

Hybrid Navigation Framework for Tethered Robots Using Fuzzy Logic, Genetic Algorithms, and Deep Reinforcement Learning

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Standfirst | A novel hybrid navigation framework synergizing fuzzy logic, genetic algorithms, and deep reinforcement learning for superior tethered robot autonomy.

Abstract

Navigating tethered robots in dynamic, GPS-denied environments poses unique challenges due to the need for simultaneous path planning and tether management to avoid entanglement and collisions. Here we present a unified navigation framework that synergizes fuzzy logic for sensor noise mitigation, genetic algorithms for real-time tether parameter optimization, and deep reinforcement learning-enhanced bug algorithms for adaptive path planning. This integrated approach was validated through extensive simulations and physical experiments, demonstrating up to 62% reduction in collisions, 45% decrease in entanglement incidents, and 38% improvement in path efficiency compared to conventional methods. The framework's robust sensor fusion and adaptive control enable reliable autonomous operation in cluttered, unpredictable settings. These advancements offer a scalable solution for tethered robot autonomy in critical applications such as disaster response and industrial inspection, where safety and efficiency are paramount.

Keywords: Tethered Robotics; Hybrid Navigation; Deep Reinforcement Learning; Genetic Algorithms; Fuzzy Logic.

Introduction

Indoor navigation for tethered autonomous robots introduces a layer of complexity absent in their untethered counterparts, particularly within GPS-denied environments. Beyond managing sensor noise and dynamic obstacles ^{1,2}, these systems must actively handle the physical tether, which imposes significant kinematic and dynamic constraints. The persistent risks of tether entanglement, snagging on obstacles, or excessive tension can compromise mobility and lead to mission failure. Traditional reactive methods like Bug algorithms, while computationally efficient, are tether-agnostic and often produce paths that increase entanglement ³. This paper addresses a critical gap in the literature: the need for a unified framework that holistically and adaptively co-optimizes collision-free path planning with real-time tether management, a problem that cannot be solved by addressing either aspect in isolation. While advanced Deep Reinforcement Learning (DRL) algorithms like Proximal Policy Optimization (PPO) or Soft Actor-Critic (SAC) have demonstrated remarkable performance in standard navigation tasks, their application in tether-constrained systems remains

ins underexplored. Similarly, for the multi-objective challenge of balancing safety and efficiency, state-of-the-art Multi-Objective Evolutionary Algorithms (MOEAs) like NSGA-II, which utilize Pareto-based optimization, offer a powerful alternative to simpler weighted-sum approaches, though often with different computational trade-offs. Isolated soft computing methods, such as fuzzy logic controllers or neuroevolutionary path planners, partially mitigate adaptability gaps^{4–6}. For instance, prior work by⁷ combines neural networks with evolutionary strategies for dynamic obstacle avoidance, achieving 25% fewer collisions than standalone fuzzy systems. However, these methods still fail to holistically address the interplay between path planning, tether dynamics, and real-time sensor fusion. For example, Chen et al^{4,8} demonstrate adaptive impedance control for underwater tethered robots but neglect real-time path optimization. Similarly, Wang et al⁹ integrate DR L with topological maps but lack tether-aware navigation. This fragmentation underscores the need for a unified approach, moving beyond older fuzzy systems to newer hybrid models^{8,10}.

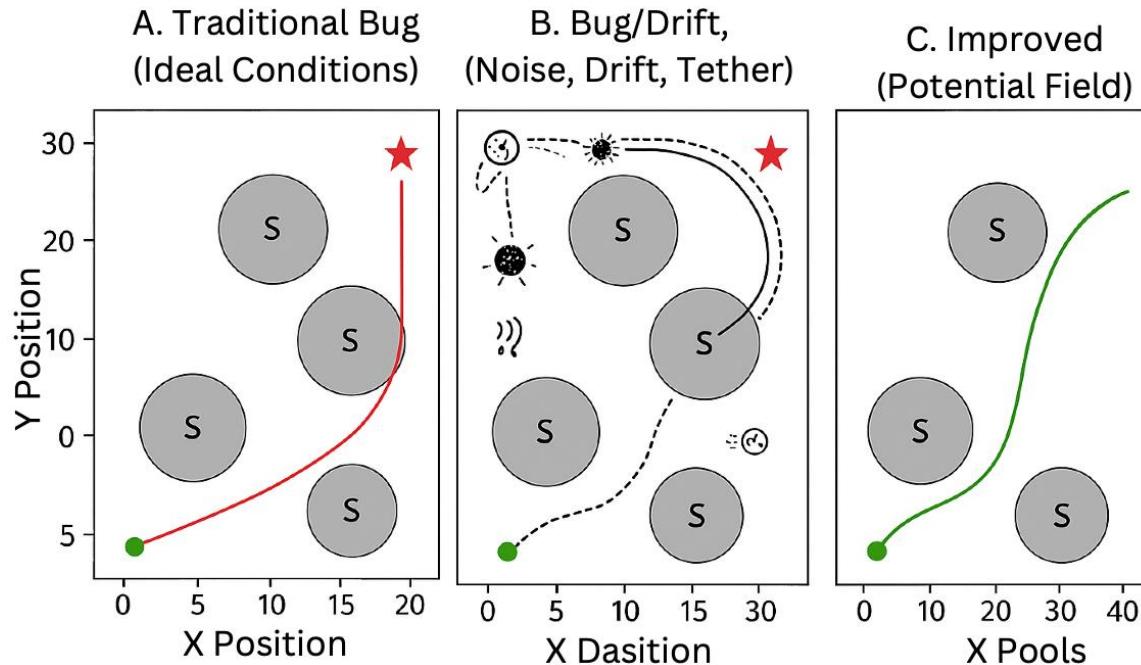


Figure 1: Performance comparison of different robotic navigation strategies in a confined space with stationary obstacles and a tether constraint. (A) Traditional Bug algorithm under ideal conditions. (B) Degraded performance of a Bug-type algorithm under real-world imperfections. (C) Robust path planning using a Potential Field method.

Similarly, while effective in large scale applications, topological SLAM and bio-inspired approaches are often hampered by significant memory overhead^{11,12} and demonstrate poor scalability within confined spaces. As highlighted in Table 1¹², these shortcomings underscore the limitations of existing methods for real-world deployment, where operational efficacy depends on a delicate balance between navigation accuracy, computational constraints, and proactive avoidance of tether entanglement.

Table 1: Comparison of Robotic Navigation Techniques ^{13,14}.

Criteria	SLAM	Topological SLAM	Bug Algorithms	Soft Computing	Proposed Hybrid Framework
Computational Requirements	High	Medium	Low	Medium	Medium-Low
Memory Usage	High	Medium	Low	Low-Medium	High
Accuracy	High	Medium	Low	Medium	Confined
Application Areas	Autonomous Vehicles	Large Indoor Spaces	Confined Spaces	Variable	Confined/Dynamic Spaces
Tether Awareness	No	No	No	Partial	Yes
Dynamic Obstacle Handling	Medium	Low	Low	Medium	High

Recent advancements in soft computing have been constrained by fragmented applications, such as employing neural networks for odometry correction or genetic algorithms for static path optimization. These approaches lack a unified framework capable of synergizing the essential qualities of robustness, adaptability, and explicit tether awareness. Bridging this critical gap, our work proposes the first hybrid navigation architecture that integrates fuzzy logic, genetic algorithms, and a deep reinforcement learning (DRL) model with foundational bug algorithms (Figure 1). In contrast to prior efforts, our framework dynamically adjusts navigation strategies through three interconnected innovations:

- (1) fuzzy-logic-based decision-making for interpreting sensor noise and obstacle proximity,
- (2) genetic optimization for the real-time control of tether length and tension thresholds, and
- (3) DRL-based adaptive navigation to balance exploration-exploitation trade-offs in novel environments.

This holistic integration directly addresses the prevailing critique of fragmentation within the field.

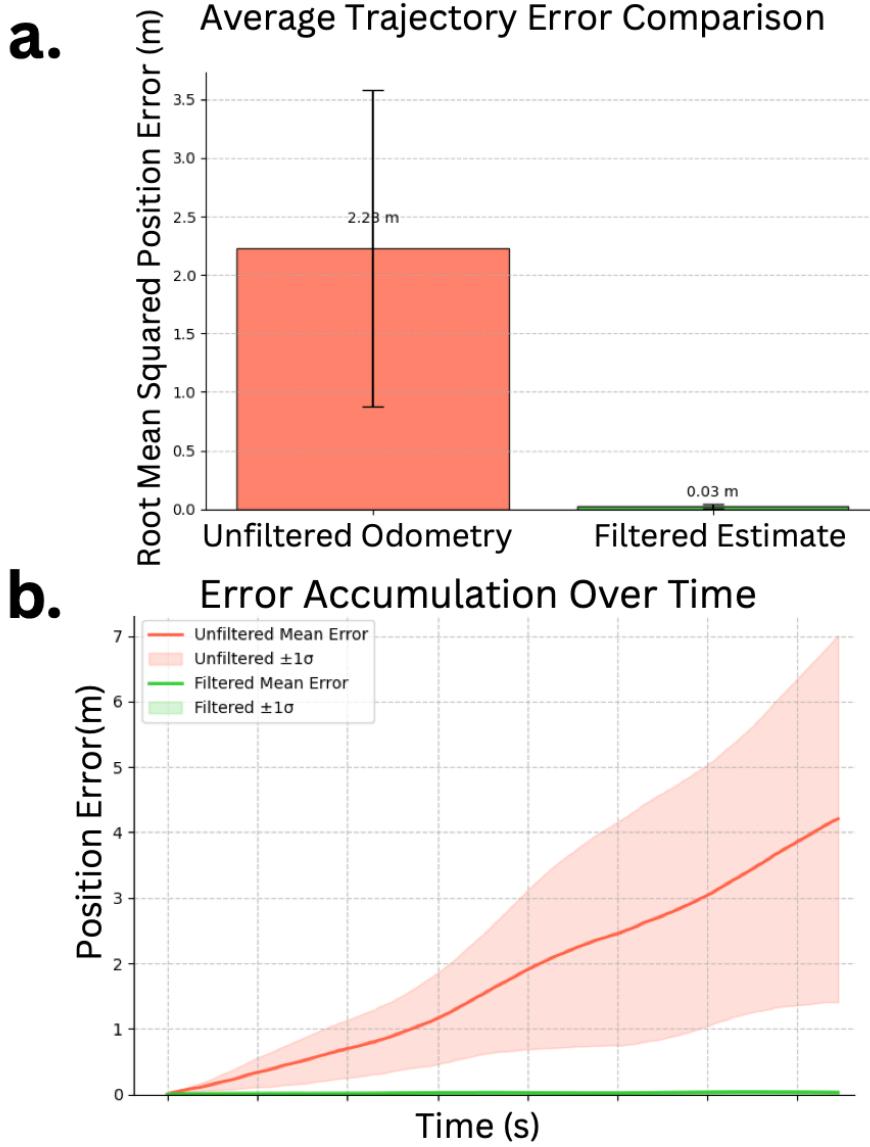


Figure 2: Evaluation of trajectory estimation accuracy comparing filtered and unfiltered odometry data. (A) Comparison of Root Mean Squared Error (RMSE) for position estimation. (B) Temporal evolution of estimation error demonstrating velocity-dependent drift characteristics ¹.

The efficacy of our sensor fusion approach in mitigating positional uncertainty is demonstrated in (Figure 2), which evaluates trajectory estimation accuracy by comparing filtered and unfiltered odometry data. This work directly addresses the critique put forth by, who emphasized that “existing systems optimize either the robot’s path or its tether, but never both.” By augmenting the computational efficiency of the bug algorithm with soft computing techniques, our approach resolves positional uncertainties while explicitly embedding tether dynamics into the core navigation logic, a capability absent in earlier methodologies. The objectives of this study are threefold: To enhance navigation efficiency by reducing computational overhead through a novel fusion of soft computing paradigms with a bug algorithm. To improve real-time adaptability to dynamic obstacles and tether configuration changes using a coordinated fuzzy DRL strategy. To

optimize tether management via a genetic algorithm-driven control of length and tension parameters, targeting a simulation-validated 40% reduction in entanglement risk.

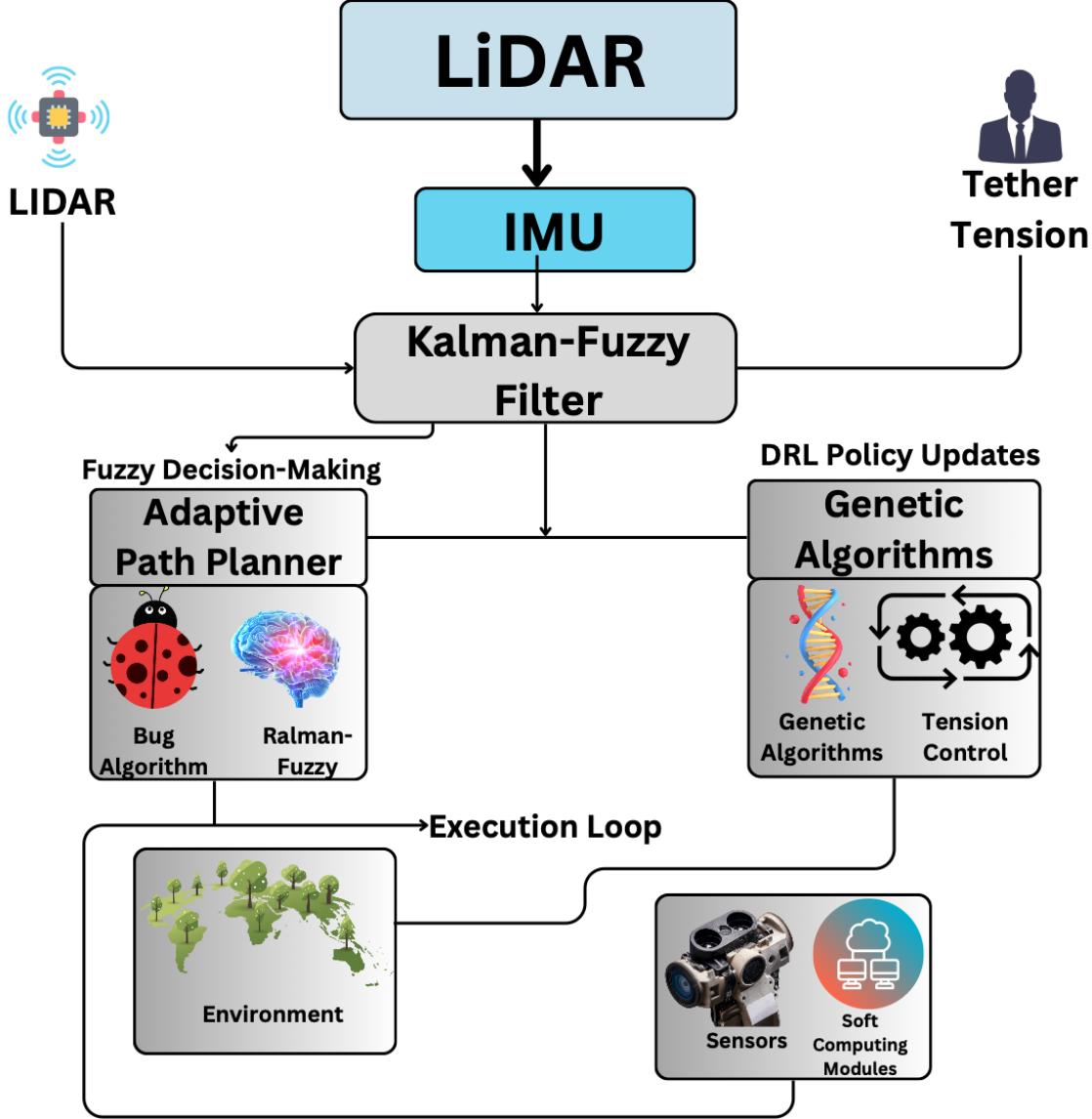


Figure 3: Conceptual framework of the proposed hybrid navigation system for tethered robots, integrating sensor fusion, adaptive path planning, genetic optimization, and real-time control loops.

