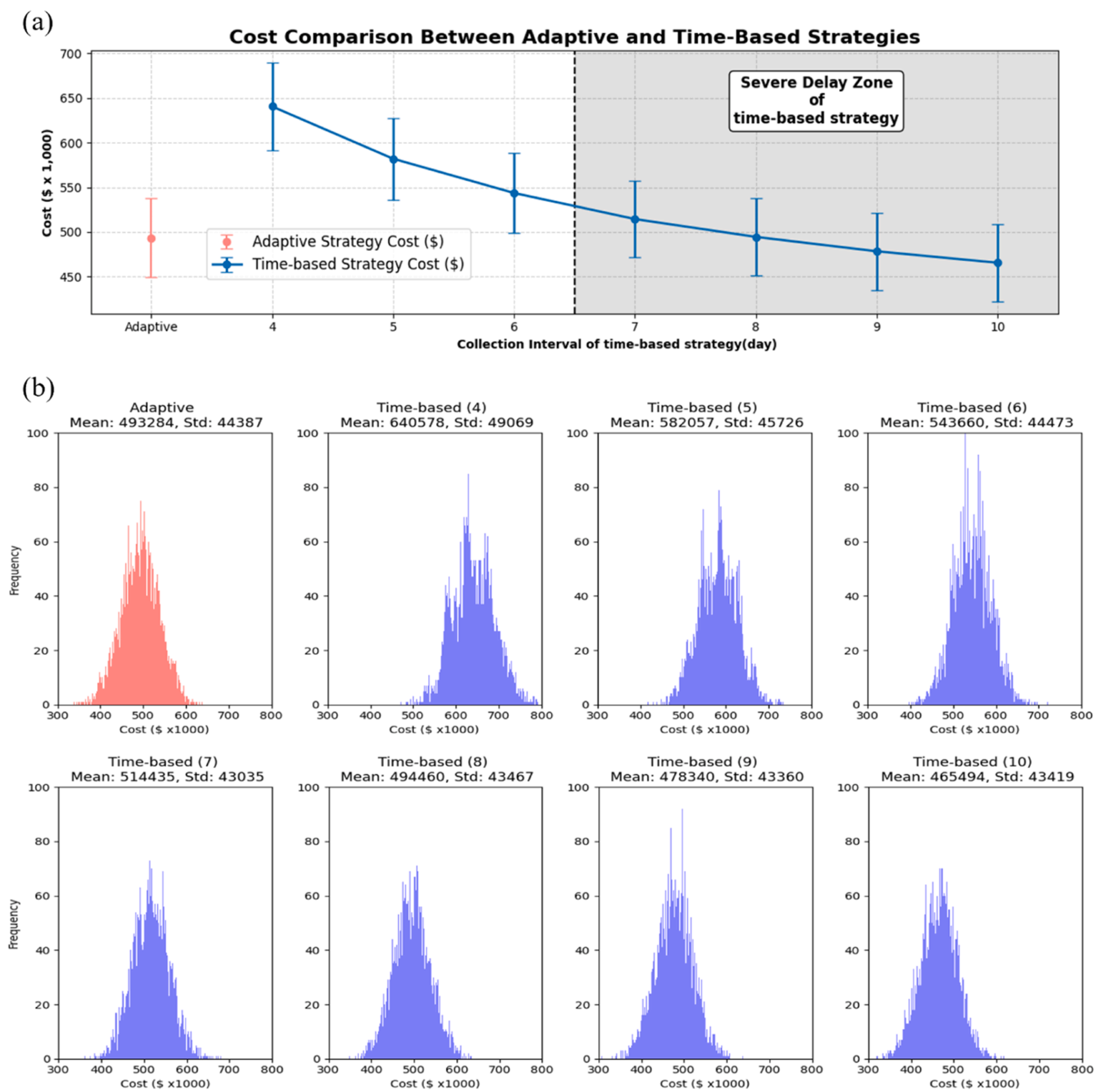

Fig. 16. Cost analysis results comparing adaptive and time-based strategies using Monte Carlo Simulation (MCS): (a) Average operational costs of adaptive and time-based strategies at varying collection intervals (4–10 days). Error bars indicate standard deviation from simulated data. Any interval resulting in delays exceeding one day is classified as a 'severe delay zone,' marked by the gray-shaded region (≥7 days). (b) Histograms illustrating cost distributions from MCS for the adaptive strategy and each fixed-interval time-based strategy (intervals 4–10 days).

