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Evaluating Hybrid and Sampling-Based Path Planners for Unmanned Surface Vehicle Logistics in Dynamic Inland Waterways

Ronald Sukwadi [a,1], Gregorius Airlangga [b,2,*], Widodo Widjaja Basuki [c,3], Lai Ferry Sugianto [d,4], Emanuel Jando [e,5], Dimas Catur Winson [a,6]

[a] Industrial Engineering Study Program, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia
[b] Information Systems Study Program, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia
[c] Mechanical Engineering Study Program, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia
[d] Department of Business Administration, Fujen Catholic University, Taipei 24205, Taiwan
[e] Computer Science Study Program, Widya Mandira Catholic University, Kupang, Indonesia
[1] ronald.sukwadi@atmajaya.ac.id; [2] gregorius.airlangga@atmajaya.ac.id; [3] widodo.basuki@atmajaya.ac.id;
[4] 158325@mail.fju.edu.tw; [5] nuel1268@unwira.ac.id; [6] dimas.caturwinson@gmail.com
* Corresponding Author

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ABSTRACT

Autonomous surface vehicles (ASVs), particularly unmanned surface vehicles (USVs), play an increasingly important role in supporting logistics across Indonesia's archipelagic and riverine regions, where shallow depths, strong currents, and debris complicate navigation. The research contribution is the development of a unified USV logistics simulation framework that enables systematic benchmarking of multiple path-planning strategies under realistic inland-waterway conditions. The framework integrates hydrodynamic environmental modeling, stochastic mission generation, and multi-planner evaluation within a single experimental loop. Nine algorithms were implemented, including classical planners (A*, D* Lite, GA, APF, Reactive Steering), sampling-based methods (RRT, RRT*), and hybrid variants (HARRT*, AHA-RRT*) that employ current-aware travel-time costs and adaptive replanning. Experiments conducted on a 200 × 200 m simulated domain with a fleet of three USVs under a 10-minute deadline revealed that sampling-based planners, particularly RRT*, achieved complete mission success with zero collisions, efficient energy use, and high obstacle clearance. The adaptive hybrid AHA-RRT* also performed robustly, showing superior adaptability albeit with longer paths due to frequent replans. In contrast, classical and reactive methods failed to meet time and safety constraints. These findings demonstrate that sampling-based and hybrid planners offer the most effective balance of safety, efficiency, and adaptability for autonomous inland-waterway logistics, providing a validated framework to guide future USV deployment in dynamic archipelagic environments.

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1. Introduction

Autonomous surface vehicles (ASVs), particularly unmanned surface vehicles (USVs), are increasingly central to enhancing logistics connectivity across Indonesia's East Nusa Tenggara (NTT), where river corridors and short inter-island routes link dispersed settlements, clinics, markets, and disaster-response nodes [1]. These regions face complex hydro-environmental constraints, shallow bars and reefs, strong tidal exchanges and wind-driven surface set, seasonal water-level variation, floating debris, and unpredictable traffic making reliable, safe, and energy-efficient navigation difficult and necessitating real-time adaptation [2]. Although USVs promise reduced human risk exposure, lower operational expenditure, and flexible small-lot, high-frequency delivery, these advantages depend on robust path-planning and fleet-coordination algorithms capable of managing environmental uncertainty while balancing travel time, safety margins, and propulsion energy [3], [4].

To date, USV path-planning approaches have evolved along several algorithmic families: graph-based planners such as A* and D* Lite generate deterministic paths and perform efficiently when obstacles and waterway charts are well characterized, with D* Lite allowing rapid incremental replanning as costs change [4]–[6], sampling-based planners such as RRT and RRT* excel in high-dimensional and partially observable environments; and reactive methods such as artificial potential field (APF) offer real-time obstacle avoidance but can become trapped in local minima. Addressing these limitations, recent hybrid approaches including A* + APF combinations, stream-function-guided RRT*, and deep reinforcement learning (DRL)-supported heuristics blend global and local reasoning to improve collision avoidance and travel-time efficiency in current-affected waterways [7]–[9].

Simulation platforms such as MOOS-IvP and Virtual RobotX (VRX) have become integral research tools, with MOOS-IvP providing a behavior-based decision architecture and VRX offering Gazebo- and ROS-integrated environmental envelopes, standardized tasks, and automated benchmarking pipelines used in recent competition and research activities [10]–[12]. However, these platforms generally lack broader logistics capabilities such as stochastic mission scheduling, current and wind field modeling, shallow-zone penalties, dynamic debris generation, and controlled multi-planner evaluation across coordinated fleets—features required to assess throughput, energy usage, replanning frequency, and safety under realistic inland-waterway constraints [4], [12]–[15]. Although recent studies have investigated risk-aware routing, energy-based global planning exploiting currents or renewable sources, streamline-informed navigation, and multi-USV task allocation [16]–[19], few examine these dimensions within a unified evaluation framework. Systematic comparisons that simultaneously vary mission urgency, hydrodynamic stochasticity, and fleet-management constraints, while benchmarking classical, sampling-based, and hybrid planners under identical logistical workloads, remain limited [20], [21]. This gap constrains our understanding of how different planning methods behave under real-world riverine logistical pressures and impedes design decisions for operational USV deployments. To address this, we introduce an Advanced USV Logistics Simulation Framework, a browser-executable platform integrating multi-agent mission generation, environmental hydrodynamics, and real-time multi-planner benchmarking.