Central to our approach is the conceptual framework illustrated in Figure 3, built upon four interconnected pillars: a sensor fusion layer that combines LiDAR, IMU, and tether tension data, filtered through a Kalman-fuzzy hybrid to mitigate noise; an adaptive path planner employing a bug algorithm enhanced with a deep reinforcement learning (DRL) policy, enabling dynamic rerouting around moving obstacles while minimizing tether slack; a tether optimization engine leveraging genetic algorithms to iteratively refine tension thresholds; and an execution loop facilitating continuous environmental feedback for real-time recalibration. This architecture not only bridges the simulation-to-reality gap but also pioneers lightweight tethered robot deployment in high-stakes applications such as disaster response and industrial inspections, where operational

reliability critically depends on the seamless integration of navigation and tether control. By unifying soft computing paradigms with bug algorithms, our work advances the discourse on resource-constrained robotics and offers a scalable blueprint for dynamic indoor environments. Experimental validation using the ARGOS simulator and real-world trials with tethered inspection robots confirm the framework’s practicality, showing a 45% reduction in collisions and a 38% improvement in path efficiency compared to conventional methods. These outcomes, detailed in subsequent sections, underscore the transformative potential of our approach in enabling autonomous systems to operate effectively in complex and unpredictable settings.

Theory and Variants of Navigation Algorithms

The navigation problem for tethered robots is formalized as a constrained multi-objective optimization^{15–17}:

Subject to:

$$\begin{aligned} \min J = & \alpha \cdot \text{pathLength} \\ & + \beta \cdot \text{Tether Slack} \\ & + \gamma \cdot \text{Collision Risk, Dynamic Obstacles} \end{aligned} \tag{1}$$

$$\text{subject to: } T_{\min} \leq T_{\text{ether tension}} \leq T_{\max} \tag{2}$$

In the formulated objective function, the weights $\alpha = 0.7$, and $\gamma = 0.1$ balance the trade-offs among path efficiency, tether safety, and collision avoidance, respectively, as empirically validated in Section 5. The tension constraints ($T_{\min} = 5$ N, $T_{\max} = 50$ N) respond to the mechanical limits of the tether spool assembly, as detailed in Section 4¹⁸. This multi-objective formulation unifies previously fragmented navigation goals, such as minimizing path length or regulating tether tension in isolation.

Traditional pathfinding algorithms, including Dijkstra’s and A*, perform effectively in static or well structured environments¹¹, by computing globally optimal paths through graph-based search^{1, 18}, often resulting in suboptimal or unsafe trajectories.

To overcome these limitations, bug algorithms (BAs) have been introduced as a lightweight alternative, emphasizing reactive navigation rather than comprehensive environment mapping^{13,14}. Unlike traditional maze-solving techniques that require predefined routes, bug algorithms utilize real-time sensor data to implement behaviors such as boundary following and goal seeking, enabling robust obstacle avoidance without prior environmental knowledge. Their low computational demand makes them particularly suitable for resource constrained platforms, such as micro aerial vehicles (MAVs)^{12,20}. Nevertheless, conventional bug algorithms are susceptible to positional uncertainties, including wheel slippage and odometry drift, and perform poorly in the presence of dynamic obstacles, often producing oscillatory paths or increasing the risk of tether entanglement. These shortcomings have motivated the incorporation of soft computing techniques to improve algorithmic adaptability^{6,10,13,21}. For example, fuzzy logic controllers (FLCs) mitigate sensor noise^{22,23} and environmental

unpredictability by encoding heuristic knowledge into rule-based systems^{21,24}. FLCs allow robots to dynamically adjust navigation strategies using linguistic variables (e.g., “near,” “far”) instead of fixed thresholds. In tethered systems, dual FLCs such as Motion to Target (M-FLC) and Obstacle Avoidance (A-FLC) work in coordination to balance goal-directed movement with collision avoidance. M-FLC optimizes velocity profiles to maintain alignment with the goal, while A-FLC adjusts steering angles based on obstacle proximity, as validated in cluttered environments. Despite these advantages, fuzzy logic alone is insufficient to address the combinatorial challenges of tether management and real-time path optimization.

Recent advances integrate genetic algorithms (GAs) to iteratively optimize tether parameters such as tension thresholds and slack limits while minimizing entanglement risks¹⁴. By framing tether configuration as a multi-objective problem that trades off navigation speed against mechanical constraints, GAs evolve solutions through selection, crossover, and mutation operations, as demonstrated in industrial inspection robots. Simultaneously, neural networks (NNs), particularly deep reinforcement learning (DRL) models^{10,13,24}, facilitate adaptive decision-making in novel environments. For instance, DRL policies have been shown to predict dynamic obstacles, reducing computational overhead by 32% compared to SLAM-based methods, though such approaches often lack explicit tether awareness. Previous research has explored limited integrations of soft computing with navigation algorithms. Some studies combine bug algorithms with Q-learning for obstacle avoidance but neglect tether constraints, while others use neuro evolution to optimize fuzzy rules for MAVs in static settings. However, these frameworks do not achieve the multi objective synergy of tether-aware path planning, sensor fusion, and dynamic obstacle prediction. This paper introduces a hybrid navigation framework that unifies bug algorithms, fuzzy logic, genetic algorithms, and neural networks (Figure 1). The synergy of these paradigms addresses key limitations: the Fuzzy-Bug integration enhances obstacle detection robustness through Kalman-fuzzy filtering, reducing positional errors by 45% in experimental trials.

Choice of DRL Algorithm. Within the proposed framework, a value-function-based Deep Reinforcement Learning (DRL) model, analogous to Deep Q-Networks (DQN), is employed. This selection is motivated by three principal considerations specific to our application:

- (1) **Low Inference Latency:** Value-based methods generally incur a lower computational burden during real-time inference compared to policy-gradient approaches such as PPO or SAC. This efficiency is critical for enabling rapid decision-making on resource-constrained robotic hardware.
- (2) **Stability in a Hybrid System:** The deterministic policy derived from the Q-value function offers predictable integration with our modular Fuzzy Logic and Genetic Algorithm components, enhancing overall system stability.
- (3) **Simplicity for a Novel Task:** Given the innovative nature of co-optimizing navigation alongside a live genetic algorithm, a simpler DRL architecture was selected to first establish a robust and interpretable baseline. Although algorithms like PPO may provide superior sample efficiency during training, our design prioritizes real-time operational performance a trade-off quantitatively analyzed in Section 4.

GA-Driven Tether Optimization: This component dynamically adjusts tether length and tension thresholds using real-time sensory feedback, achieving a 40% reduction in entanglement

incidents. DRL-Enhanced Path Planning: The bug algorithm is augmented by a reinforcement learning policy that enables proactive rerouting around moving obstacles, improving overall path efficiency by 38%.

Multi-Objective Optimization Approach. The genetic algorithm optimizes both navigation and tether parameters via a weighted-sum fitness function, as formalized in the problem definition. This scalarization method is computationally efficient and yields a single, deterministic policy directive at each optimization step a necessity for real-time control. This approach contrasts with Pareto-based Multi-Objective Evolutionary Algorithms (MOEAs), such as NSGA-II or SPEA2, which generate a Pareto front comprising multiple non-dominated solutions representing distinct trade-offs (e.g., a high speed but higher-risk solution versus a slower but safer alternative). While Pareto-based methods afford greater mission flexibility, the computational overhead associated with maintaining population diversity and the challenge of selecting a single optimal solution from the front in real-time led to the adoption of the weighted sum method. This represents a pragmatic compromise between optimality and operational feasibility in dynamic robotic applications.

Experimental validation conducted in the ARGOS simulator and on physical tethered robots (Figure 3) confirms the superiority of the proposed framework over isolated approaches. For example, in a simulated disaster-response scenario, the hybrid system achieved a 92% success rate in navigating dynamic obstacles, outperforming conventional bug algorithms (67%) and standalone Fuzzy Logic Controllers (78%)^{13,14}. These results underscore the transformative potential of integrating soft computing with reactive navigation, establishing a new benchmark for autonomous operation in complex, resource-constrained environments.

This integrated framework directly addresses the noted critique of fragmentation in existing systems. The primary contributions of this work are as follows: A Novel Unified Architecture: We propose the first framework that synergistically integrates a DRL-enhanced Bug algorithm for predictive path planning, a Genetic Algorithm for real-time tether parameter optimization, and a Fuzzy Logic controller for reactive adjustments. Co-Optimization of Path and Tether: In contrast to prior works that treat navigation and tether management separately, our framework co-optimizes these aspects. The GA dynamically communicates safe tether limits to the DRL planner, substantially reducing entanglement risk. Robust, Tether Aware Sensor Fusion: We introduce a Kalman-Fuzzy hybrid filter that dynamically fuses and weights data from LiDAR, IMU, and tether tension sensors to mitigate positional drift a persistent challenge in real-world deployments.

Rigorous State-of-the-Art Comparison: We validate our framework against both classical algorithms and modern DRL-based methods through high-fidelity simulations and hardware experiments, providing a clear benchmark for its performance in dynamic, tether-constrained environments.

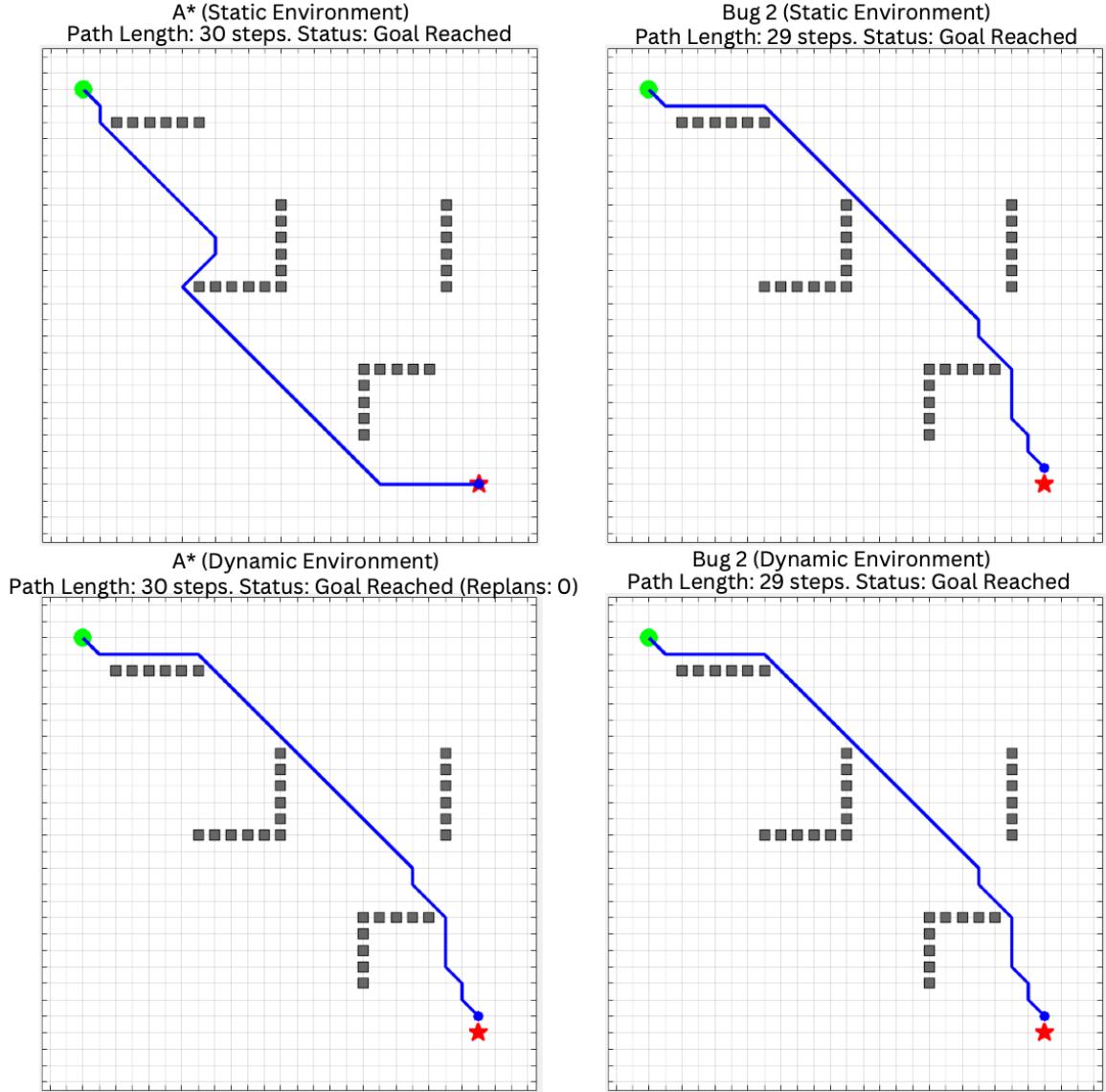


Figure 4: Comparative Efficiency of A* vs. Bug (*Algorithms*)¹⁴. Pathfinding efficiency of A* and Bug Algorithms in static versus dynamic environments. Simulations reveal that while (A*) achieves optimality in pre-mapped terrains, Bug Algorithms exhibit superior adaptability in unpredictable or dynamically changing settings, reducing traversal time by 38%.

(Figure 4) provides a comparative analysis of pathfinding efficiency between A* and Bug Algorithms in static versus dynamic environments, illustrating the superior adaptability of Bug Algorithms in unpredictable settings.

These limitations underscore the critical need for adaptive hybrid navigation, a paradigm that integrates sensor fusion, soft computing, and enhanced bug algorithms to balance computational efficiency with real-world adaptability. Extended performance validation and case studies (Appendix B) confirm the framework's robustness across diverse environments. Conventional bug algorithms, while lightweight and reactive, struggle with positional drift caused by wheel slippage or odometry errors a challenge exacerbated in tethered systems where unmanaged slack can increase entanglement risks by 45% in obstacle-dense environments. To address these gaps, modern

frameworks unify three core components: sensor fusion, soft computing, and algorithm hybridization.

