Chapter 1
Reactive Planning for Marine Debris Collection in Dynamic Ocean Environments

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Abstract This study investigates real-time marine waste collection in dynamic ocean environments. The task is modelled as a Team Orienteering Problem with Moving Targets (TOP-MT), in which drifting plastic hotspots are collected by vessels using a reactive greedy heuristic. The objective is to maximise the total collected value and the central question is whether target selection should prioritize value or proximity. Results show that a proximity-focused yet value-aware mixed strategy yields the most effective routing. These findings underscore the importance of integrating environmental dynamics into real-time marine operations planning.

1.1 Introduction

Plastic pollution in the oceans poses a growing environmental threat. In convergence zones such as the Great Pacific Garbage Patch (GPGP), debris accumulates under the influence of ocean currents. The GPGP is is a vast dispersed accumulation zone with irregular distribution of debris, rather than a contiguous floating mass. [8], making retrieval a complex task. However, clean-up efforts are essential, as degradation and biological colonization of plastic increase the risk of sinking [6]. Locating and collecting debris is therefore crucial. The marine debris in this study is simplified as discrete, high-density "hotspots" whose motion is governed by forecasted ocean currents. These are modelled with OpenDrift [3] using real ocean current forecast data [2].

Unlike classical models such as the Vehicle Routing Problem (VRP), real-world ocean clean-up missions often employ mobile support vessels that retrieve debris directly from the collecting units, eliminating the need for return-to-depot routing [4]. Therefore, the task in this study is modelled as a Team Orienteering Problem with Moving Targets (TOP-MT), with the objective of maximizing the collected value within a given time horizon.

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Existing approaches often rely on predefined plans or periodic replanning [1, 7, 9]. In contrast, this study proposes a fully reactive heuristic that continuously adapts to both target and vessel movement during a simulation.

The problem is defined over a discrete time horizon $\mathbb{T} = \{0, 1, \ldots, T\}$, where each simulation step has a duration of Δt. The total mission time is fixed to $T \cdot \Delta t$. During this period, a fleet of vessels $\mathcal{K} = \{1, \ldots, K\}$ is deployed to collect drifting plastic hotspots. At each time step $t \in \mathbb{T}$, the set $\mathcal{N}_t$ contains all currently accessible targets, each located at position $\mathbf{p}_i(t) \in \mathbb{R}^2$ and associated with a non-negative value $\pi_i(t) \geq 0$. The trajectories $\mathbf{p}_i(t)$ are externally provided by drift simulations and not modelled within the optimization.

Each vessel $k \in \mathcal{K}$ has a current position $\mathbf{q}_k(t)$, a controllable speed $v_k(t)$, and is influenced by an exogenous environmental flow vector $\mathbf{c}_k(t) \in \mathbb{R}^2$, representing the ocean current at the current location.

The binary decision variable $z_{i,k}(t) \in \{0, 1\}$ indicates whether vessel k targets hotspot i at time t. Each vessel always moves directly toward its assigned target, following the unit direction vector

$$\mathbf{u}_k(t) = \frac{\mathbf{p}_i(t) - \mathbf{q}_k(t)}{\|\mathbf{p}_i(t) - \mathbf{q}_k(t)\|} \quad \text{if } z_{i,k}(t) = 1.$$

A hotspot is considered collected if the vessel is within a predefined radius ϵ. This is captured by the derived indicator variable $x_{i,k}(t) := \mathbb{I}\left[\|\mathbf{q}_k(t) - \mathbf{p}_i(t)\| \leq \epsilon \wedge z_{i,k}(t) = 1\right]$.

Objective Function: Maximise the total value of collected hotspots:

$$\max \sum_{t \in \mathbb{T}} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{N}_t} \pi_i(t) \cdot x_{i,k}(t) \tag{1.1}$$

Constraints:

(C1) Each target can be collected at most once:
$$\sum_{t \in \mathbb{T}} \sum_{k \in \mathcal{K}} x_{i,k}(t) \leq 1 \quad \forall i \in \bigcup_t \mathcal{N}_t$$

(C2) Each vessel can target only one hotspot at each time step:
$$\sum_{i \in \mathcal{N}_t} z_{i,k}(t) \leq 1 \quad \forall k \in \mathcal{K},\ \forall t \in \mathbb{T}$$

(C3) The vessel position updates according to propulsion and drift:
$$\mathbf{q}_k(t+1) = \mathbf{q}_k(t) + v_k(t) \cdot \mathbf{u}_k(t) \cdot \Delta t + \mathbf{c}_k(t) \cdot \Delta t \quad \forall k,\ t < T$$