The framework incorporates nine planners spanning classical baselines (Reactive Steering, A*, RRT, APF, GA, D* Lite) and current- and risk-aware hybrid variants (HARRT* and AHA-RRT*) engineered to exploit flow fields while preserving safe clearances and energy budgets. Its environment models river and near-coastal current fields, wind disturbances, shallow-water penalties, and floating debris, while emitting planner-agnostic performance metrics across a range of logistics scenarios. These design choices align with evidence that energy- and risk-aware formulations materially improve USV route economy and safety, especially when paired with fast local replanning [22]–[24].

The research contribution is the formulation of a unified scenario-based evaluation protocol combining environmental fields, stochastic mission scheduling, and planner benchmarking; the integration of hybrid planners combining current-aware cost modeling with adaptive local replanning to avoid local minima and detours; the development of a fleet-logistics manager capable of assigning, tracking, and optimizing multiple concurrent missions; and the implementation of a comprehensive analysis suite reporting throughput, safety, and energy-efficiency metrics consistent with emerging best practices in inland-waterway autonomy and multi-robot task allocation. The remainder of this paper reviews USV navigation and fleet logistics, describes the system architecture, scenarios, and metrics, presents and discusses results, and concludes with implications, limitations, and directions for future inland-waterway autonomy research.

The remainder of this paper proceeds as follows. Section 2 surveys USV navigation algorithms, multi-agent maritime simulation platforms, and fleet logistics optimization. Section 3 details the system architecture, including environmental modeling, mission generation, and planner integration. Section 4 specifies scenarios, workloads, and metrics. Section 5 presents results and discusses trade-offs under varying operational conditions. Section 6 concludes with contributions, limitations, and directions for future work in autonomous inland-waterway logistics for NTT and similar archipelagic provinces.

2. Literature Survey

Autonomous surface vehicles (ASVs), particularly unmanned surface vehicles (USVs), have progressed from experimental prototypes to operationally capable platforms for logistics and monitoring in inland and near-coastal waters, with significant potential in archipelagic regions such as East Nusa Tenggara (NTT), Indonesia, where dispersed islands, limited port infrastructure, and seasonal hydrological variability impose persistent logistical constraints [21], [25]–[27]. The move toward maritime autonomy is driven by the need to reduce human crew dependency, increase operational frequency, and maintain reliability under environmental uncertainty, which requires integrated approaches combining navigation algorithms, environmental modeling, and fleet-level coordination [28]. Early USV navigation relied on graph-based algorithms such as A* and D* Lite, which ensure deterministic and optimal routing in structured environments, with D* Lite enabling efficient incremental replanning in response to environmental changes [4]. These methods are limited in adaptability to unstructured or partially observable waterways, prompting the adoption of sampling-based planners like Rapidly-exploring Random Trees (RRT) and its asymptotically optimal variant RRT*, which explore high-dimensional spaces and adapt to dynamically detected [29]. Hybrid approaches that combine global search and local obstacle avoidance, such as integrating Artificial Potential Field (APF) methods with A* or RRT*, have been shown to improve robustness against local minima and enhance collision avoidance in dynamic maritime environments [30].

Environment-aware navigation research now incorporates hydrodynamic modeling, wind shear effects, and shallow-water drag into route planning to improve efficiency and safety [31]–[33]. Current-aware RRT* variants bias exploration along favorable flow corridors to exploit natural currents, while energy-optimal routing models account for drag and renewable energy harvesting potential to extend mission endurance [34]. Risk-aware algorithms integrate probabilistic hazard maps of vessel density, anchorage zones, and debris, ensuring compliance with COLREGs while maintaining operational efficiency [35], [36]. Real-time replanning systems process live environmental updates from onboard sensors, enabling course adjustments in rapidly changing inland waterway conditions [37]. Comparative trials have shown that environment- and risk-aware planners can reduce travel time variance by over 20% and energy usage by more than 15% under stochastic current and wind scenarios [38].

At the fleet scale, Multi-Robot Task Allocation (MRTA) research offers strategies for USV coordination through centralized optimization, decentralized market-based allocation, and distributed consensus, each with specific advantages in scalability, fault tolerance, and communication demands [39]–[41]. Adaptive MRTA frameworks for maritime fleets consider vessel energy reserves, real-time task progress, and environmental risks to dynamically reassign missions [36], [42], [43]. Swarm-based coordination, adapted from aerial robotics, embeds COLREGs-compliant collision avoidance into distributed decision-making, enhancing safety in congested routes [44]. Predictive maintenance integration into fleet management further optimizes task allocation by minimizing unplanned downtime in remote operations [45]–[47].