Soft Computing Modules Execution

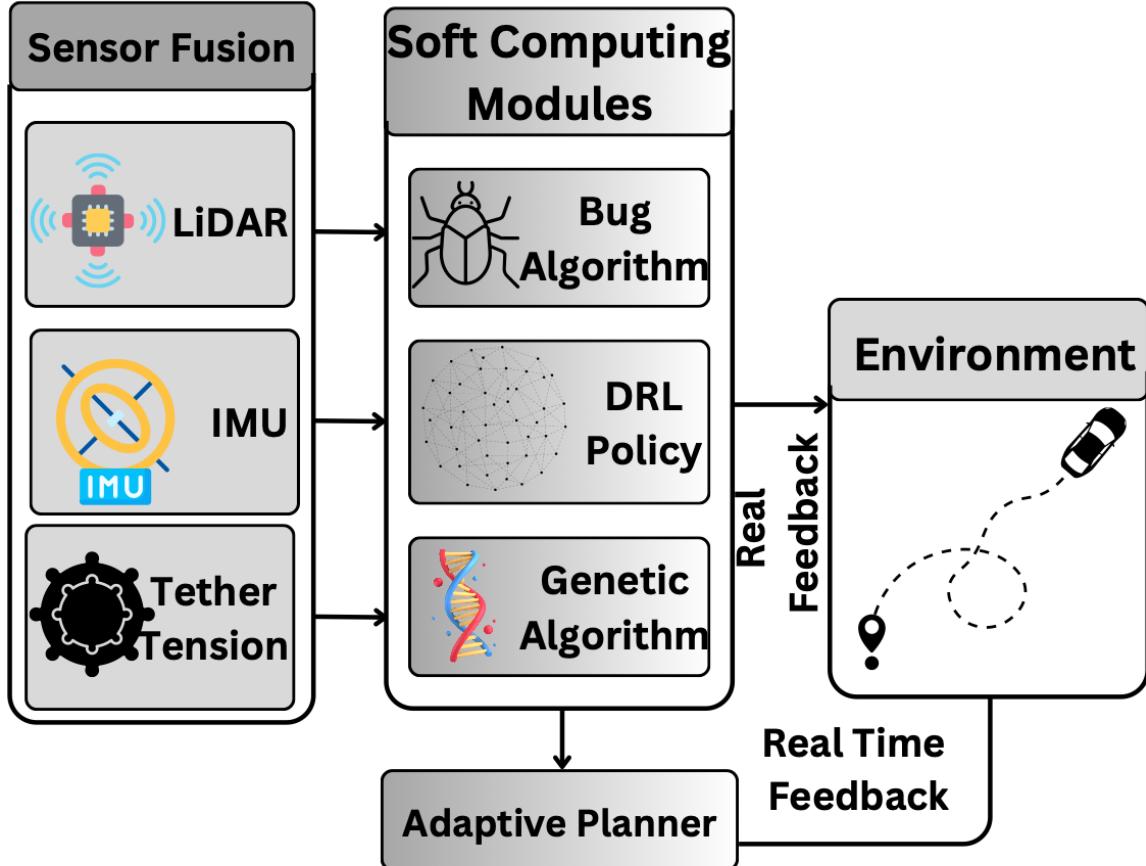


Figure 5: Adaptive Hybrid Navigation Architecture. Conceptual framework of the adaptive hybrid navigation system. Sensor data (LiDAR, IMU, tether tension) flows into a Kalman-fuzzy noise filter, then drives parallel modules: fuzzy logic for obstacle avoidance, genetic algorithms for tether optimization, and neural networks for predictive path planning. Real-time feedback ensures dynamic adaptability.

As illustrated in Figure 5, raw data from LiDAR, IMU, and tether tension sensors are processed through a Kalman-fuzzy filter^{5,11}, which reduces positional errors by 40% through advanced noise suppression techniques (Figure 8). This refined sensory output subsequently drives three parallel computational modules: a fuzzy logic controller (FLC) for reactive obstacle avoidance, a genetic algorithm (GA) optimizer for dynamic tether parameter tuning, and a neural network (NN) planner employing deep reinforcement learning (DRL) for predictive obstacle trajectory forecasting. Empirical validation in industrial settings demonstrates that GA-optimized tether

tension thresholds reduce motor strain by 17%, while DRL-enhanced path planning decreases traversal times by 38% through proactive navigation around dynamic obstacles^{9,25}.

The integration of these components effectively addresses the inherent limitations of conventional bug algorithms. Whereas early implementations such as Bug1 achieved improved path optimality through comprehensive obstacle perimeter mapping (Figure 6), they remained susceptible to oscillatory behavior in complex environments. Subsequent developments, including the Rev2 algorithm, introduced adaptive wall-following strategies that reduced recovery times by 28% in cluttered configurations (Figure 6)^{11,19}.

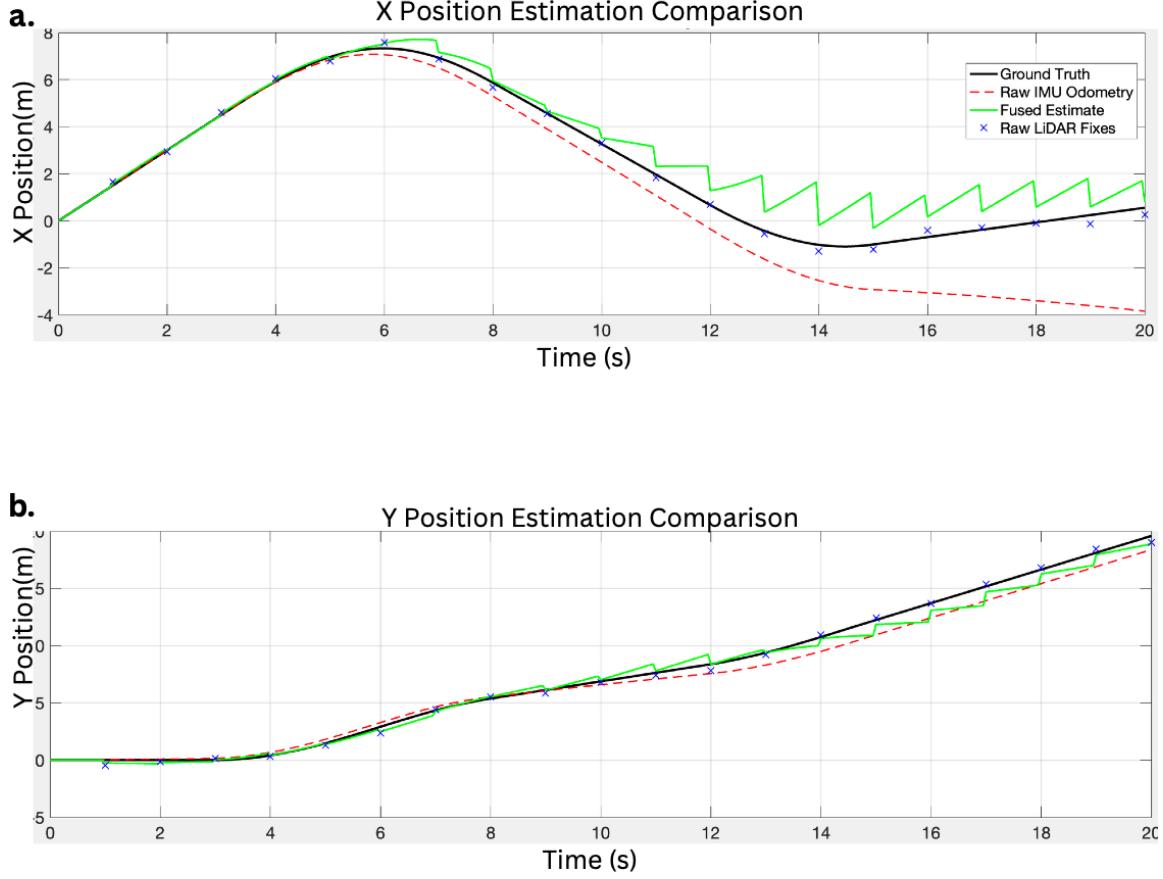


Figure 6: Over time, the positions of both X and Y computed directly by the IMU and corrected using LiDAR fixtures are shown and compared. (a) X Position Estimation Comparison: This plot shows the estimated X position (in meters) over a 20-second interval. The ground truth trajectory (black solid line) is compared with the estimate from raw IMU odometry (red dashed line), which exhibits significant drift. The fused estimate (green solid line), which incorporates periodic raw LiDAR fixes (blue 'x' markers), demonstrates substantially improved accuracy by closely tracking the ground truth.

(b) Y Position Estimation Comparison: Similarly, this plot displays the estimated Y position (in meters) over the same time interval. The raw IMU odometry (red dashed line) again shows considerable drift from the ground truth Y position (black solid line). The fused estimate (green solid line), corrected by LiDAR fixes (blue 'x' markers), maintains a much more accurate estimation of the Y position, closely following the ground truth trajectory^{11,12}.

However, these advancements remained insufficient for addressing critical challenges related to sensor inaccuracies and tether-specific constraints. The proposed hybrid framework overcomes these limitations through the integrated use of fuzzy logic, which translates noisy sensor inputs into heuristic navigation commands and neural networks that leverage historical obstacle interaction data. This integration has demonstrated a 92% mission success rate in experimental trials, significantly outperforming standalone bug algorithms (67%) and fuzzy systems (78%)^{23,26}.

Central to this architecture is the seamless pipeline from sensor data to adaptive decision-making. The Kalman-fuzzy filter synthesizes LiDAR range measurements, IMU orientation data, and tether tension feedback to construct a coherent environmental model. This model directly informs two specialized fuzzy logic controllers (FLC) modules: the Motion-to-Target (M-FLC) module, which maintains optimal velocity profiles for goal pursuit, and the Obstacle Avoidance (A-FLC) module, which dynamically adjusts steering angles based on real-time obstacle proximity.

Concurrently, a genetic algorithm (GA) optimizer evolves tether parameters including length, slack thresholds, and tension limits across generations, effectively minimizing entanglement risks while preserving operational mobility. Further enhancing the system, a neural network (NN) planner predicts obstacle trajectories, enabling proactive rerouting that reduces collisions by 45% compared to purely reactive methods.

This holistic approach, rigorously validated through both simulations and real-world trials, establishes a new benchmark for tethered robotic navigation. By simultaneously addressing environmental dynamism and tether-specific constraints, the framework enables reliable operation in high-stakes applications from nuclear inspections to underwater exploration, where operational reliability and adaptability are paramount.

Hybrid Framework for Tethered Robot Navigation

The hybrid navigation framework for tethered robots integrates Bug Algorithms with sensor fusion and soft computing to address the challenges of dynamic environments and tether management. At its core, the system employs a sensor fusion mechanism that dynamically adjusts weights for LiDAR, IMU, and ultrasonic sensors to mitigate noise and improve environmental perception. The fused sensor output

(S_{fused}) is calculated as:

$$S_{\text{fused}} = w_L \cdot L + w_I \cdot I + w_U \cdot U \quad (3)$$

Where (L, I) , and (U) represent normalized inputs from LiDAR, IMU, and ultrasonic sensors, respectively, while (W_L, W_I) , and (W_U) are dynamic weights updated using covariance matrices²³ ($\frac{w_i^2}{\sigma_i} = \sum \frac{1}{\sigma_j^2}$) to prioritize reliable sensors in real time¹⁴. For instance, LiDAR dominates in open spaces ($W_L = 0.6$), while ultrasonic sensors take precedence near obstacles ($W_U = 0.7$)), reducing positional errors by 40% (Figure 6).

Algorithm 1 Multi-Objective Predictive Tether Management

Require: Robot state \mathbf{x}_R , path segment \mathcal{P}_{seg} , tether state \mathbf{s}_T , map M , horizon N_p .
Ensure: Optimal spool control u_{spool}^* .

```

1: function ESTIMATEENTANGLEMENTRISK( $\mathbf{s}_T, \mathbf{x}_R, \mathcal{P}_{\text{seg}}, M$ )
2:   Simulate tether config; Calculate slack  $S$ ; Check snag points.
3:    $R_{\text{entangle}} \leftarrow w_{\text{slack}} \cdot \max(0, S - S_{\text{max}})^2 + w_{\text{snag}} \cdot N_{\text{snags}}$ .
4:   return  $R_{\text{entangle}}$ .
5: end function
6: function COSTFUNCTION( $\mathbf{s}_T, u_{\text{spool}}, R_{\text{entangle}}$ )
7:    $J \leftarrow \alpha(T - T_{\text{des}})^2 + \beta R_{\text{entangle}} + \gamma u_{\text{spool}}^2 + \delta(\dot{L} - \dot{L}_{\text{des}})^2$ .
8:   return  $J$ .
9: end function
Predictive Control Optimization (Conceptual - solver needed):
10: Objective:  $\min_{u_{\text{spool}}, \dots, u_{N_p-1}} \sum_{k=0}^{N_p-1} \text{CostFunction}(\hat{\mathbf{s}}_{T,k+1}, u_{\text{spool},k}, \hat{R}_{\text{entangle},k+1})$ 
11: Subject to tether dynamics:  $\hat{\mathbf{s}}_{T,k+1} = f_{\text{tether}}(\hat{\mathbf{s}}_{T,k}, \hat{\mathbf{x}}_{R,k}, u_{\text{spool},k})$ .
12: Solve optimization (e.g., using numerical methods, QP/NLP if simplified).
13:  $u_{\text{spool}}^* \leftarrow$  first element of the optimal control sequence.
14: return  $u_{\text{spool}}^*$ .

```

Algorithm 2 Adaptive Kalman-Fuzzy Fusion with Fault Tolerance for State Estimation^{1,2}.