Table 6
Trash collection cost and delay time derived from MCS.

		Adaptive	Time-based						
			Collection Cycle (day)						
			4	5	6	7	8	9	10
Cost ($)	Mean	493,284	640,578	582,057	543,660	514,435	494,460	478,340	465,494
	Std	44,385	49,067	45,723	44,471	43,033	43,465	43,357	43,416
Delay time (day)	Mean	0.938	0.185	0.514	0.954	1.468	2.031	2.645	3.285
	Std	0.133	0.073	0.155	0.243	0.327	0.413	0.496	0.575

accumulation rates, not only optimizes resource utilization but also significantly curtails unnecessary expenses and mitigates delays in trash collection. As depicted in the cost distribution histograms (Fig. 16(b)), the adaptive strategy exhibits lower mean costs and reduced variability compared to fixed-interval time-based methods, reflecting greater economic efficiency and reliability. These results underscore the critical importance of adopting adaptive scheduling strategies in waste management, particularly within dynamic environments characterized by variable trash generation rates.

6. Conclusion

This study has successfully demonstrated the feasibility of constructing a comprehensive pipeline that integrates trash detection and valuation, indicating the capability to estimate the weight of trash from its quantity. A significant challenge is the absence of benchmark data to verify the accuracy of our system's output against real-world datasets. Without these comparative measures for the weight or value of floating trash, the study's scope is constrained to presenting the integrated model as a proof-of-concept. It is important to acknowledge that the conversion values can vary with the location and time of data collection, indicating a need for site-specific indicators to ensure precision in future applications of our model.

Our research sought to develop a novel collection strategy to automate one of the fundamental solutions to floating trash, i.e., trash collection from rivers. We proposed a computer vision-based framework and constructed a practical pipeline to verify its feasibility.

Our proposed collection process is segmented into three distinct functionalities. The first function, trash detection, is based on computer vision. By utilizing YOLOv7, we were able to identify six categories of floating trash with a performance of 95.1% mAP. This demonstrates the application potential of object detection algorithms to analyze trash accumulated by river barriers.

The second functionality entailed remote weight estimation and economic analysis of the detected trash. Our approach for this function relied on statistical data. We proposed a quantity-weight conversion formula based on credible sources, specifically, the marine waste investigation data from the Korean government. Using this formula, we were able to derive an estimated weight and subsequent valuation of the detected trash.

Through Monte Carlo simulations, we assessed the potential cost-effectiveness of our proposed trash collection strategy. Specifically, we aimed to answer two key research questions: (1) Does the proposed adaptive trash collection framework offer greater economic advantages compared to the conventional time-based collection method? and (2) If so, to what extent can it enhance cost efficiency? The experimental results clearly answered these questions by demonstrating that the adaptive trash collection strategy achieves approximately a 10% to 30% reduction in operational costs compared to the conventional approach. This confirms that adopting our adaptive framework significantly enhances economic efficiency in managing water trash collection.

This study represents a significant advancement in automating floating trash collection through a computer vision-based system. One of the most notable contributions is the use of MCS to quantitatively validate the superiority of the proposed frameworks. While MCS was instrumental in demonstrating its effectiveness, it is not required for actual implementation, significantly reducing execution time to just 3 to 5 s. Another key strength of the system is its ease of deployment, as it requires only video equipment and a desktop computer for processing. This minimal hardware requirement makes it highly adaptable and applicable in various river environments without the need for specialized infrastructure.

Beyond its technical contributions, the study highlights the potential for shifting floating trash collection from experience-based management to data-driven decision-making. By optimizing collection routes through automated analysis, the system could improve both operational efficiency and cost-effectiveness. The research also holds broader implications for environmental sustainability, as its widespread adoption could lead to a significant reduction in waste leakage into natural water bodies, contributing to ecosystem preservation while offering economic benefits for municipalities and organizations responsible for waterway maintenance.

Despite these contributions, certain limitations must be acknowledged. The absence of benchmark datasets presents challenges in verifying the accuracy of the system's output. Additionally, the study relies on assumptions and variables specific to South Korea, limiting the generalizability of the findings to other regions. Since all experiments were conducted in laboratory conditions and through simulations, real-world testing remains essential to assess the system's adaptability in diverse environmental contexts. Variations in water conditions across different locations could impact detection performance, making it necessary to validate the approach with real-world data.