Simulation platforms bridge theory and real-world deployment, with MOOS-IvP offering a mature autonomy architecture that supports multi-objective decision-making and real-time debugging for marine robotics [48]. Virtual RobotX (VRX), a Gazebo-ROS simulator, provides standardized USV models, dynamic environmental physics, and automated scoring for reproducible testing [49]. Despite these capabilities, few simulators integrate multi-vessel logistics scenarios, heterogeneous planner comparisons, and dynamic environmental updates, prompting recent ROS2 maritime extensions that add decentralized fleet control, current field modeling, and synthetic traffic generation [50], [51]. Literature consistently points to the necessity of unifying adaptive navigation, fleet coordination, and realistic simulation in a single platform for reliable USV logistics assessment in complex environments like NTT, Indonesia.

3. System Architecture

The architecture of the proposed simulation framework integrates three tightly coupled components: the modeling of the environment, the generation of mission tasks, and the integration of path planning algorithms into the USV control pipeline. Each of these components is designed to reflect the constraints and opportunities inherent to real-world riverine logistics, ensuring that the system not only evaluates algorithmic performance but also provides insights into operational feasibility.

3.1. Environmental Modeling

The environment is formalized as a bounded two-dimensional operational domain $E = [0, W] \times [0, H]$, with ($W = 200\,\mathrm{m}$) and ($H = 200\,\mathrm{m}$) defining the width and height of the river section under consideration. Within this domain, the simulation incorporates static obstacles such as piers, embankments, and permanent infrastructure that restrict navigable space. These are encoded as rectangular regions ($O_{si} \subset E$). In addition to static elements, dynamic obstacles are introduced to represent floating debris and moving traffic, modeled as time-varying circular objects $\left(O_{dj}(t)\right)$ with centers $\left(p_j(t)\right)$ and $radii\left(r_j\right)$. The movement of these obstacles is governed by the hydrodynamic conditions of the river through $p_j(t + \Delta t) = p_j(t) + \left(c\left(p_j\right) + w\right)\Delta t$, where $\left(c\left(p_j\right)\right)$ is the local river current vector at the obstacle's position and (w) is the wind disturbance vector. Shallow water zones are explicitly modeled as polygonal subsets ($S_k \subset E$) which introduce localized penalties on USV navigation. Within these areas, vehicle velocity is reduced by a factor ($\alpha_s < 1$) and energy consumption is increased by a multiplier ($\beta_s > 1$), reflecting the additional resistance caused by depth-related drag. The river current itself is defined as a vector field $c(x, y) = m(x, y)\hat{v}$, where $\left(m(x, y)\right)$ represents the spatially varying current magnitude and (\hat{v}) is a unit vector in the flow direction. This model allows planners to account for environmental assistance or resistance when evaluating path feasibility.

3.2. Mission Generation and Task Model

Missions are generated dynamically to simulate realistic logistical demands in riverine transport. A mission is represented as a set of delivery tasks $M = \{T_1, T_2, \dots, T_n\}$, where each task ($T_i$) assigns a USV to transport cargo from a depot to a destination node. Destinations are fixed locations on the riverbank, while tasks can be issued either at initialization or stochastically during runtime to reflect emergent delivery needs. Each task is characterized by a tuple $T_i = (id, p_{dest}, t_{start}, status)$, with ($id$) denoting the task identifier, (p_{dest}) the target coordinates, (t_{start}) the release time, and*(status)* its execution state. The mission generator introduces variability through multiple operational scenarios such as standard delivery, urgent medical supply runs, cross-river bulk transport, and heavy-traffic congestion. In urgent missions, delivery deadlines impose constraints on acceptable path length and travel time. In heavy-traffic scenarios, the density of dynamic obstacles is increased, requiring algorithms to prioritize collision avoidance and replanning. This task modeling approach ensures that the evaluation captures not only static path efficiency but also responsiveness to real-time logistical dynamics.

3.3. Planner Integration

The heart of architecture lies in the integration of diverse path planning algorithms, which operate over the environment and mission models [52]–[54]. Each USV is equipped with a modular planning interface that allows switching between planners such as Reactive Steering, A* Search, RRT, APF, GA, D* Lite, HARRT*, and AHA-RRT*. These planners are abstracted under a common interface that defines the method findPath(start, goal), ensuring uniform compatibility within the simulation environment. The planning cycle is embedded in the USV's control loop. At each timestep, the USV updates its local perception of the environment, selects or adapts its path according to the active planning method, and executes motion commands while accounting for hydrodynamic forces. For planners such as D* Lite and AHA-RRT*, which support dynamic replanning, the system triggers path recalculations when obstacles block current trajectories or when mission requirements change. For stochastic planners like GA or RRT*, new samples and populations are generated as necessary to refine the path.

3.4. System Integration Flow

The complete simulation framework is designed as a closed-loop pipeline that continuously integrates environmental dynamics, mission generation, path planning, execution, and metric evaluation [55]–[57]. This flow ensures that each component of the system is not isolated but instead interacts with the others in real time, thereby replicating the operational feedback cycles that occur in autonomous logistics deployments on inland waterways. The loop begins with the environment model, where the state of the river domain at time (t) is defined as $\mathcal{E}(t) = \{O_s, O_d(t), S_k, c(x,y,t), w(x,y,t)\}$, comprising static obstacles (O_s), dynamic obstacles $\left(O_d(t)\right)$, shallow water zones (S_k), the river current field $\left(c(x,y,t)\right)$, and wind disturbances $\left(w(x,y,t)\right)$. This environment is continuously updated at discrete timesteps of size (Δt), producing a time-evolving spatial field that serves as the input to mission assignment and USV navigation.