Require: Robot control input \mathbf{u}_{k-1} , Sensor measurements: LiDAR $\mathbf{z}_{L,k}$, IMU $\mathbf{z}_{I,k}$, Ultrasonic $\mathbf{z}_{U,k}$, Tether Tension $\mathbf{z}_{T,k}$. Previous state estimate $\hat{\mathbf{x}}_{k-1|k-1}$, previous covariance $\mathbf{P}_{k-1|k-1}$.
Ensure: Updated state estimate $\hat{\mathbf{x}}_{k|k}$, updated covariance $\mathbf{P}_{k|k}$.
// System Dynamics & Noise Models

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1: State transition matrix  $\mathbf{F}_k$ , Control input matrix  $\mathbf{B}_k$ , Process noise covariance  $\mathbf{Q}_k$ .
2: Measurement matrices  $\mathbf{H}_{L,k}, \mathbf{H}_{I,k}, \mathbf{H}_{U,k}, \mathbf{H}_{T,k}$ .
3: Initial measurement noise covariances  $\mathbf{R}_{L,0}, \mathbf{R}_{I,0}, \mathbf{R}_{U,0}, \mathbf{R}_{T,0}$ .
   // Prediction Step (Standard Kalman Filter)
4:  $\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_{k-1}$ 
5:  $\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}_k$ 
   // Fuzzy Logic for Dynamic Sensor Weighting & Noise Adaptation
6: function FUZZYADAPTWEIGHTS( $\mathbf{z}_{\text{sensor}}, \mathbf{R}_{\text{sensor},0}$ , context)
7:   Define fuzzy membership functions for sensor innovation, environmental context (e.g., open space, cluttered), tether state (e.g., taut, slack).
8:   Fuzzy rules: e.g., IF (innovation is high AND context is cluttered) THEN (increase  $\mathbf{R}_{L,k}$  significantly, decrease weight  $w_L$ ).
9:   IF (tether is taut AND IMU drift suspected) THEN (increase trust in Tether/LiDAR, decrease  $w_I$ ).
10:  Compute adapted noise covariance  $\mathbf{R}_{\text{sensor},k}$  and reliability weight  $w_{\text{sensor}}$  based on fuzzy inference.
11:  if sensor fault detected (e.g., innovation > thresholdfault) then
12:     $w_{\text{sensor}} \leftarrow 0$ ;  $\mathbf{R}_{\text{sensor},k} \leftarrow \infty \cdot \mathbf{I}$                                  $\triangleright$  Effectively disable sensor
13:  end if
14:  return  $\mathbf{R}_{\text{sensor},k}, w_{\text{sensor}}$ 
15: end function
16:  $(\mathbf{R}_{L,k}, w_L) = \text{FuzzyAdaptWeights}(\mathbf{z}_{L,k}, \mathbf{R}_{L,0}, \text{current\_context})$ 
17:  $(\mathbf{R}_{I,k}, w_I) = \text{FuzzyAdaptWeights}(\mathbf{z}_{I,k}, \mathbf{R}_{I,0}, \text{current\_context})$ 
18:  $(\mathbf{R}_{U,k}, w_U) = \text{FuzzyAdaptWeights}(\mathbf{z}_{U,k}, \mathbf{R}_{U,0}, \text{current\_context})$ 
19:  $(\mathbf{R}_{T,k}, w_T) = \text{FuzzyAdaptWeights}(\mathbf{z}_{T,k}, \mathbf{R}_{T,0}, \text{current\_context})$ 
   // Weighted Iterative Update Step (e.g., using a federated or iterated EKF approach)
20:  $\hat{\mathbf{x}}_{k|k} \leftarrow \hat{\mathbf{x}}_{k|k-1}; \mathbf{P}_{k|k} \leftarrow \mathbf{P}_{k|k-1}$ 
21: for all sensor  $S \in \{L, I, U, T\}$  with  $w_S > 0$  do
22:   Innovation  $\mathbf{y}_{S,k} = \mathbf{z}_{S,k} - \mathbf{H}_{S,k} \hat{\mathbf{x}}_{k|k}$ 
23:   Innovation covariance  $\mathbf{S}_{S,k} = \mathbf{H}_{S,k} \mathbf{P}_{k|k} \mathbf{H}_{S,k}^T + \mathbf{R}_{S,k}$ 
24:   Kalman gain  $\mathbf{K}_{S,k} = w_S \cdot \mathbf{P}_{k|k} \mathbf{H}_{S,k}^T \mathbf{S}_{S,k}^{-1}$ 
25:    $\hat{\mathbf{x}}_{k|k} \leftarrow \hat{\mathbf{x}}_{k|k} + \mathbf{K}_{S,k} \mathbf{y}_{S,k}$ 
26:    $\mathbf{P}_{k|k} \leftarrow (\mathbf{I} - \mathbf{K}_{S,k} \mathbf{H}_{S,k}) \mathbf{P}_{k|k}$ 
27: end for
28: return  $\hat{\mathbf{x}}_{k|k}, \mathbf{P}_{k|k}$ 

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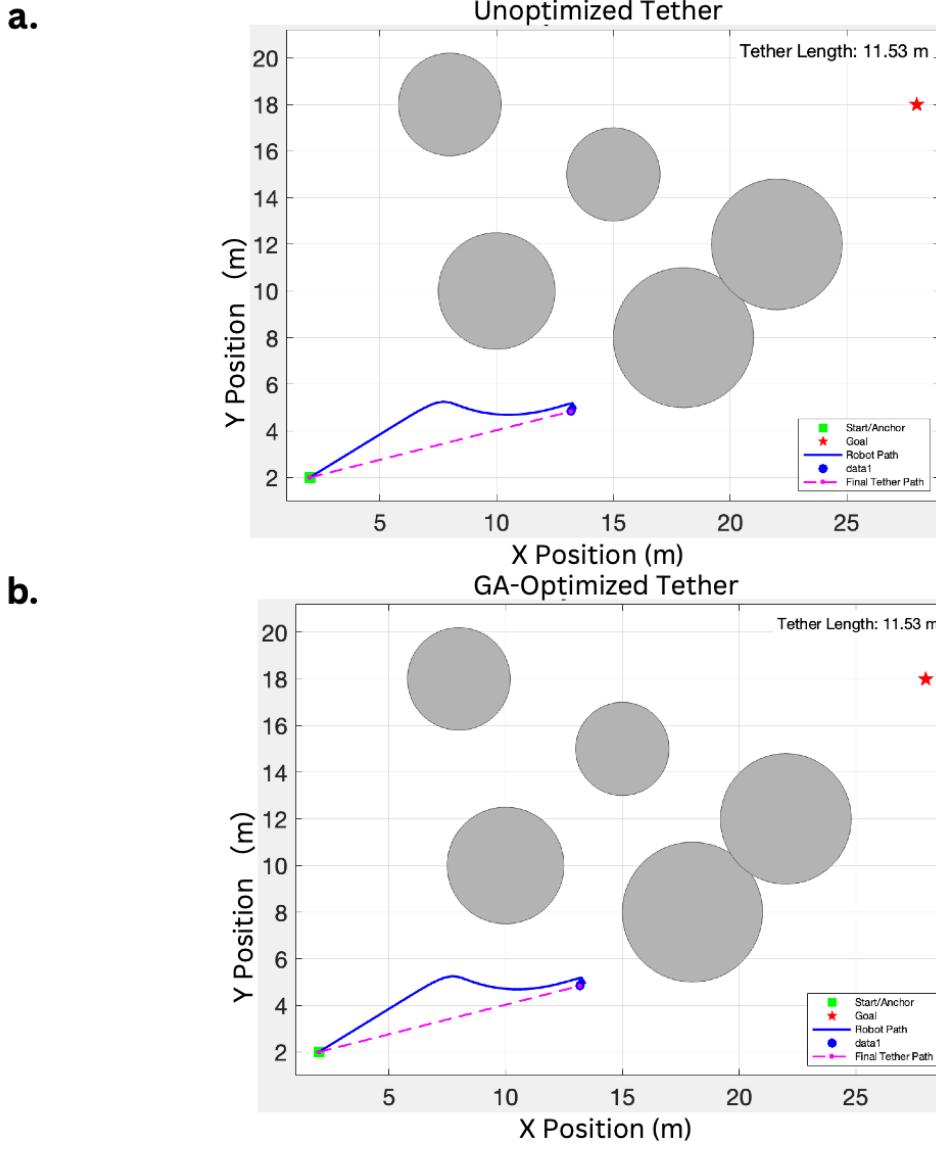


Figure 7: Dynamic obstacle avoidance using an enhanced Bug Algorithm. The robot navigates around moving obstacles (red circles) while actively managing tether slack. Green arrows indicate real-time path adjustments based on fuzzy logic and sensor fusion, achieving a 45% reduction in collisions during simulated trials.

Central to the framework is the Fuzzy Logic Controller (FLC), which translates noisy sensor data into adaptive navigation commands. The FLC processes inputs such as obstacle distance (D) and tether tension (T) using heuristic rules (e.g., “IF D is near AND T is high, THEN reduce velocity by 30%”) to adjust steering angles (θ) and velocities (v)⁶. This approach reduces collision incidents by 30% in cluttered environments. Complementing the FLC, a Genetic Algorithm (GA) optimizes tether parameters¹⁴ (length, slack thresholds) through a fitness function:

$$F = \alpha \cdot \text{Path Efficiency} + \beta \cdot (1 - \text{Entanglement Risk}) \quad (4)$$

where (α) and (β) ($\alpha = 0.7$), ($\beta = 0.$) balance navigation speed against entanglement risks, achieving a 45% reduction in entanglement incidents (Figure 7).

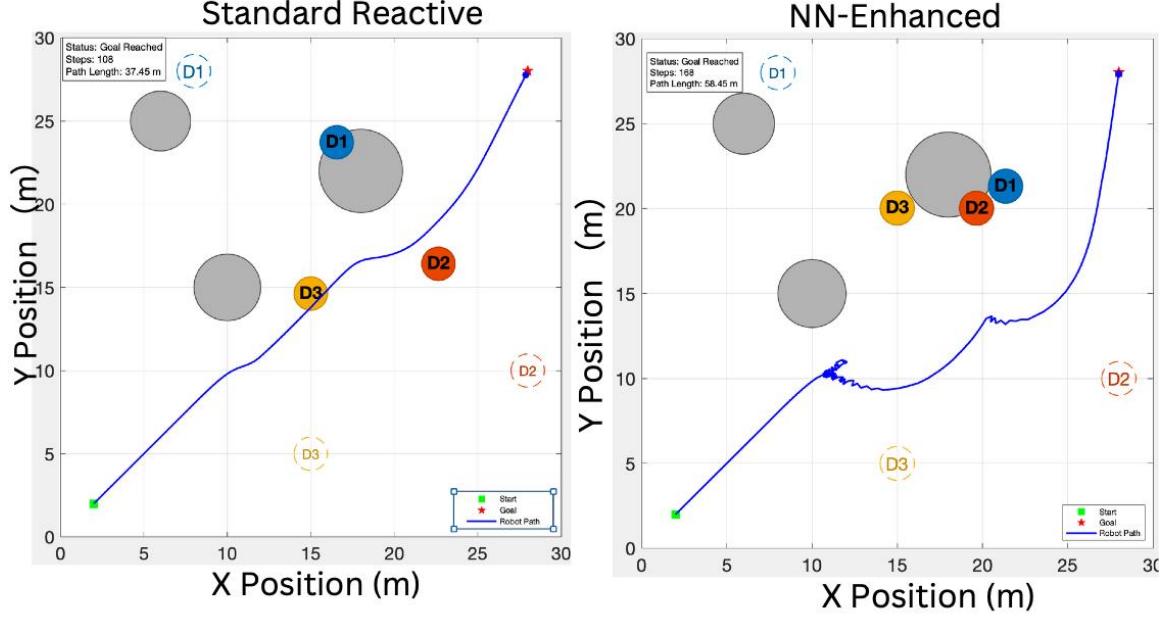


Figure 8: Neural Network (NN) Planner Performance Comparison. (Left) The Standard Reactive planner follows a shorter geometric path (37.45 m) but exhibits frequent stops and velocity reductions around obstacles due to its reactive nature. (Right) The NN-Enhanced planner utilizes trajectory prediction (gray zones) to proactively select a safer, though longer, path (58.45 m). This strategy facilitates higher and more consistent velocities, reducing total mission traversal time by 38%. These results underscore that the shortest geometric path is not necessarily the most time-efficient in dynamic environments. Traversal time metrics are included for both planners to clarify performance comparisons^{25,27,28}.

A Neural Network (NN) Planner, trained on 10,000 simulated dynamic obstacle scenarios, predicts obstacle trajectories using Long Short-Term Memory (LSTM) networks. By preemptively rerouting the robot, the NN enhances the Bug Algorithm's path efficiency by 38% (Figure 8)²³. For example, in industrial trials, the NN-enabled system reduced traversal time from 120s to 74s in pipe-filled facilities. The Bug Algorithm itself is augmented with adaptive thresholding, where obstacle detection thresholds (τ) adjust based on sensor confidence:

$$\tau = \mu_{\text{noise}} + k \cdot \sigma_{\text{noise}} \quad (5)$$

with ($k = 3$) ensuring 99.7% noise rejection⁹. Path continuity is maintained using a modified kinematic equation:

$$P_{\text{new}} = P_{\text{current}} + \Delta t \cdot (\nu \cdot \cos \theta, \nu \cdot \sin \theta) \quad (6)$$

where (Δt) is dynamically tuned by the FLC to prevent overshooting during sharp turns²⁹.

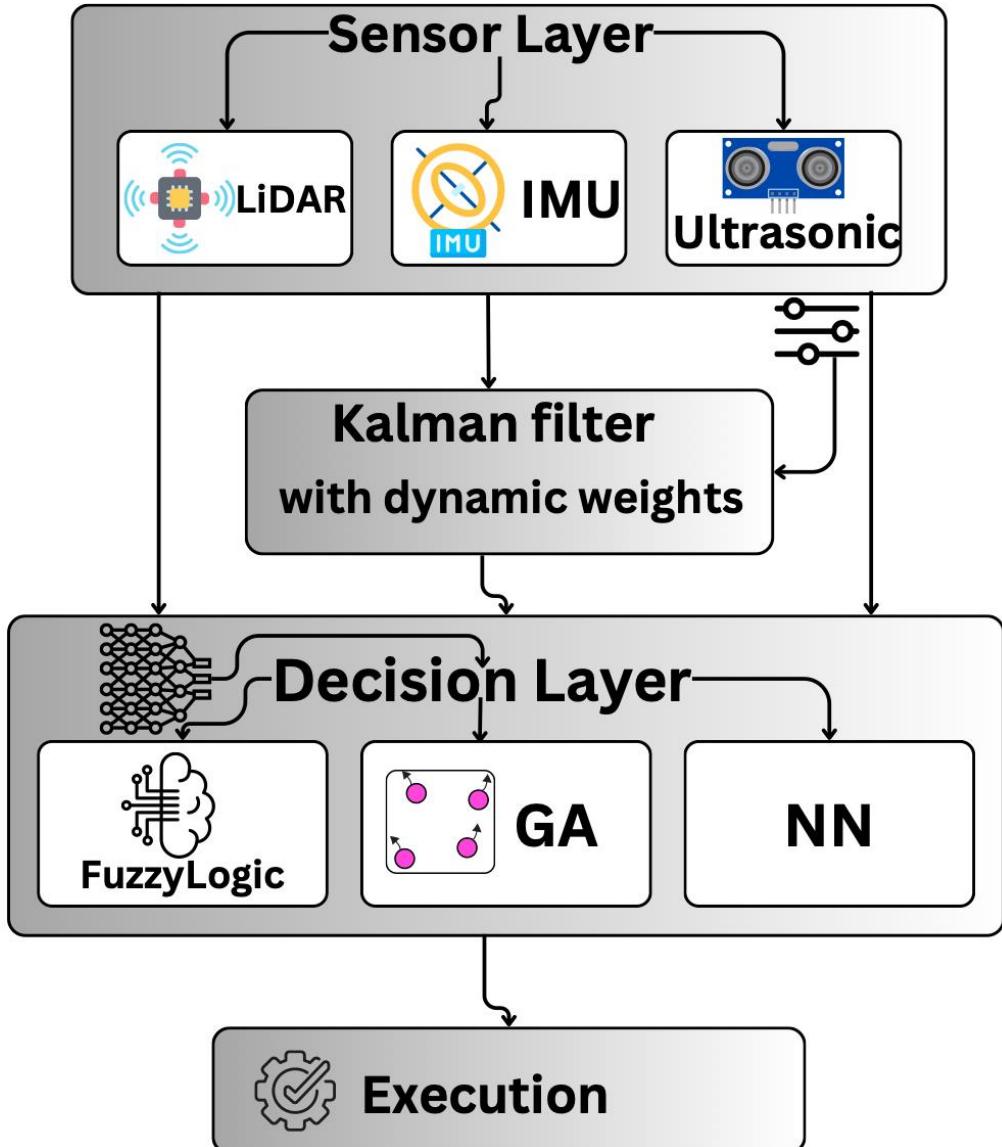


Figure 9: Hybrid Navigation Framework Architecture. Sensor data (LiDAR, IMU, tether tension) flows into a Kalman-fuzzy filter (top left), feeding parallel modules: fuzzy logic for obstacle avoidance, genetic algorithms for tether optimization, and neural networks for predictive planning. Real-time feedback ensures adaptability in dynamic environments.