Future research should focus on collecting and analyzing real-world data to enhance system robustness, testing the framework in diverse water environments to evaluate its performance under different conditions, and further optimizing collection route planning to determine whether the proposed approach truly outperforms existing methods in practical applications. Addressing these challenges is crucial for transitioning from a proof-of-concept model to a fully operational automated trash collection system. If successfully implemented, this research could provide a scalable solution for improving waste management efficiency worldwide, offering a new technological pathway for reducing water pollution and protecting aquatic ecosystems.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT in order to proofread the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Seokhwan Kim: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Taegeon Kim:** Validation, Software, Data curation. **Minhyun Lee:** Writing – review & editing, Validation. **Jonghwa Won:** Data curation, Conceptualization. **Hongjo Kim:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition.

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.

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Appendix 1. Styrofoam

Year		2009	2010	2011	2012	2013	2014	2015	2016	2017	Sum
1st	**Count(EA)**	1396	1255	899	922	1467	429	1236	987	947	9538
	Weight(kg)	132.1	189.4	108.8	410.4	213.3	490.1	328.9	307.3	162.6	2342.9
	Volume(ℓ)	2876.5	1349.3	2538.3	1566.2	2212.3	2229.1	4230.1	3677.5	2536.2	23,215.5
2nd	**Count(EA)**	1804	1131	1175	1115	744	634	1283	1498	1330	10,714
	Weight(kg)	173.3	110.7	88.3	181	164.3	58.1	310.2	309.9	164.1	1559.9
	Volume(ℓ)	2419.5	1328.3	2004.5	1895.5	1036	1803.4	4268.9	4147	2794.4	21,697.5
3rd	**Count(EA)**	1213	1415	1141	1426	893	804	2087	2129	1497	12,605
	Weight(kg)	149.4	174.6	177	245.4	247.7	83.9	5906.1	535.2	285.2	7804.5
	Volume(ℓ)	2918.6	3675.4	2157.2	2389.5	2502.5	1614.2	22,812.3	4988.8	5347.9	48,406.4
4th	**Count(EA)**	1556	6521	2617	1926	1431	704	1954	1848	1237	19,794
	Weight(kg)	458	426.6	301.4	414.6	414	356.6	363.6	505.4	590.8	3831
	Volume(ℓ)	3595.1	4587.5	3545.3	2744.5	1505.8	3322.4	4230.6	4880.1	5077.5	33,488.8
5th	**Count(EA)**	1490	2817	2108	1611	2301	2367	2301	2386	1624	19,005
	Weight(kg)	112.8	468.3	452	486.6	1722.8	609.5	482.2	579.2	262	5175.4
	Volume(ℓ)	1803.9	3450.6	3419.8	4719.6	5238.2	3448.8	7198	3951.3	4113.1	37,343.3
6th	**Count(EA)**	1570	1982	1995	1001	839	1157	1816	989	1061	12,410
	Weight(kg)	186.8	101.6	341.4	278	357.8	423.8	441.9	170.2	477	2778.5
	Volume(ℓ)	4254.2	1479.6	2850.4	3545.5	2145.3	4923.7	5773.5	2478	4569.5	32,019.7