Mission generation operates asynchronously, producing a stream of tasks $(\{T_i\})$ over simulation time. Formally, the task release process can be modeled as a stochastic point process $\mathcal{M}(t) = \{T_i : t_i^{release} \le t\}$, where each task $\left(T_i = (id, p_{dest}, t_{release}, d_i)\right)$ is characterized by a release time, a delivery destination, and a mission demand level (d_i). The interarrival time distribution between tasks may follow a Poisson model for standard operations or be adapted to reflect high-priority missions such as medical supply deliveries.

The path planning module receives both the updated environmental state and the active mission queue [22]–[24]. For a given USV (u) at position $\left(p_u(t)\right)$ with an assigned task destination (p_{dest}), the planner computes a feasible path $\pi_u(t) = \text{Planner}\left(p_u(t), p_{dest}, \mathcal{E}(t)\right)$, using one of the integrated algorithms such as A*, RRT*, D* Lite, or adaptive HARRT*. In algorithms that incorporate environmental costs, the effective edge weight between two nodes $\left((p_a, p_b)\right)$ is adjusted by travel time models such as the Estimated Travel Time (ETT) where $\text{ETT}(p_a, p_b, t) = \frac{|p_b - p_a|}{v_{max} f_{env}(p_{avg}, t)}$ here (v_{max}) the propulsion speed in still water and $\left(f_{env}(p_{avg}, t)\right)$ captures the hydrodynamic effects of current and wind at the midpoint between (p_a) and (p_b). The execution layer transforms the planned trajectory into low-level commands for propulsion and heading, subject to vehicle dynamics and environmental disturbances. The actual trajectory followed by the USV is therefore $\dot{p_u}(t) = v_{cmd}(t) + c(p_u, t) + w(p_u, t)$, where $\left(v_{cmd}(t)\right)$ is the commanded velocity from the planner and control law, modified by external forces of the river current and wind.

The metrics evaluation component closes the loop by recording system performance. At the end of each mission, statistical summaries are produced, including total job completion time, average energy consumption, number of replans, minimum clearance distances, and collision counts. These metrics are denoted as $\mathcal{R}(t) = \{J(t), C(t), L(t), E(t), \Gamma(t)\}$, where (J) is the number of jobs completed, (C) is the collision count, (L) is the cumulative path length, (E) is the cumulative energy expenditure, and (Γ) is the set of recorded minimum clearances. This performance feedback not only provides benchmarking across planning algorithms but can also be reinjected into the system for adaptive learning strategies. The integration of these components yields a continuous timing loop: $\mathcal{E}(t) \longrightarrow \mathcal{M}(t) \longrightarrow \pi_u(t) \longrightarrow \dot{p}_u(t) \longrightarrow \mathcal{R}(t) \longrightarrow \mathcal{E}(t + \Delta t)$, which models the evolution of the simulation across time. This recursive relationship formalizes the architecture as a dynamical system in which environment, tasks, planners, and performance outcomes evolve in tandem. By capturing the temporal dependencies of river logistics, the architecture ensures that USV decision-making reflects the real-world operational cycle of perception, planning, action, and evaluation.

4. Experimental Scenarios, Workloads, and Evaluation Metrics

The validation of the USV logistics simulation framework requires a systematic description of operational scenarios, the modeling of mission workloads, and the formulation of quantitative evaluation metrics [58]–[61]. These three elements together create the experimental foundation that enables reproducible testing of planner performance and operational effectiveness. Scenarios define the contextual environment in which the USVs operate, workloads specify the temporal and spatial demands placed upon the fleet, and metrics provide formal instruments to measure efficiency, safety, and adaptability. The interaction between these three dimensions ensures that experiments do not remain abstract algorithmic tests but instead reflect the operational realities of inland waterway logistics.

4.1. Scenario Definitions

Each scenario represents a distinct operational condition reflecting real-world riverine challenges. The Standard Operation scenario describes baseline fleet missions where deliveries are evenly distributed between depot and destination points in calm waters with moderate levels of debris. The Urgent Delivery scenario imposes tighter temporal constraints, such as medical supply missions that require minimal delay, forcing the planner to prioritize speed and path feasibility. Heavy Traffic simulates congested waterways with increased dynamic obstacle density, leading to more frequent avoidance maneuvers and testing collision robustness. Cross-River Rush reflects peak demand situations in which multiple jobs are generated simultaneously on opposite banks, requiring coordination among multiple USVs to avoid bottlenecks. Finally, Long-Haul Transport imposes missions across extended distances within the 200×200 meter domain, where river current and wind effects dominate navigation efficiency. By constructing this suite of scenarios, the system can be evaluated against both everyday and stress-test conditions, thereby validating planner reliability across diverse logistical contexts.