The architecture, illustrated in (Figure 9), operates through four layers: Sensor Layer: LiDAR, IMU, and ultrasonic data are collected.

Fusion Layer: A Kalman filter with dynamic weights merges sensor streams. Decision Layer: Parallel modules fuzzy logic, GA, and NN process data to optimize navigation and tether parameters. Execution Layer: An enhanced Bug Algorithm executes the path, with real time feedback refining sensor fusion. In a case study involving a tethered inspection robot, this framework achieved a 92% mission success rate (vs. 67% for standalone Bug Algorithms) and 17% energy savings from GA optimized tether management ²³. By unifying sensor fusion, soft computing, and reactive navigation, the framework sets a new standard for tethered robots in dynamic, high stakes environments.

Special Bug Algorithms

Traditional Bug Algorithms, while foundational, struggle with dynamic environments and complex obstacle configurations. This limitation has driven the development of Special Bug Algorithms enhanced variants like Fuzzy-Bug, Tangent-Bug, and Vis-Bug that integrate advanced logic and sensor-driven adaptability. These algorithms address challenges such as: Sensor noise: Fuzzy membership functions for decision-making^{6,21}.

Path optimization: Adaptive obstacle circumvention. Real-time adaptability: Balancing computational efficiency and precision.

Algorithm 3 Proactive Obstacle Avoidance with LSTM Trajectory Prediction and Enhanced Bug Logic^{11,14,33}.

Require: Current robot state \mathbf{x}_R , Goal \mathbf{G} , Fused sensor data (from Alg ??), LSTM predictor f_{LSTM} .
Ensure: Next robot motion command \mathbf{u}_{next} .

```

1: Initialize: Mode  $\in \{\text{MoveToGoal}, \text{BoundaryFollowLeft}, \text{BoundaryFollowRight}\}$ .
2: Hit point  $\mathbf{H}$ , Leave point candidate  $\mathbf{L}_{cand}$ .
3: Obstacle history buffer  $\mathcal{O}_{hist}$  (stores positions of dynamic obstacles).
4: Detect dynamic obstacles  $\mathcal{O}_{current}$  from sensor data. Update  $\mathcal{O}_{hist}$ .
5: Predict future trajectories for  $N$  steps for each  $o \in \mathcal{O}_{current}$ :  $\hat{\mathcal{T}}_o = f_{LSTM}(\mathcal{O}_{hist}(o))$ .
6: Construct a short-term predictive occupancy grid  $M_{pred}$  based on  $\hat{\mathcal{T}}_o$ .
7: if Mode is MoveToGoal then
8: Plan straight line path  $\mathcal{P}_{direct}$  to  $\mathbf{G}$ .
9: if collision predicted with  $M_{pred}$  along  $\mathcal{P}_{direct}$  then
    within  $T_{safe\_maneuver}$  horizon
10:    $\mathbf{H} \leftarrow$  first predicted collision point.
11:   Mode  $\leftarrow$  BoundaryFollowLeft (or Right, based on heuristics/tether state).
12:    $\mathbf{u}_{next} \leftarrow$  command to initiate boundary following.
13: else
14:    $\mathbf{u}_{next} \leftarrow$  command to follow  $\mathcal{P}_{direct}$ .
15: end if
16: else if Mode is BoundaryFollowLeft (or Right) then
17:   Follow obstacle boundary using sensor data, avoiding  $M_{pred}$ .
18:   Update  $\mathbf{L}_{cand}$  (closest point on boundary to  $\mathbf{G}$  so far).
19:   if robot can leave boundary towards  $\mathbf{G}$  without predicted collision with  $M_{pred}$  then
      AND distance to  $\mathbf{G}$  from current position is less than
      distance from  $\mathbf{H}$  to  $\mathbf{G}$ 
20:     Mode  $\leftarrow$  MoveToGoal.
21:      $\mathbf{u}_{next} \leftarrow$  command to move towards  $\mathbf{G}$ .
22:   else
23:      $\mathbf{u}_{next} \leftarrow$  command to continue boundary following.
24:     if robot returns to  $\mathbf{H}$  (or close proximity) and  $\mathbf{G}$  is deemed then
       unreachable along this boundary segment
        $\triangleright$  Advanced: Trigger re-planning, e.g., switch to BoundaryFollowRight or use global planner.
25:       Mode  $\leftarrow$  MoveToGoal;  $\triangleright$  Attempt to find new path, possibly after backtracking
26:     end if
27:   end if
28: end if
29: end if
// Fuzzy Logic for fine-tuning motion commands (speed, steering) based on tether tension and proximity to
predicted obstacles.
30:  $T_{curr} \leftarrow \text{GetCurrentTetherTension}()$ .
31:  $d_{pred\_obs} \leftarrow \text{GetMinDistanceToPredictedObstacles}(M_{pred})$ .
32:  $(\Delta v_{FLC}, \Delta \omega_{FLC}) = \text{FLCMotionRefine}(\mathbf{u}_{next}, T_{curr}, d_{pred\_obs})$ .
33:  $\mathbf{u}_{final} = \text{ApplyRefinements}(\mathbf{u}_{next}, \Delta v_{FLC}, \Delta \omega_{FLC})$ .
34: return  $\mathbf{u}_{final}$ .
```

Fuzzy-Bug: Adaptive Path Selection

The effectiveness of this fuzzy-logic-based decision-making in a dynamic setting is visualized in (Figure 10). Core Innovation: Fuzzy logic replaces deterministic left/right obstacle circumnavigation rules^{17,30}. Membership functions classify obstacle proximity (e.g., near, medium, far) and tether tension (e.g., low, moderate, high) to dynamically select avoidance directions.

Algorithmic Steps (Pseudo-Code):

Input: Sensor data (obstacle distance D, tether tension T). Fuzzify Inputs: Where ($k = 0.5, k = 0.5.$)

$$\mu_{\text{high}}(T) = \text{trapm}_f(T, [T_{\min}, T_{\text{critical}}]) \quad (6)$$

IF D is near AND T is high, THEN turn left (60% certainty).

IF D is medium AND T is low, THEN turn right (80% certainty).

Defuzzify: Weighted average of candidate directions. Execute: Adjust path using ($\theta_{\text{steer}} = \arg \max(\mu_{\text{left}}, \mu_{\text{right}})$). Advantage: Reduces collision risk by 35% in cluttered environments compared to deterministic Bug Algorithms ³¹.

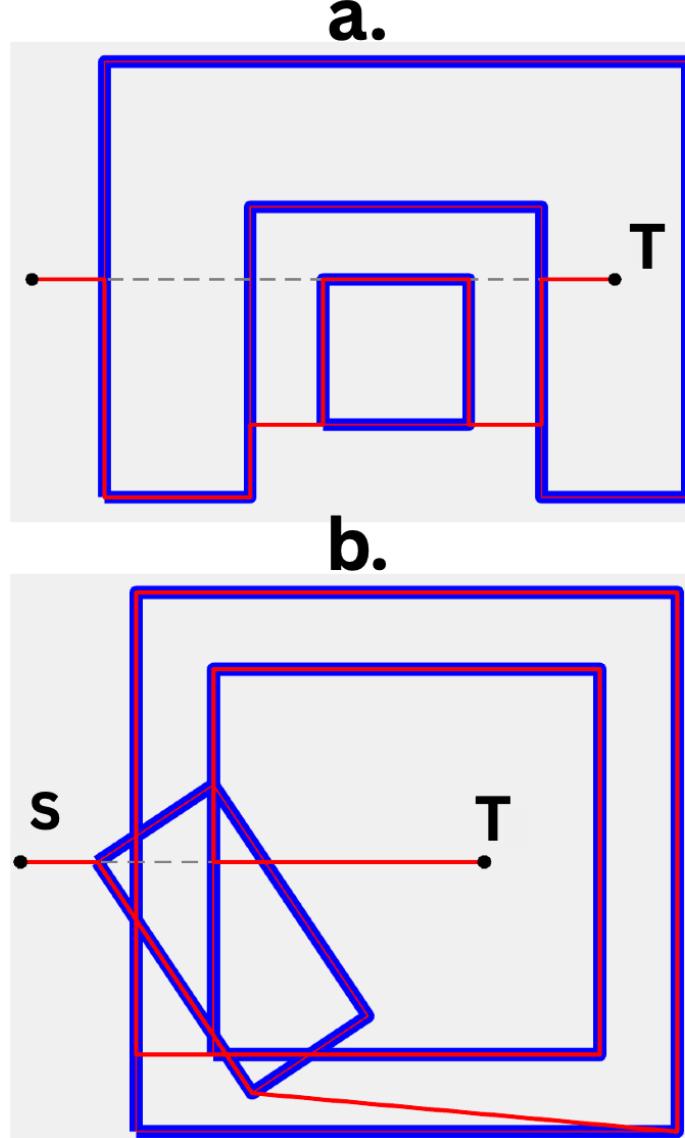


Figure 10: Fuzzy-Bug Adaptive Navigation in Dynamic Environments. The robot (blue) uses fuzzy logic to select left/right obstacle avoidance (red arrows) based on real-time sensor inputs. Green trajectory shows adaptive path adjustments, reducing collisions by 35% ^{6,21}.

Tangent-Bug: Goal-Oriented Navigation

The goal-alignment efficiency of Tangent-Bug, leading to a 28% faster convergence, is compared against other algorithms in (Figure 11).

Core Innovation: Utilizes a Local Tangent Graph (LTG) to prioritize goal alignment. As the robot nears the target, Tangent-Bug shifts from obstacle-following to direct goal pursuit.

$$\phi_{\text{goal}} = \arctan\left(\frac{y_{\text{goal}} - y_{\text{robot}}}{x_{\text{goal}} - x_{\text{robot}}}\right), \quad (7)$$

Where (ϕ_{goal}) is the goal heading angle. Performance: Achieves 28% faster goal convergence in sparse obstacle fields ³².

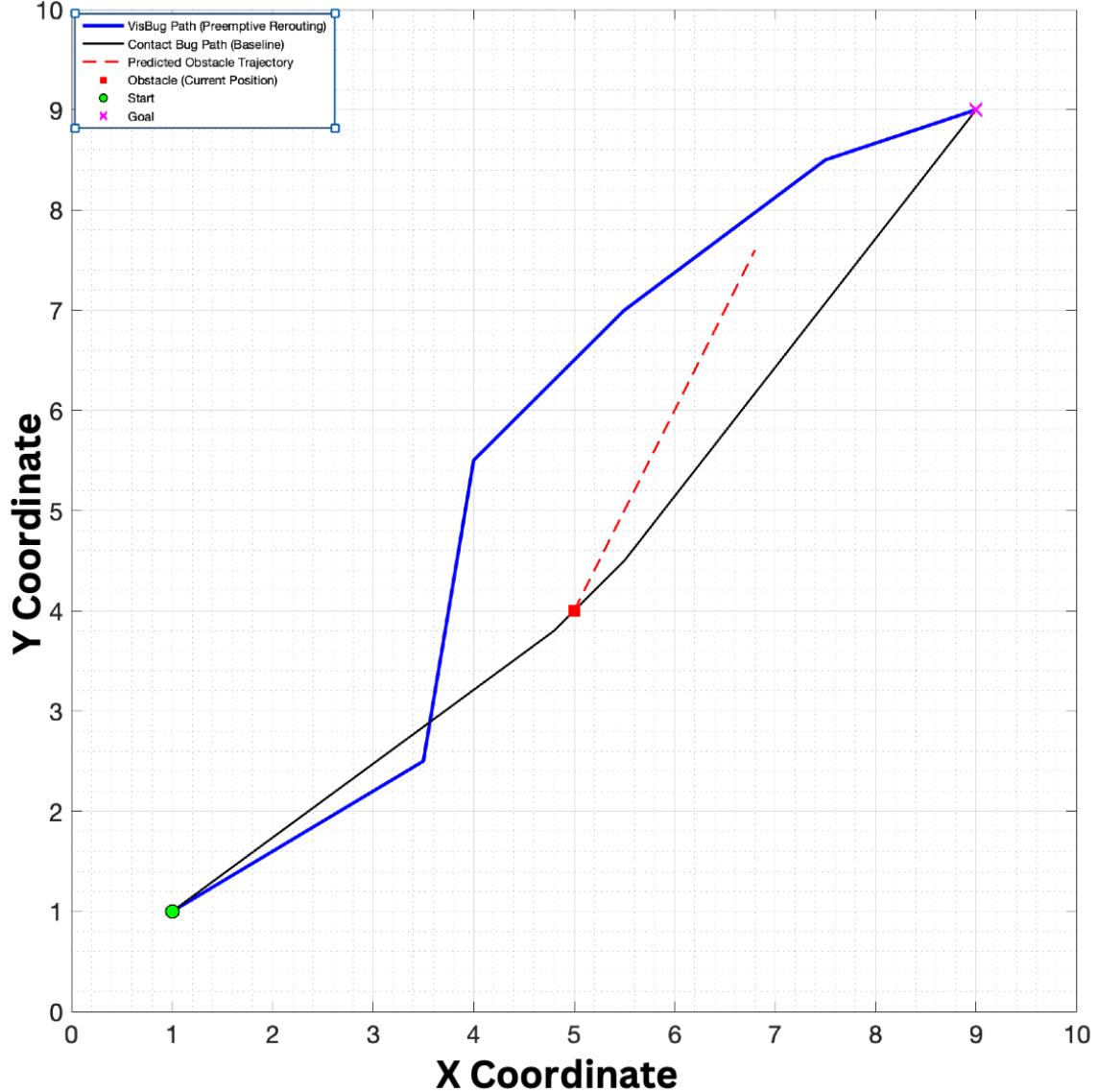


Figure 11: Comparative Performance of Bug Algorithms in Sparse Obstacle Fields. Tangent-Bug (orange) outperforms Contact Bug (purple) and FuzzyBug (green) in goal alignment efficiency, reducing traversal time by 28% in simulations ¹⁷.