(C4) Each vessel starts from a fixed initial position:
$$\mathbf{q}_k(0) = \mathbf{q}_k^{\text{start}} \quad \forall k \in \mathcal{K}$$

(C5) Each target can be followed by at most one vessel at a time:
$$\sum_{k \in \mathcal{K}} z_{i,k}(t) \leq 1 \quad \forall i \in \mathcal{N}_t,\ \forall t \in \mathbb{T}$$

No global routing constraints are required, since targets are assigned independently and deactivated after collection. Each vessel $k \in \mathcal{K}$ navigates continuously based on its current target assignment $z_{i,k}(t)$, and moves in the Euclidean direction of the assigned hotspot. The vessel's position is updated at each simulation step using the motion rule: $\mathbf{q}_k(t+1) = \mathbf{q}_k(t) + v_k(t) \cdot \mathbf{u}_k(t) \cdot \Delta t + \mathbf{c}_k(t) \cdot \Delta t$.

1.2 Outline of the Algorithm

To determine the values of $z_{i,k}(t)$, vessels without an active target are assigned to one of the available hotspots based on a greedy scoring function. This function considers either the spatial proximity, the estimated collection value, or a weighted combination of both. The resulting rule-based assignment enables the fleet to continuously adapt its routing decisions to the evolving environmental conditions.

To allocate targets to collection vessels, different scoring strategies were explored. The goal is to dynamically assign vessels to favourable hotspots based on their spatial position and associated value. Each vessel evaluates the set of currently available hotspots and selects the one that maximises the following score:

$$S_i = \alpha \cdot \left(1 - \frac{d_i}{d_{\max}}\right) + (1 - \alpha) \cdot \left(\frac{v_i}{v_{\max}}\right) \tag{1.2}$$

where v_i is the value of hotspot i, d_i is the Euclidean distance between vessel and hotspot, and $v_{\max}, d_{\max}$ normalize the respective scales. The weighting parameter $\alpha \in [0, 1]$ determines the preference: $\alpha = 1$ yields proximity-driven selection, while $\alpha = 0$ prioritizes value. This flexible formulation supports both static and dynamic tuning of fleet behaviour.

Once a target has been assigned, a vessel advances toward the hotspot's most recent position by covering the maximum Euclidean distance it can travel within one time step. Travel times cannot be precomputed easily, as dynamic drift prevents static distance matrices.

Upon reaching the immediate vicinity of its target hotspot, the hotspot is considered collected. Its value is added to the vessels total collected value, and the hotspot is removed from the simulation. The vessel receives a new assignment based on the current environment and scoring function.

1.3 Experimental Results

To demonstrate the algorithm, vessel trajectories under two extreme routing strategies one purely proximity-based and the other purely value-based—are first presented. The effectiveness of the reactive strategy with a mixed strategy is then evaluated through performance analysis across a broad range of simulation scenarios.

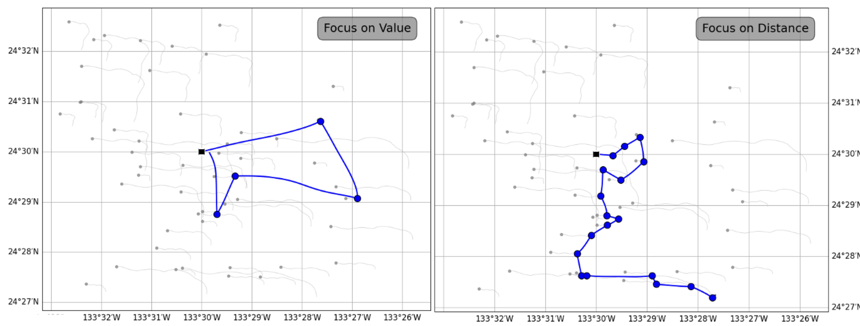

Fig. 1.1 Trajectories under extreme routing strategies. Left: value-focused strategy (α = 0.0). Right: proximity-focused strategy (α = 1.0).

Figure 1.1 highlights the behaviour of the two extremes. The proximity-based strategy produces compact and dense trajectories that efficiently cover local areas, but often miss high-value hotspots. Conversely, the value-focused strategy leads to long, sparse routes targeting high-value hotspots at the expense of local opportunities.