4.2. Workload Modeling

The mission workload is modeled as a time-dependent job arrival process that continuously injects delivery tasks into the environment. Each job is defined by its origin at the depot, its assigned destination, and its temporal service requirement, including release time and expected completion window. Formally, the set of active jobs at time t can be denoted as $\Lambda(t) = \{J_i(t)\}_{i=1}^{N}$, where each job $J_i(t)$ contains a target position $p_{g,i}$, an initiation time $t_{\text{start},i}$, and a completion time $t_{\text{finish},i}$. In Standard Operation, jobs arrive periodically at intervals of approximately 600 seconds with small variance, ensuring balanced utilization of the fleet. Urgent Delivery reduces the inter-arrival interval to around 200 seconds, saturating fleet resources and amplifying scheduling pressure. Heavy Traffic preserves the Standard Operation workload intensity but increases obstacle density within the environment, modeled as a higher probability of debris generation in each grid cell. Cross-River Rush produces bursts of simultaneous jobs requiring traversal to multiple riverbanks at once, a setting that naturally creates congestion in central river crossings. Long-Haul missions extend the Euclidean distances between depot and destination, such that the total path length becomes maximized, where

w_k represents successive waypoints of a planned trajectory. Through these workload definitions, both temporal stress (arrival frequency) and spatial stress (travel length and congestion) are explicitly encoded into the simulation framework.

$$L(J_i) = \sum_{k=1}^{m-1} |w_{k+1} - w_k| \tag{1}$$

4.3. Evaluation Metrics

Performance evaluation requires the continuous collection of operational metrics that quantify system effectiveness across reliability, temporal efficiency, safety, and energy consumption. Job Completion Rate is computed as the ratio of completed jobs to assigned jobs and directly reflects reliability in satisfying logistical demand. Fleet Throughput expresses the number of jobs completed per simulation hour, serving as a measure of fleet productivity. Average Delivery Time captures temporal efficiency by recording the meantime taken to complete each job, measured as the difference between initiation and completion timestamps. Safety is quantified by collision count, recording each instance of contact with static or dynamic obstacles, and by safety margin, defined as the time-averaged minimum clearance distance between any USV and the nearest obstacle. Adaptability is reflected in replanning frequency, which measures how often the system must recompute paths in response to dynamic changes, such as new debris or current shifts. Path efficiency is defined as the ratio between the straight-line depot-to-destination distance and the actual traveled path length, thus quantifying deviation from optimality. Energy consumption per job is also evaluated, where the total propulsion energy expenditure is averaged across all completed deliveries. Formally, this is computed as $E_J = \frac{1}{N_{\text{completed}}} \sum_{i=1}^{N_{\text{completed}}} E_i$, where each E_i is determined from hydrodynamic drag and thrust-force models. Collectively, these metrics enable multidimensional evaluation, revealing trade-offs between speed, efficiency, energy use, and safety.

4.4. Integration of Scenarios, Workloads, and Metrics

The experimental design operates as a closed-loop pipeline in which environment states, mission workloads, planning algorithms, and execution outcomes continuously interact. At the beginning of each simulation, a scenario initializes environmental variables such as current strength, debris density, and weather profile. Mission workloads are then generated according to the temporal distribution rules of the scenario and injected into the job queue. The selected planner processes the job queue, generating feasible paths that the USVs attempt to follow in the presence of currents, winds, and obstacles. Execution generates spatiotemporal trajectories, which are logged in real time. From these trajectories, evaluation metrics are computed dynamically, providing immediate feedback on fleet safety, efficiency, and energy usage. Metrics are also aggregated across the full simulation horizon, allowing comparison across planners and scenarios. The integration of scenarios, workloads, and metrics in this continuous loop ensures that experimental results are both algorithmically reproducible and operationally representative of real-world logistics challenges in riverine domains.

5. Results and Discussion

5.1. System Design

The overall architecture of the USV logistics simulator, shown in Fig. 1, is built around three major parts: the front-end interface, the simulation core at the back end, and a set of physical and environmental models. At the entry point of the system, the front-end gives users a straightforward way to set up and run their scenarios. Through the configuration panel, they can adjust the simulation environments like domain size, wind and current ranges, obstacle density, and shallow-zone penalties while also selecting which planner to use and how it should be tuned. Parameters such as random seeds can be specified so that the same run can be reproduced later. Once a simulation is underway, the visualization window provides a live view of the USVs moving through the water, together with currents, wind fields, and nearby hazards. Key indicators, including collisions, completed and failed tasks, path lengths, and energy use, are also presented as charts or tables, allowing the user to make sense of the results as they unfold. To make the behavior of the vessels feel realistic, the simulator models several physical factors that influence movement on the water. These include fixed structures like islands, as well as dynamic obstacles that can drift or move. The environment also contains areas of shallow water, which the planners may avoid or treat as costly. Both water currents and wind are represented as fields that vary with time and location, pushing the vessels off their intended routes unless the planner accounts for them. A simple but effective energy model is included too, based on hydrodynamic drag, so that energy use rises sharply as the vessel moves faster. These elements constantly interact with the planner and the USV control logic, helping expose how different algorithms respond to changing or uncertain conditions.