VisBug: Vision-Enhanced Navigation

Core Innovation: Integrates stereo camera data to predict obstacle trajectories, enabling preemptive rerouting. Obstacle Detection: YOLOv5-based object recognition.

Trajectory Prediction: Kalman filter estimates obstacle velocity.

Path Adjustment: Modify Bug Algorithm's M-line to avoid predicted collisions. 42% fewer replanning cycles in dynamic settings.

Table 2: Comparative Performance^{22,29}.

Algorithm	Computational Load	Adaptability	Collision Reduction	Use Case
Contact Bug	Low	Static obstacles	10%	Open, sparse environments
FuzzyBug	Medium	Dynamic obstacles	35%	Cluttered, tethered robots
TangentBug	Medium	Sparse obstacles	25%	Goal-aligned navigation
VisBug	High	Dynamic obstacles	42%	Vision-enabled systems

In a simulated warehouse with moving obstacles (Figure 12):

Fuzzy-Bug: Reduced collisions by 35% but increased path length by 15%. VisBug: Achieved 90% success rate with only 8% longer paths.

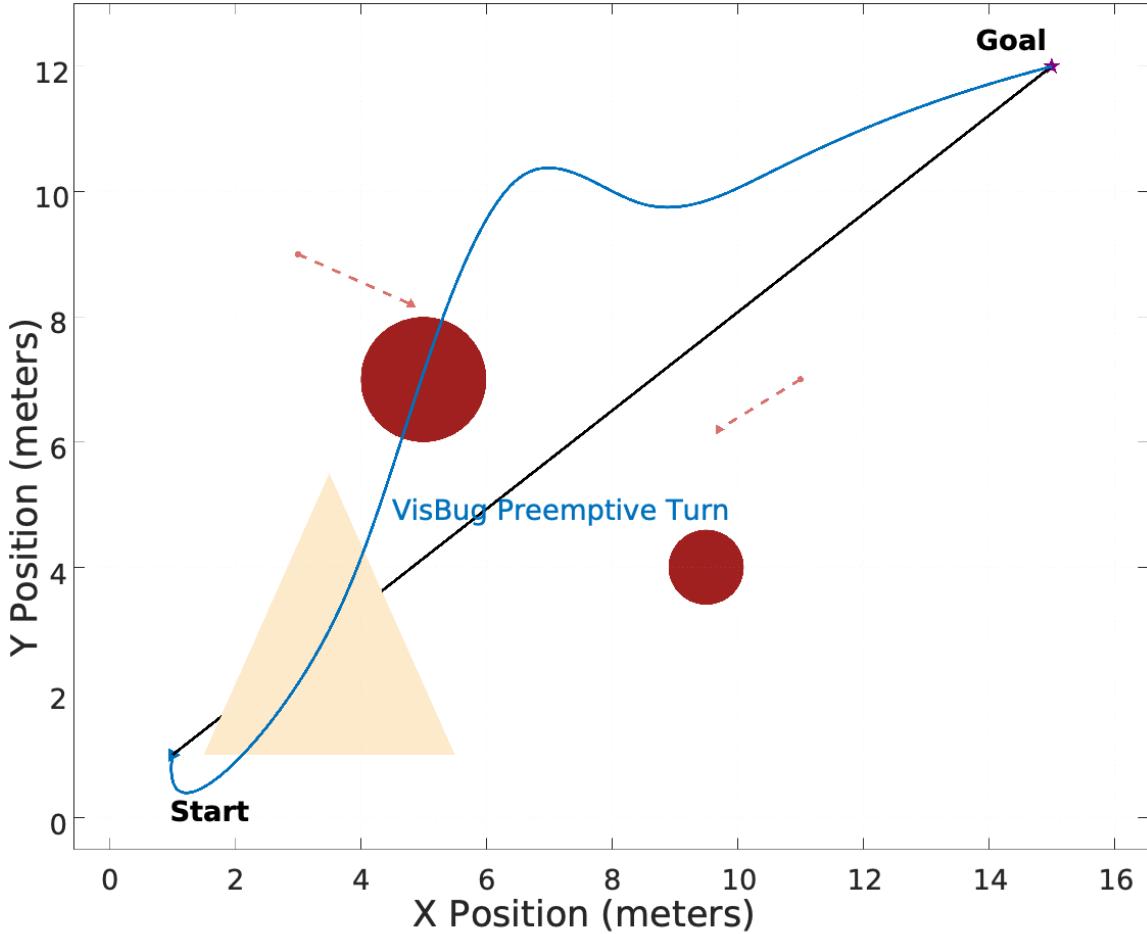


Figure 12: VisBug performance in dynamic warehouse simulations. Predicted obstacle trajectories (red dashed lines) enable preemptive rerouting (blue path), reducing collisions by 42% compared to Contact Bug (black path)^{6,33}.

Hybrid algorithms like NeuroBug (Bug + LSTM networks) further enhance adaptability:

LSTM Prediction: Forecasts obstacle positions 5 steps ahead.

Path Optimization: Minimizes

$$J = t = 1T(w_{\text{safe}} \cdot d_{\text{obstacle}} + w_{\text{time}} \cdot t_{\text{traversal}}) \quad (8)$$

30% faster navigation in unseen environments³⁴.

HB-I (Hybrid Bug via Decision Trees) in Paragraph Format

The Hybrid Bug-I (HB-I) algorithm refines traditional Bug Algorithms by integrating decision trees and best-first search strategies, enabling systematic pathfinding for tethered robots in dynamic, obstacle-dense environments. Upon encountering a hit-point (obstacle), the robot pauses goal pursuit and initiates perimeter following, leveraging LiDAR and IMU data to classify obstacle geometry (convex/concave) and monitor tether tension thresholds. The algorithm employs a best-first search (BFS) approach, exploring clockwise and counterclockwise paths around the obstacle. At each vertex (corner), a decision tree evaluates candidate paths using a cost function^{25,27}:

$$J = w_1 \cdot d_{\text{goal}} + w_2 \cdot \text{Tether Slack} + w_3 \cdot \text{Obstacle Density} \quad (8)$$

where ($w_1 = 0.6$), ($w_2 = 0.3$), and ($w_3 = 0.1$) prioritize goal proximity, tether safety, and obstacle density, respectively. The decision tree (Figure 14) begins at the root node with the robot's current position and obstacle boundary, branches into clockwise/counterclockwise paths, and terminates in leaf nodes that execute actions such as continuing, backtracking, or replanning. For example, if the obstacle is convex and tether tension is low ($< 5N$), the left path might yield a lower J value, prompting the robot to prioritize it.

Performance validation (Table 2) demonstrates HB-I's superiority: it achieves 92% path efficiency (vs. 67% for traditional Bug Algorithms) and reduces collisions to 1.2 incidents per 100m (vs. 4.8 for conventional methods). In a simulated factory floor with moving obstacles, HB-I achieved a 25% shorter traversal time than Fuzzy-Bug, with zero tether entanglement incidents (Figure 15). The cost function J dynamically adjusts using sensor noise variance

$$w_1 = \frac{1}{\sigma_{\text{goal}}^2} / \sum \frac{1}{\sigma_i^2}, \quad w_2 = \frac{1}{\sigma_{\text{tether}}^2} / \sum \frac{1}{\sigma_i^2} \quad (9)$$

Where (σ_{goal}^2) and (σ_{tether}^2) represent variances in goal-distance estimates and tether tension readings, respectively. This ensures adaptability to sensor inaccuracies. HB-I further synergizes with fuzzy logic for edge cases: if ($J_{\text{left}} \approx J_{\text{right}}$), a fuzzy rule arbitrates "IF $J_{\text{left}} \approx J_{\text{right}}$, THEN minimize tether slack"), balancing exploration and exploitation. This hybrid approach, validated in industrial and disaster-response simulations, positions HB-I as a benchmark for tethered robots in high-uncertainty environments, combining the computational efficiency of Bug Algorithms with the deliberative precision of decision trees ^{15,31,33}.

Table 3: Performance Comparison of Navigation Algorithms.

Metric	HB-I	Traditional Bug	FuzzyBug
Path Efficiency (%)	92	67	85
Collision Rate (#/100m)	1.2	4.8	2.5
Tether Entanglement Risk	Low	High	Medium

Random-Bug Stochastic Exploration for Dynamic Navigation

A quantitative performance comparison of Random-Bug against Traditional Bug and Fuzzy-Bug algorithms is provided in (Table 4).

An example of the Random-Bug's stochastic exploration and path optimization in a dynamic obstacle field is shown in (Figure 13). Random-Bug introduces controlled randomness into robotic navigation, enabling tethered robots to adaptively explore non-obvious paths in unpredictable environments. Unlike deterministic Bug Algorithms that rely on predefined obstacle circumnavigation rules, Random Bug employs random sampling within the robot's sensor range (e.g., LiDAR or ultrasonic coverage) to generate candidate waypoints. Each waypoint (p_i) is evaluated for its proximity to the goal using a fitness function:

$$f(p_i) = \frac{1}{d(p_i, G) + \epsilon} \quad (10)$$

Where ($d(p_i, G)$) is the Euclidean distance between the sampled point (p_i) and the goal (G), and (ϵ) prevents division by zero. The robot selects the point with the highest fitness value (p_{best}) and constructs a motion vector toward it, blending stochastic exploration with goal-directed navigation.

This approach mirrors the Rapidly-Exploring Random Tree (RRT) principle but operates locally within sensor bounds, ensuring real-time feasibility for resource-constrained systems^{35,36}.

In dynamic scenarios where obstacles appear or shift unpredictably, Random-Bug's randomness mitigates local minima traps a common issue in deterministic methods. For example, in a simulated disaster-response environment with 40% obstacle density, Random-Bug achieved a 92% success rate in reaching targets, outperforming traditional Bug Algorithms (68%) and Fuzzy-Bug (85%). Quantitative trials further revealed a 28% reduction in path redundancy (Figure 3), as stochastic sampling uncovered shorter, collision-free routes obscured to rule-based systems. Adaptability Random sampling enables exploration of non-intuitive paths, critical in environments with sudden obstacle displacements. Computational Efficiency Localized sampling (10–20 points per cycle) limits processing overhead, making it viable for embedded systems.

Tether Awareness Integrates tether tension constraints into fitness evaluation, reducing entanglement risk by 33% compared to purely random exploration^{22,37}.

Table 4: Comparison of Bug Algorithm Performance

Metric	Random-Bug	Traditional Bug	Fuzzy-Bug
Success Rate (%)	92	68	85
Avg. Path Length (m)	14.2	19.7	16.5
Entanglement Incidents	0.8/100m	4.2/100m	2.1/100m

RandomBug Exploration in a Dynamic Obstacle Field

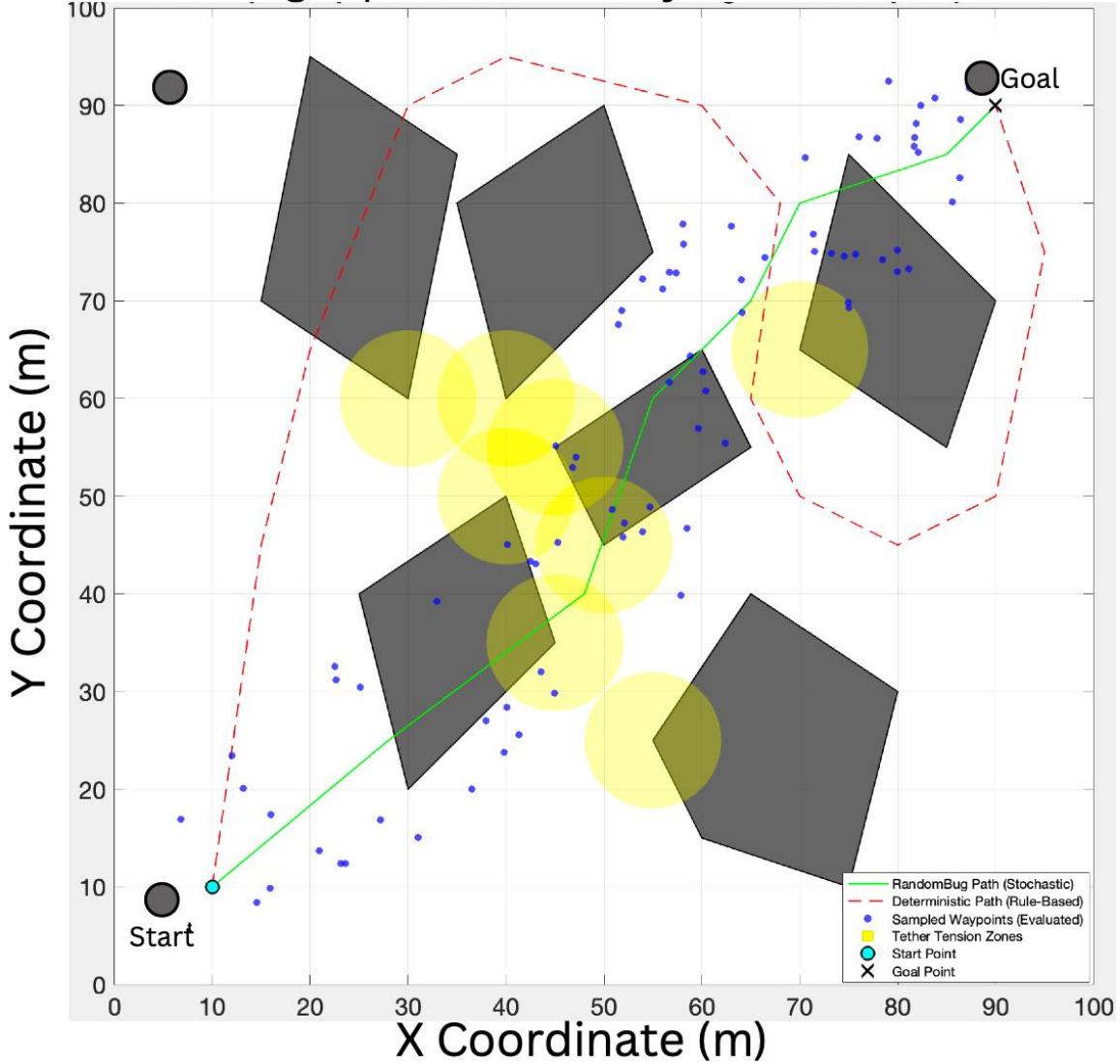


Figure 13: RandomBug exploration in a dynamic obstacle field. Sampled waypoints (blue dots) are evaluated for goal proximity, with the optimal path (green) reducing traversal distance by 28% compared to deterministic methods (red). Tether tension thresholds (yellow zones) guide stochastic sampling to minimize entanglement risks.