Appendix 2. Wood

Year		2009	2010	2011	2012	2013	2014	2015	2016	2017	Sum
1st	**Count(EA)**	667	313	372	329	277	218	827	498	458	3959
	Weight(kg)	550.3	274	225.2	167.1	216.5	386.1	320.3	300.9	244.3	2684.7
	Volume(ℓ)	2657.7	977.5	745.5	1016	594.5	910.8	1492.7	1130.9	763.1	10,288.7
2nd	**Count(EA)**	804	428	310	328	268	281	427	851	520	4217
	Weight(kg)	758	345.6	304.1	222.7	230.8	161.7	201.4	415.5	297.6	2937.4
	Volume(ℓ)	2193	1015.5	1231.9	706.7	360.8	646.7	872.9	1071.8	1395.9	9495.2
3rd	**Count(EA)**	821	636	544	395	338	199	480	444	492	4349
	Weight(kg)	659.5	495.3	423.2	473.8	338.4	139.3	535.7	306.7	272.5	3644.4
	Volume(ℓ)	2937.8	1670.1	1267.4	1179.3	920.2	359.5	1639.7	1049.5	787.1	11,810.6
4th	**Count(EA)**	550	601	503	361	361	274	665	704	429	4448
	Weight(kg)	602.1	779	867.3	388.8	324.5	201.4	343.1	414	437.3	4357.5
	Volume(ℓ)	2001	2319.2	1789.5	1086.9	766.5	403.5	1410.2	1369.8	1041.3	12,187.9
5th	**Count(EA)**	333	558	354	829	393	717	525	463	1449	5621
	Weight(kg)	417.9	1117.1	727.7	524.5	615.7	542.3	324.4	360.2	442.9	5072.7
	Volume(ℓ)	1092.2	1958.7	1457.6	1762.4	1422.7	2265.9	1522.2	1043.9	1722.7	14,248.3
6th	**Count(EA)**	869	1043	356	230	228	550	546	530	615	4967
	Weight(kg)	625.3	614.2	266.5	199.8	362	346.9	322.6	364	351.7	3453
	Volume(ℓ)	2249.5	1323.8	777.5	465.8	664.4	1046	1078.2	1417.6	1292.3	10,315.1

Appendix 3. Paper

Year		2009	2010	2011	2012	2013	2014	2015	2016	2017	Sum
1st	**Count(EA)**	111	143	85	134	109	114	304	171	165	1336
	Weight(kg)	3.7	1.5	4.6	2.9	12.5	5	12.1	9.2	12	63.5
	Volume(ℓ)	18.7	23.3	27.9	29.8	46	19.9	69.4	67.6	76.1	378.7
2nd	**Count(EA)**	164	178	108	261	124	129	304	469	229	1966
	Weight(kg)	4	8.6	2.8	204.9	4.6	8.9	16.1	14	13.6	277.5
	Volume(ℓ)	41.2	118.5	25.6	103.3	17	32.5	104.2	62.8	93.5	598.6
3rd	**Count(EA)**	249	164	289	280	237	146	313	435	330	2443
	Weight(kg)	5.2	4.2	11.6	6.8	5.6	4.5	14.6	10.7	11.9	75.1
	Volume(ℓ)	62	50.4	102.5	116	44.8	18.2	70.5	115	78.6	658
4th	**Count(EA)**	135	386	190	216	139	144	344	303	305	2162
	Weight(kg)	9.4	9.3	6.6	8.9	10.5	7.4	12.6	15.2	18.6	98.5
	Volume(ℓ)	467.6	122.6	101.3	40.9	90.1	40.5	166.6	84.9	136.3	1250.8
5th	**Count(EA)**	63	361	179	107	122	373	267	214	288	1974
	Weight(kg)	12.5	13	10.4	12.7	207.8	22	53.4	11.8	26.5	370.1
	Volume(ℓ)	20.8	120.4	48.7	43.3	1269.7	60.4	118.4	55.4	204.4	1941.5
6th	**Count(EA)**	92	105	98	134	94	251	167	347	179	1467
	Weight(kg)	3.8	3.3	2.4	5.9	4.6	9.9	4.3	11.8	9.5	55.5
	Volume(ℓ)	25.8	16.4	31.5	35.5	37.8	28.1	34.4	57.3	113.4	380.2

Appendix 4. Plastic

Item	Weight per count (kg/EA)
Banana milk bottle	0.036
Paint can	1.128
Plastic milk jug	0.0025
Pen belt	0.384
Lid of side dish container	0.12
Side dish container	0.0581
Mean	0.2881

Appendix 5. Bottle

Item	Weight per count (kg/EA)
PET bottle	0.108
Soju bottle	0.432
Beer bottle	0.6336
Beverage bottle	0.6336
Small beverage bottle	0.216
Makgeolli bottle	0.072
Yogurt bottle	0.024
Drink bottle	0.1584
2 L Water bottle	0.135
350 ml Water bottle	0.075
Soy sauce bottle	0.0576
Plastic water bottle	0.36
Mean	0.2421

Appendix 6. Vinyl

Item	Weight per count (kg/EA)
Ramen bag	0.01
Plastic bag	0.018
Kim packaging bag	0.003
Envelope	0.01
Snack bag	0.01
Mean	0.0102

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