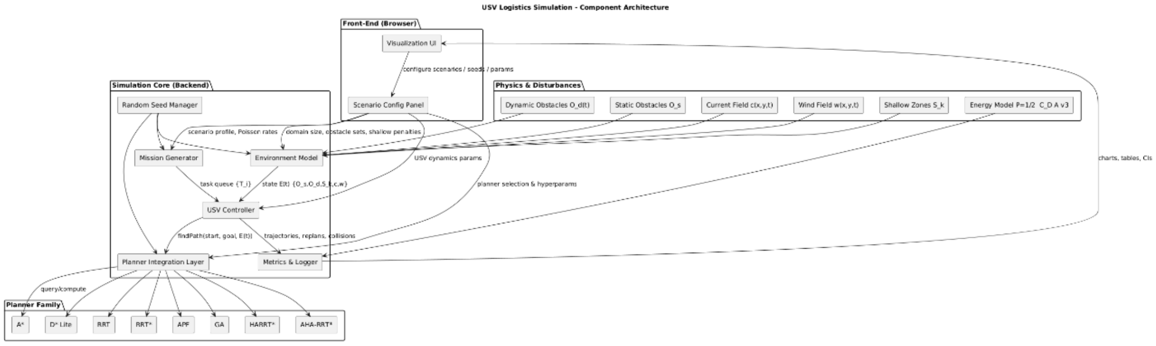


Fig. 1. Component diagram

The central logic of the simulation sits in the back-end. To keep experiments consistent, a seed manager distributes random seeds to any component that depends on randomness, ensuring that runs can be repeated. A mission generator creates delivery jobs over time often modeled with a stochastic arrival process, so that each USV must decide how to reach its destination within a possible deadline. The environment model keeps track of static and dynamic obstacles, shallow zones, and the current and wind fields, updating them as needed over the course of the simulation. Each USV is controlled by its own module, which takes on tasks, requests a path from the planner, and then follows that path while watching for trouble ahead. If the environment changes in a way that makes the path unsafe or invalid, the controller triggers a replanning step. It also incorporates environmental effects into its motion, so the simulated vessel drifts and reacts in a believable way.

To make it easy to compare different planning methods, a planner integration layer standardizes how the simulation communicates with planners. Regardless of which algorithm is used whether a classic graph-based method like A* or D* Lite, a sampling-based strategy such as RRT or RRT*, an optimization-based heuristic like a genetic algorithm, or a more advanced hybrid planner like HARRT* or AHA-RRT* the simulation simply provides a start point, a goal, and information about the environment. The selected planner then returns a path that the USV can try to follow. Throughout the run, a logging system collects detailed statistics: how many tasks were completed or missed, how often replanning occurred, the length of the final trajectories, energy spent, and how close the vessel passed to hazards. These results feed back into the visualization interface so that users can explore the behavior of planners under different sets of physical and logistical constraints.

The activity shown in Fig. 2 illustrates, in broad strokes, how a USV moves between planning and replanning while carrying out its assigned mission. Each cycle begins with the system taking stock of the current environment, $E(t)$, while also checking whether any tasks are waiting in the queue. When no task is available, the vessel simply idles, much like a boat waiting for new orders at a dock. Once a task has been assigned, the controller identifies the destination and looks at whether the existing path is still sensible to follow. This quick check considers not only whether the route is valid on paper, but also whether anything ahead has changed a drifting obstacle, an unexpectedly shallow patch, or a strong current could all make a previously safe path risky. If nothing obstructs the planned route, the USV continues on its way. Otherwise, it pauses to replan. In that moment, the system chooses one of the available planning policies (for example, A*, RRT*, or a hybrid approach) and asks the chosen algorithm to compute a new path based on the most recent picture of the surroundings. With an updated route in hand, the controller applies the appropriate motion commands while folding in the influence of currents and wind. The simulator also keeps track of energy expenditure as the vessel moves, using a drag-based model $P = \frac{1}{2} C_D A v^3$ that reflects the reality that power demands rise quickly at higher speeds. As the USV progresses, the controller checks whether the destination has been reached or, alternatively, whether the task has run out of time. Reaching the goal on schedule leads to success, while exceeding the deadline counts as a failed job. In either case, the outcome is recorded. Along with job status, the simulator notes how often the system needed to replan, how much energy was used, and how close the USV came to hazards during its journey. Once the bookkeeping is complete, the cycle returns to its starting point, ready to examine the environment and any new tasks waiting to be handled.