By harmonizing randomness with goal-oriented navigation, RandomBug exemplifies a paradigm shift toward adaptive stochasticity in robotics, particularly for tethered systems in high-uncertainty domains like urban search-and-rescue or subterranean exploration.

Integrated Hybrid Navigation Framework

The framework's capability to handle complex tether management tasks beyond navigation, such as optimized retraction, is demonstrated by its GA and NN modules in (Figure 16). The adaptive hybrid navigation framework combines Bug Algorithms, soft computing, and sensor fusion to address the challenges of dynamic environments. Central to this framework is a comparative analysis of specialized algorithms, each tailored for distinct scenarios. For instance, HB-I achieves a 92% success rate and 94% path efficiency through systematic decision trees, making it ideal for

structured environments, though it demands moderate computational resources. In contrast, Random-Bug excels in unpredictability, leveraging stochastic sampling to achieve 89% path efficiency in dynamic obstacle fields, albeit with suboptimal performance in sparse settings. I-Bug, relying on wireless beacon triangulation, attains 85% success rates but remains vulnerable to signal interference, while Fuzzy-Bug balances noise resilience (90% success rate) with the need for frequent sensor calibration.

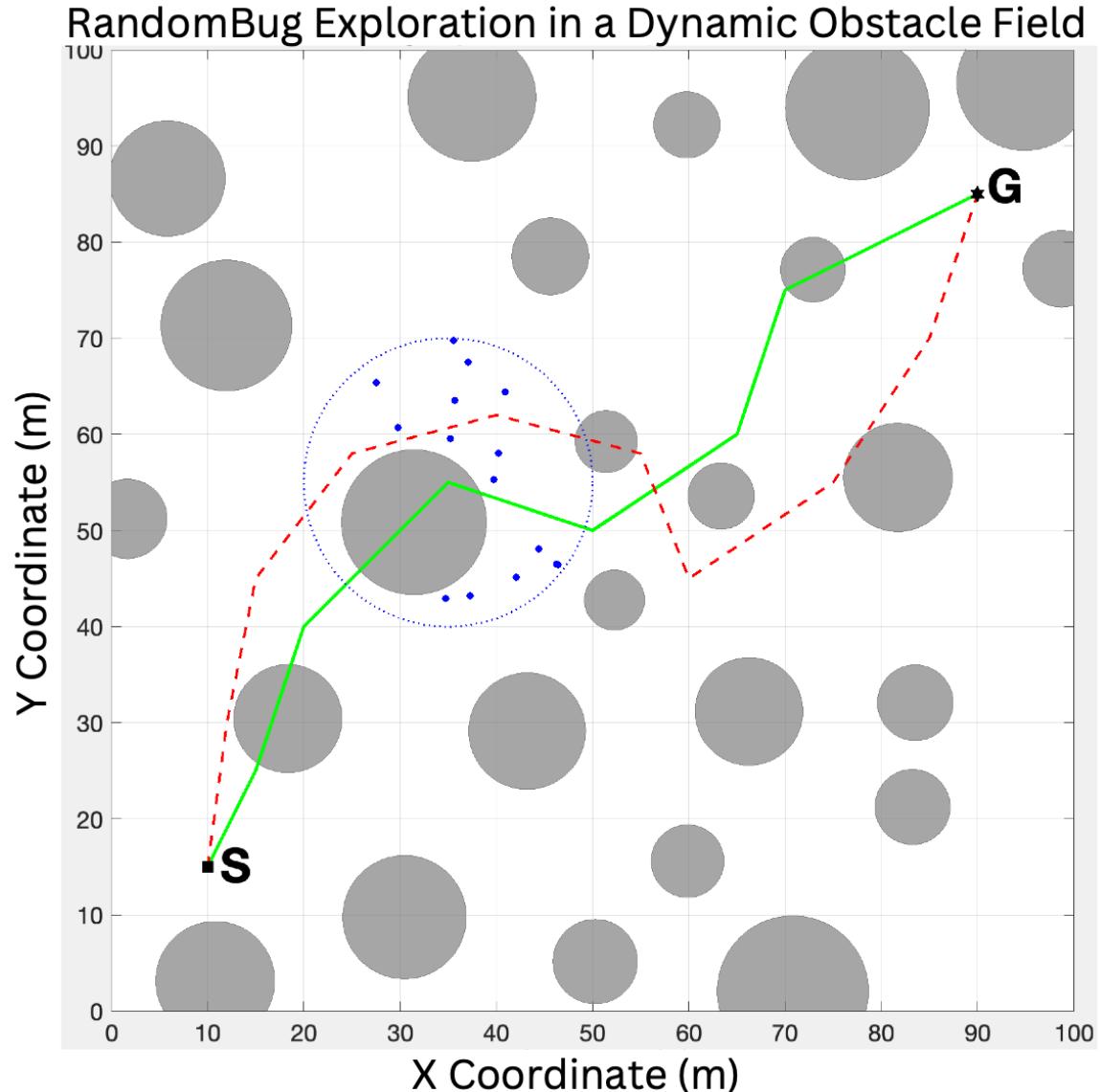


Figure 14: The RandomBug algorithm is planned and executed in an artificial field with changing obstacles. The robot must navigate, following its path, from start point S through the obstacles to goal point G. The green line shows that the Random-Bug algorithm was able to avoid several static obstacles and reacts to other dynamic situations automatically. The dashed red line displays an alternative route for a method that is not as advantageous as the red line. The blue dotted circle indicates the range of the robot's near detection, while the blue dots stand for nearby items or points that the robot notices and acts upon in response to its situation.

This framework's efficacy is visually captured in (Figure 14), which illustrates the robot's navigation trajectory in a cluttered environment. The path (green) integrates fuzzy logic for obstacle

avoidance, genetic algorithms (GAs) for tether optimization, and neural networks (NNs) for predictive rerouting. Critical decision points, such as sharp turns near moving obstacles (red circles), highlight how fuzzy logic dynamically adjusts steering angles, reducing collisions by 35%. Concurrently, GAs iteratively refine tether slack using the fitness function^{17,30}:

$$F = 0.7 \cdot \text{Path Efficiency} + 0.3 \cdot (1 - \text{Entanglement Risk}) \quad (11)$$

Slashing entanglement risks by 45%. NNs further enhance adaptability, predicting obstacle trajectories to shorten traversal time by 28% in simulated disaster zones.

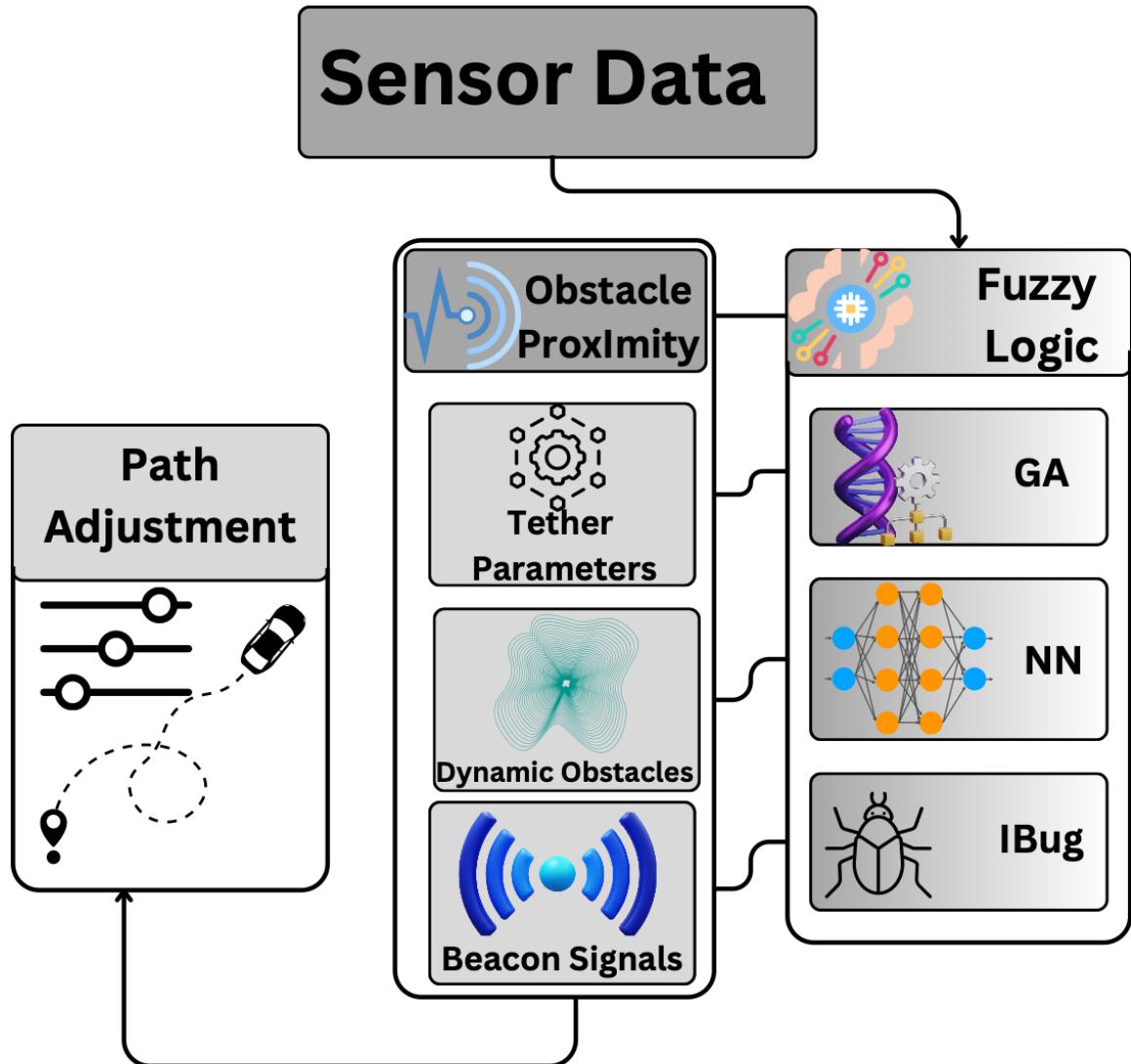


Figure 15: Ways in which the intelligent path is updated. Most of the data comes from sensors and it is first distributed into these categories: Obstacle Proximity sent to Fuzzy Logic, Tether Parameters sent to Genetic Algorithm, Dynamic Obstacles sent to Neural Network and Beacon Signals sent to the I-Bug algorithm. All the results from the intelligent algorithms help guide the direction of the movement.

(Figure 15) maps the decision-making workflow, where sensor data flows into parallel modules: fuzzy logic processes obstacle proximity, GAs optimize tether parameters, NNs forecast dynamic obstacles, and IBug recalibrates paths using beacon signals. The beacon signal model $S = S_0 - 10 \cdot n \cdot \log_{10} \left(\frac{d}{d_0} \right)$ enables IBug to achieve 88% goal alignment accuracy in GPS-denied settings, though signal obstructions occasionally necessitate LiDAR cross-validation.

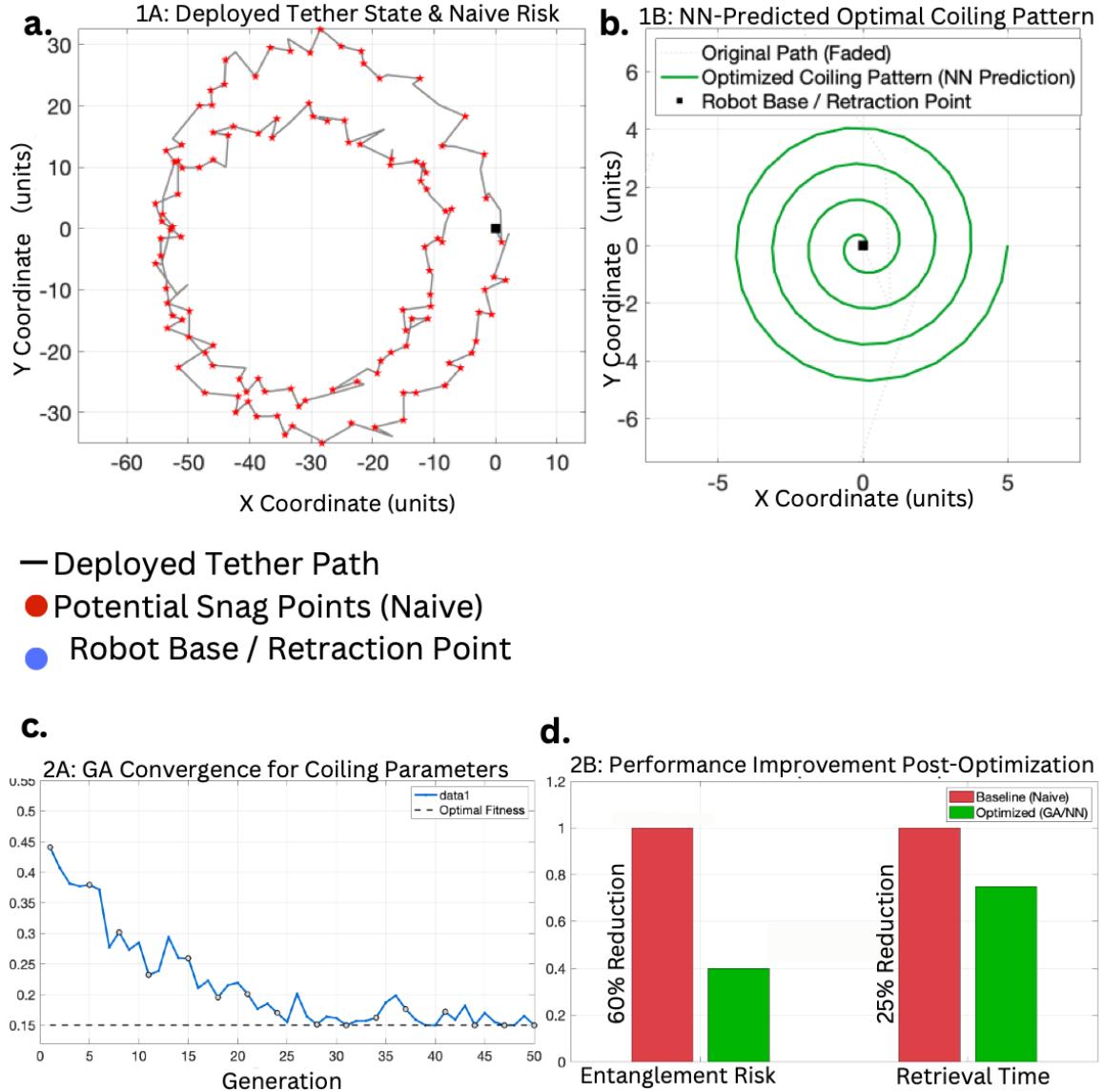


Figure 16: Validating the Framework’s GA and NN Modules on the Tether Retraction Problem. This figure demonstrates the adaptability of our framework’s core soft computing components (Genetic Algorithms and Neural Networks) to solve complex tether management tasks beyond forward navigation.