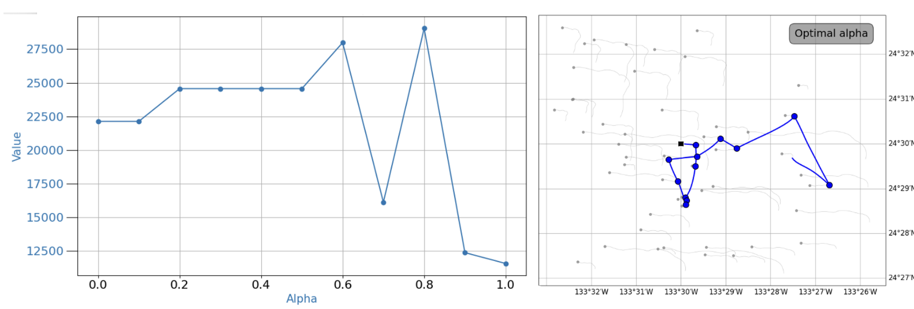

Fig. 1.2 Left: Collected value as a function of α. Right: Vessel trajectories under optimized strategy (α = 0.8).

To quantify this trade-off, Figure 1.2 shows the collected value as a function of the weighting parameter α. As α increases from 0 to 1, the collected value initially rises, peaks at a local optimum of α = 0.7, and declines thereafter before reaching the optimum at α = 0.8 This confirms that neither extreme is optimal. The results underscore the importance of careful parameter calibration, as suboptimal weighting can significantly reduce performance

Table 1.1 Comparison of collected values under different routing strategies

Strategy	α	**Collected Value**
Value-focused	0.0	22 136
Proximity-focused	1.0	11 579
Optimized	0.8	29 043
Static	-	33 986

Table 1.1 shows: the optimized configuration outperforms both extreme solutions significantly. For comparison, an idealized upper bound was computed using a solver that assumes static target positions (i.e., no drift). Under this assumption, the theoretical maximum collection value is 33 986. The reactive greedy strategy (despite operating under dynamic and uncertain drift conditions) achieves a value only 4 943 points lower. This relatively small gap underscores the efficiency of the reactive approach.

Table 1.2 Scenario overview with optimal α, collected values, and relative improvement

Scenario	**Time**	**Hotspots**	**Radius**	**Boats**	$V_{\alpha=0}$	$V_{\alpha=1}$	V_{opt}	α_{opt}	**Improvement [%]**
Short Time	50	50	10.0	2	13476	11206	19260	0.70	42.9
Long Time	500	50	10.0	2	51785	60801	62163	0.90	2.2
Few Hotspots	100	20	10.0	2	22065	17714	28111	0.66	27.4
Many Hotspots	100	500	10.0	2	27675	30598	54488	0.75	78.1
Narrow Radius	100	50	2.0	2	54217	57131	61020	0.83	6.8
Wide Radius	100	50	50.0	2	2584	2823	5025	0.76	78.0
Few Boat	100	50	10.0	1	15771	10985	21073	0.63	33.6
Many Boats	100	50	10.0	5	39490	38619	51178	0.76	29.6
Vast and Dense	100	300	30.0	1	5000	5666	12543	0.67	121.4

Table 1.2 provides a comprehensive evaluation across different operational scenarios. Each entry reports average outcomes from 20 simulations with randomized initial hotspots. Each single simulation run completed in under two seconds, confirming the efficiency of the approach.

The adaptive strategy consistently outperforms fixed baselines. In high-pressure scenarios, such as short time windows, few boats, large radii, vast and dense or many hotspots—the gain is significant. More importantly, the optimal α varies by context: 0.9 for a long time horizon, 0.6–0.7 under resource constraints. This shows that no single heuristic dominates across all conditions. Interestingly, the optimal value of α tends toward the proximity side of the spectrum, rather than lying exactly in the middle. This suggests that in dynamic marine environments, spatial efficiency plays a slightly more critical role than pure value optimization. The findings underscore that context-aware, dynamically tuned heuristics are crucial for robust, high-impact marine clean-up operations in uncertain environments.

1.4 Summary and Outlook

This study demonstrates the effectiveness of a reactive routing strategy for collecting marine debris under dynamic drift conditions. The heuristic performs well across various scenarios and adapts flexibly to environmental change. The experimental results highlight the crucial role of the weighting parameter, with mixed strategies significantly outperforming purely proximity- or value-driven approaches.

Future improvements may include adaptive parameter tuning, where vessels dynamically adjust α based on the current situation. Adding retargeting capabilities would allow vessels to revise their destination mid-transit, reducing myopic behaviour and increasing responsiveness. Benchmarking against static global planners would help evaluate the true value of drift-aware reactivity. Lightweight coordination mechanisms between vessels could mitigate redundancy and improve coverage in dense fields. Furthermore, model realism could be enhanced by considering fuel constraints, heterogeneous fleet properties, and hotspot dynamics such as merging or decay.

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