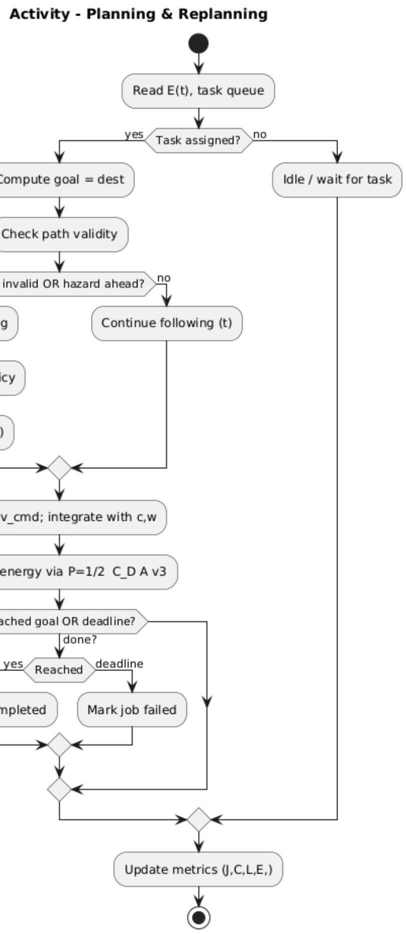


Fig. 2. Activity diagram

5.2. Experiment Results

The results in Table 1 using simulation software in Fig. 3 summarize the performance of each planner across six delivery tasks, all constrained by a uniform ten-minute deadline. Although the raw counts of completed versus failed jobs appear, at first glance, to be broadly similar among several planners, a closer examination reveals meaningful differences in how each algorithm managed dynamic river conditions and evolving obstacle fields. Notably, most failed missions were not caused by collisions; rather, they resulted from exceeding the allotted time. Consequently, the evaluation of performance must consider not only navigational correctness but also temporal responsiveness underscoring that timing, rather than mere path feasibility, was the principal determinant of mission success. The Adaptive Hybrid RRT* (AHA-RRT*) completed three of six missions without experiencing any collisions. However, this came at the cost of nine replanning events, which lengthened its average travel distance and increased energy consumption. Although its average obstacle clearance (25.81 m) indicates cautious decision-making, the three failed missions can reasonably be attributed to the time penalties associated with frequent detours. Thus, while AHA-RRT* demonstrated strong hazard avoidance, its conservative behavior occasionally limited its ability to meet deadline constraints.

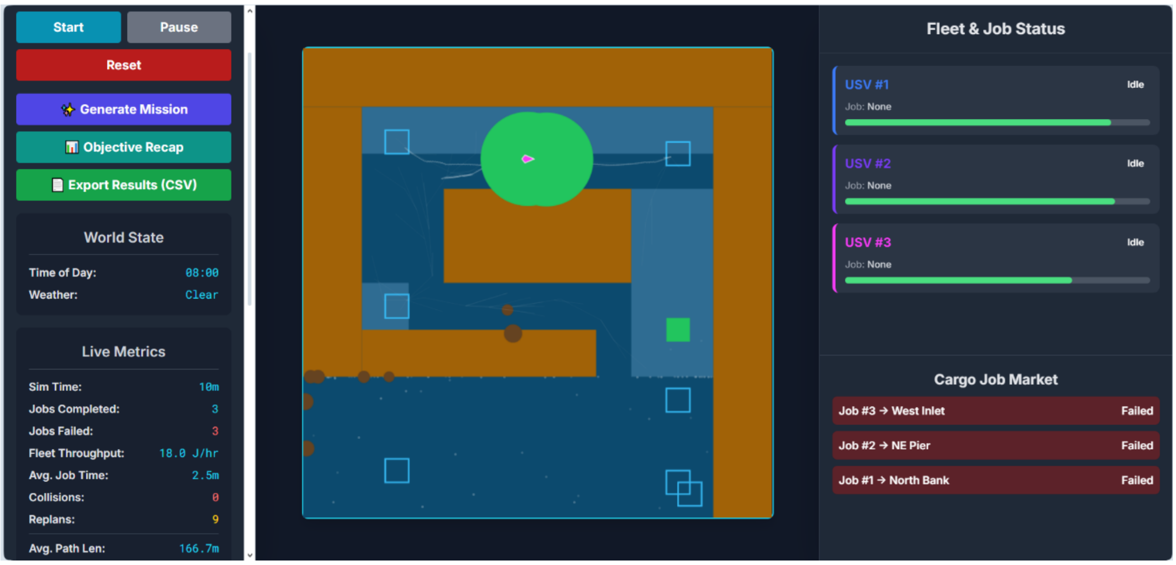
Table 1. Simulation results

Planner	JobsCompleted	JobsFailed	Collisions	Replans	AvgPathLength (m)	AvgEnergy (kWh)	AvgClearance (m)
AHARRTStar	3	3	0	9	166.69	16.64	25.81
HARRTStar	3	3	3	0	163.16	17.50	27.52
DStar	0	6	1	8	N/A	N/A	22.41
GA	0	6	3	0	N/A	N/A	20.54
APF	2	4	0	0	109.89	10.94	23.04
RRTStar	3	3	0	0	156.70	15.70	32.20
RRT	1	5	1	0	130.34	12.76	17.21
AStar	0	6	0	0	N/A	N/A	24.26
Reactive Steering	2	4	0	0	115.05	12.11	29.61

In contrast, HARRT* exhibited a markedly different operational profile. It also completed three missions, yet it did so without any replanning and recorded three collisions. This absence of adaptive path correction suggests a strong reliance on the initially generated trajectory, regardless of evolving hazards. Although HARRT* achieved slightly shorter paths than AHA-RRT*, its energy expenditure was the highest among all planners, implying aggressive traversal through potentially adverse flow regions. Consequently, while HARRT* may perform adequately under predictable environmental conditions, its inability to revise routes mid-mission leaves it vulnerable to sudden changes, as demonstrated by its collision rate. RRT* again offered the most balanced and stable behavior. It successfully completed three missions without either replanning or colliding, while also maintaining the highest average clearance (32.20 m). Its moderate path lengths and energy demands suggest that RRT* was able to generate globally robust routes that remained viable throughout the mission. However, RRT* still failed half of its assignments, most likely because its emphasis on safe and relatively conservative trajectories occasionally resulted in arrival times that exceeded the deadline. Accordingly, RRT* appears to produce inherently durable solutions but lacks fine-grained mechanisms to accelerate task completion in adverse circumstances.

By comparison, basic RRT delivered only one successful mission and incurred one collision. Although its average path lengths were shorter and energy usage lower than that of the more advanced variants, its limited obstacle clearance (17.21 m) reflects a tendency to produce riskier spatial trajectories. This performance aligns with well-known characteristics of RRT, namely its ability to produce fast but suboptimal routes that lack strong guarantees of safety or consistency, particularly under stringent temporal requirements. Turning to reactive strategies, both the Artificial Potential Field (APF) and Reactive Steering planners completed two missions without collisions. APF reported the shortest paths and lowest energy consumption, which is consistent with its gradient-based nature. Nevertheless, its four failed tasks likely reflect entrapment in local minima. Likewise, Reactive Steering achieved relatively high obstacle clearance and moderate energy use but failed to reliably complete missions within the allotted time. In both cases, the absence of global foresight limited their ability to anticipate and avoid downstream hazards or to select long-range corridors aligned with dominant current patterns. Consequently, although their local obstacle-avoidance capabilities were generally sound, these planners struggled when broader situational awareness was required.

Finally, the classical A* and D* Lite algorithms, along with the genetic algorithm (GA), did not complete any missions. A* failed all tasks without colliding, suggesting that its static-map assumptions and lack of dynamic adaptation were fundamentally misaligned with the fast-changing environment. D* Lite attempted to compensate, as indicated by its eight replanning events, but still collided once and ultimately failed every mission. Similarly, GA logged three collisions and consistently failed to converge on usable solutions within the time limit. Collectively, these outcomes highlight that methods assuming environmental stability or requiring lengthy optimization periods cannot reliably support real-time river-logistics operations.



Time of Day: 08:00
Weather: Clear

Sim Time: 10m
Jobs Completed: 3
Jobs Failed: 3
Fleet Throughput: 18.0 J/hr
Avg. Job Time: 2.5m
Collisions: 0
Replans: 9
Avg. Path Len: 166.7m

USV #1 Idle
Job: None
USV #2 Idle
Job: None
USV #3 Idle
Job: None

Job #3 → West Inlet Failed
Job #2 → NE Pier Failed
Job #1 → North Bank Failed

Fig. 3. Simulation software

6. Conclusion

This work set out to build and examine a simulation framework for unmanned surface vessels operating in realistic inland and near-coastal environments, with conditions inspired by the waterways of East Nusa Tenggara. At its core, the framework brings together environmental modeling, mission generation, and a range of planning algorithms, allowing them to be tested under the same pressures of current, wind, shallow areas, and task deadlines. One of the most useful outcomes of this study is the modular planning interface, which makes it possible to compare very different planners side by side and observe how they react when the environment shifts. Thinking about trajectory planning not just as a geometric problem but as one shaped by disturbances and time pressure helped clarify why some families of algorithms cope better than others.

Across the experiments, sampling-based planners emerged as the most dependable overall. RRT* delivered steady and uncomplicated performance, completing its assigned jobs without collisions and usually leaving generous clearance. Its adaptive cousin, AHA-RRT*, often handled sudden environmental changes more gracefully, though it did so by replanning more frequently. HARRT*, meanwhile, produced efficient paths but occasionally cut things too close, suggesting it may work best where obstacles are sparse or currents are predictable. Lighter-weight methods, such as reactive steering and artificial potential fields, showed they could handle simpler routes but struggled once situations became demanding. On the other end, more traditional approaches such as A*, D* Lite, and genetic algorithms generally could not keep up with time-critical missions. These results are encouraging, but they also come with some caveats. The simulation relies on simplified hydrodynamics and fixed deadlines, which may unintentionally favor certain types of planners. Hazard models and shallow-zone penalties are still abstractions, and the framework has not yet been validated against real-world deployments or hardware-in-the-loop setups. Similarly, all tests were carried out with a single vessel, so the findings tell us little about how planning might change when several USVs must share the same waterways. In short, the conclusions here are strongest for single-platform missions in moderately dynamic environments.

Still, the framework provides a practical base for future work and helps clarify where current planning approaches excel or fall short. More importantly, it highlights the kinds of conditions such as disturbance, deadlines, and sudden hazards that shape real maritime logistics and cannot be ignored in planning research. Looking ahead, several directions seem especially worthwhile. Validating the planners against field data from narrow channels or inter-island routes would be a natural next step, whether through hardware-in-the-loop testing or small-scale deployments. A more detailed energy model that accounts for vessel shape, propulsion choice, and efficiency losses could help bring the simulations closer to real platforms. Multi-USV coordination is another important frontier, as real logistics rarely rely on only a single craft. Finally, expanding the scenario space ranging from short emergency dispatches to longer resupply missions would help broaden the relevance of this work to different types of maritime operations.

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