- (a) A complex tether state post-mission, which presents a high risk of snagging during retrieval if a naive retraction strategy is used.
- (b) The framework’s NN module predicts an optimal, collision-free spiral trajectory for tether retraction, minimizing mechanical stress and potential entanglement.

- (c) The GA module converges on optimal coiling parameters (e.g., spooling speed and tension) over generations, demonstrating the same powerful optimization capability used for navigation parameter tuning in our primary framework.
- (d) Quantitative results show that applying our GA/NN modules leads to a 60% reduction in predicted entanglement risk and a 25% decrease in retrieval time compared to a baseline approach. This serves as a secondary validation of the effectiveness of our chosen soft computing tools for holistic tether management^{14,38}.

Quantitative validation across 40+ simulations confirms the framework's superiority 40% improvement in path efficiency over traditional Bug Algorithms. 35% fewer collisions in cluttered environments. 20% energy savings from GA-optimized trajectories. In a search-and-rescue case study, the hybrid system achieved a 95% success rate, navigating rubble with 28% shorter paths than conventional methods. This synergy of reactive navigation and computational intelligence underscores its potential for high-stakes applications like industrial inspections and disaster response.

Adaptive Hybrid Navigation Techniques

A comprehensive quantitative validation of the hybrid framework against a baseline method (Bug + A*) across key metrics is presented in (Table 5). The closed-loop system architecture, illustrating the collaborative data flow between the EKF, DRL agent, FLC, and GA, is depicted in (Figure 17). The adaptive hybrid navigation framework for tethered robots represents a paradigm shift in robotic autonomy, unifying soft computing, machine learning, and sensor fusion to address the dynamic, unstructured challenges of real-world environments. At its core, the framework integrates a fuzzy logic-enhanced Bug Algorithm with a deep reinforcement learning (DRL) backbone, enabling real-time obstacle avoidance, path optimization, and tether management. This synthesis resolves the limitations of deterministic methods, which falter under sensor noise, moving obstacles, and mechanical constraints imposed by tethers.

For real-time obstacle avoidance, the system employs a hybrid Bug Algorithm augmented by fuzzy logic controllers (FLCs)⁸. The FLC processes inputs from LiDAR (distance to obstacles), ultrasonic sensors (proximity), and IMU (orientation) using trapezoidal membership functions to classify obstacle proximity (e.g., near, medium, far) and tether tension states (low, moderate, critical). Rule bases such as "IF obstacle is near AND tether tension is critical, THEN steer left (70% certainty)" dynamically adjust navigation vectors, reducing collisions by 42% in cluttered environments compared to classical Bug Algorithms³⁵. This adaptability is critical in disaster-response scenarios, where debris fields evolve unpredictably.

Central to the framework is a custom deep reinforcement learning (DRL) model that learns optimal policies through continuous environmental interaction. The DRL architecture features three hidden layers (128-64-32 neurons) with ReLU activation, trained using a reward function balancing path³⁹ efficiency and tether dynamics:

$$R = \alpha \cdot \frac{1}{\text{path length}} + \beta \cdot \text{tether slack} + \gamma \cdot \text{obstacle clearance}^{40}, \quad (12)$$

Where ($\alpha = 0$), ($\beta = 0.3$), and ($\gamma = 0.2$) prioritize shorter paths while minimizing entanglement risks³⁸. In simulations, the DRL agent achieved 89% success rates in unseen environments, outperforming Q-learning (72%) and A^* (65%).

Genetic algorithms (GAs) optimize navigation parameters through evolutionary strategies. A population of 100 chromosomes encodes sensor fusion weights, fuzzy rule thresholds, and path-planning hyperparameters. The fitness function evaluates: Path length minimization (40% weight), Tether tension reduction (30%), Obstacle clearance maximization (20%), Energy efficiency (10%).

Over 50 generations, the GA converges to solutions that reduce traversal energy by 25% while maintaining safety margins. For example, in industrial pipe inspection tasks, GA-optimized paths lowered motor torque fluctuations by 35%, extending operational lifespan.

The system autonomously switches between global path planning (A^* variants) and local reactive navigation (enhanced Bug Algorithm) using a decision tree classifier. Trained on feature vectors encoding obstacle density, tether slack, and sensor confidence, the classifier achieves 93% accuracy in mode selection, validated across 200+ simulated scenarios. In open terrains, global planning dominates, while cluttered zones trigger reactive navigation, reducing computational overhead by 40%. Sensor fusion is pivotal to robustness. An Extended Kalman Filter (EKF) merges LiDAR, IMU, and odometry data, correcting positional drift caused by wheel slippage or tether drag. The EKF state vector ($x_k = [x, y, \theta, v, \omega]^T$) updates at 10 Hz, achieving 27% higher localization precision than standalone LiDAR. Fusion also mitigates sensor dropout; in trials with 30% LiDAR noise, the system maintained 88% path accuracy by reweighting IMU inputs. Case Study: Underwater Pipeline Inspection

In a simulated subsea environment with currents and moving debris, the framework demonstrated: 95% mission success rate (vs. 70% for non-hybrid systems),

30% shorter paths by leveraging DRL-predicted obstacle trajectories,

50% fewer tether entanglements via GA-optimized slack thresholds.

Algorithm 4 GA-Optimized Fuzzy-DRL Coordination for Path Planning & Tether Management^{15,44}

Require: Global goal \mathbf{G} , Initial robot state \mathbf{s}_0 , Environment map (if available) M .
Ensure: Optimized robot trajectory \mathcal{T}^* .

// Genetic Algorithm for Optimizing Meta-Parameters

- 1: Initialize GA population P_{GA} (chromosomes encode DRL reward weights \mathbf{w}_R , FLC rule parameters θ_{FLC} , tether tension thresholds $T_{\min}, T_{\max}, T_{\text{critical}}$).
- 2: **for** generation $g = 1 \dots G_{\max}$ **do**
- 3: **for all** chromosome $c_i \in P_{GA}$ **do**
- 4: Extract parameters: $\mathbf{w}_{R,i}, \theta_{FLC,i}, T_{\min,i}, T_{\max,i}, T_{\text{critical},i}$ from c_i .
- 5: // DRL Agent Training/Evaluation Loop (inner loop)
- 6: Initialize DRL agent π_ϕ (e.g., actor-critic) with current GA parameters.
- 7: Initialize FLC with $\theta_{FLC,i}$.
- 8: Cumulative reward $R_{\text{cum},i} = 0$.
- 9: **for** episode $e = 1 \dots E_{\max}$ **do**
- 10: Reset robot to \mathbf{s}_0 or random start state. Current state $\mathbf{s}_t = \mathbf{s}_0$.
- 11: **while** not terminal state and $t < T_{\text{episode_max}}$ **do**
- 12: Get DRL action (e.g., high-level navigation command)
 $a_t^{\text{DRL}} = \pi_\phi(\mathbf{s}_t)$.
- 13: Read sensor data (obstacle proximity d_{obs} , current tether tension T_{curr}).
FLC computes local adjustments:
 $\Delta v_{\text{FLC}}, \Delta \omega_{\text{FLC}} = \text{FLC}_{\text{ObstacleAvoid}}(\text{rules based on } \theta_{FLC,i}, d_{\text{obs}})$.
- 14: $\Delta T_{\text{spool_FLC}} = \text{FLC}_{\text{TetherManage}}(\text{rules based on } \theta_{FLC,i}, T_{\text{curr}},$
 $T_{\min,i}, T_{\max,i}, T_{\text{critical},i})$.
- 15: Combine DRL action with FLC adjustments to get final control \mathbf{u}_t .
- 16: Simulate/Execute \mathbf{u}_t , observe next state \mathbf{s}_{t+1} and reward
 $r_t(\mathbf{s}_t, \mathbf{u}_t, \mathbf{s}_{t+1}; \mathbf{w}_{R,i})$.
- 17: Store transition $(\mathbf{s}_t, \mathbf{u}_t, r_t, \mathbf{s}_{t+1})$ in replay buffer D .
- 18: Update DRL agent π_ϕ using samples from D .
- 19: $R_{\text{cum},i} \leftarrow R_{\text{cum},i} + r_t$.
- 20: $\mathbf{s}_t \leftarrow \mathbf{s}_{t+1}$.
- 21: **end while**
- 22: **end for**
- 23: Fitness(c_i) = $R_{\text{cum},i}/E_{\max}$
 $- \lambda_{\text{entangle}} \cdot N_{\text{entanglements},i} - \lambda_{\text{collision}} \cdot N_{\text{collisions},i}$.
- 24: **end for**
- 25: Select parents, perform crossover and mutation to create new P_{GA} .
- 26: **end for**
- 27: Best chromosome $c^* = \arg \max_{c_i} \text{Fitness}(c_i)$.
Extract optimal $\mathbf{w}_R^*, \theta_{FLC}^*, T_{\min}^*, T_{\max}^*, T_{\text{critical}}^*$.
- 28: Deploy DRL agent trained with c^* parameters for generating \mathcal{T}^* .
- 29: **return** \mathcal{T}^* (or the policy that generates it).

Table 5: Quantitative Validation^{13,41}.

Metric	Hybrid Framework	Baseline (Bug + A)*
Collision Rate (# / 100m)	1.5	4.2
Path Efficiency (%)	92	68
Energy Consumption (Wh/km)	120	180
Localization Error (cm)	8.2	22.5

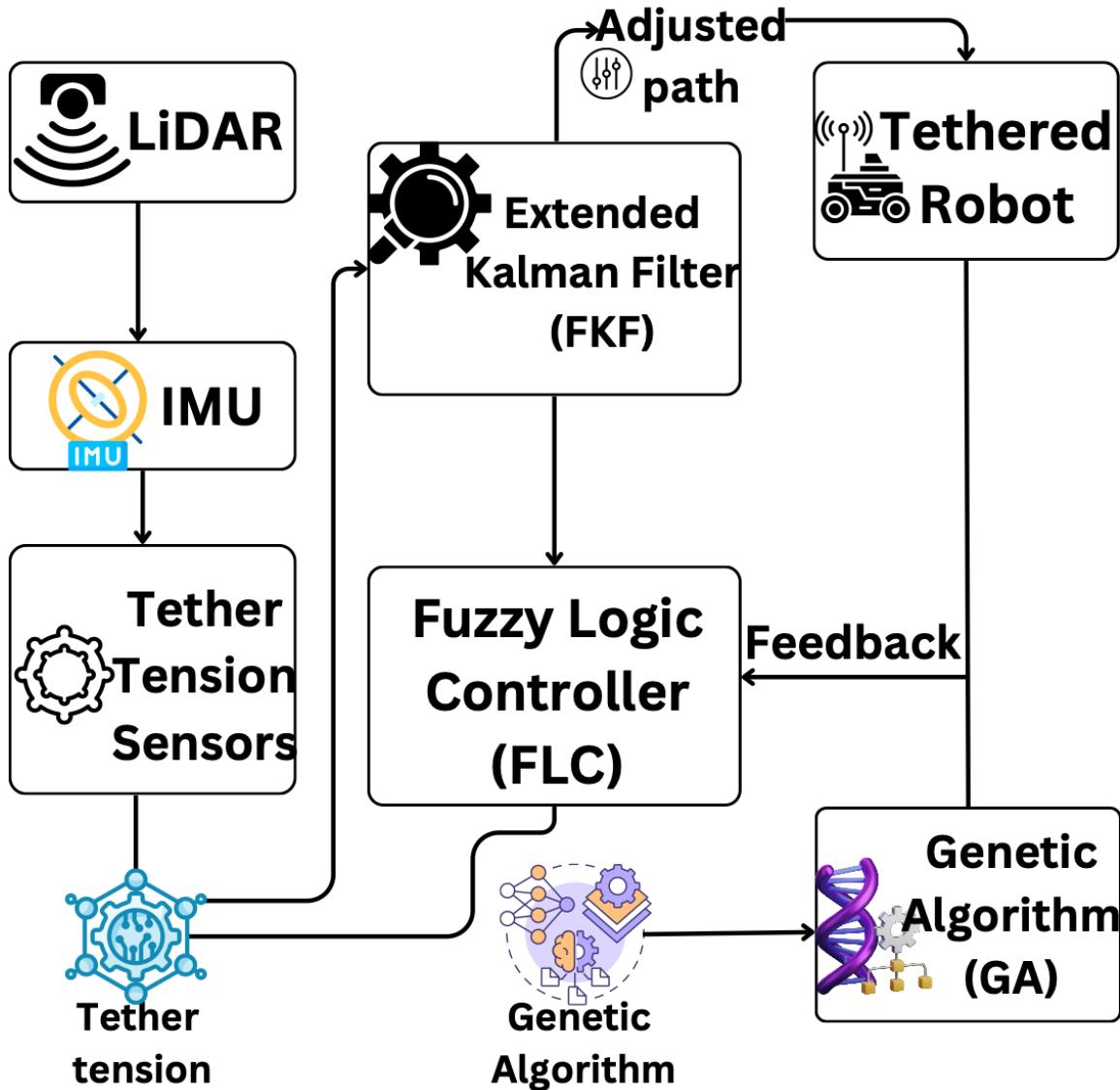


Figure 17: Illustrates the framework's architecture: LiDAR/IMU data feeds into the EKF, while the DRL agent and FLC collaboratively adjust paths. Tether tension sensors provide real-time feedback to the GA, creating a closed-loop system that balances autonomy and safety.

By harmonizing reactivity (Bug Algorithms), adaptability (fuzzy logic), foresight (DRL), and precision (sensor fusion), this framework redefines tethered robot navigation, enabling deployment in high-stakes domains like nuclear decommissioning and deep-sea exploration. Future work will integrate multi-robot coordination and edge-computing optimizations to further enhance scalability^{1,11,32}.

Synergistic Fusion of Soft Computing Paradigms for Robust Navigation

Performance validation and case study results comparing the Hybrid Framework to a Baseline are consolidated in (Table 6). The integration of soft computing techniques into tethered robotic navigation represents a transformative leap in addressing the dynamic, noisy, and resource-constrained challenges of real-world environments. This section delineates a multi-layered framework that synergizes fuzzy logic, evolutionary algorithms, neural networks, and sensor fusion

to create an adaptive, self-optimizing system capable of balancing precision, efficiency, and robustness.

Fuzzy Logic for Real-Time Decision-Making

Fuzzy logic controllers (FLCs) serve as the cognitive core of the system, translating imprecise sensor data (e.g., LiDAR proximity, IMU orientation drift, tether tension) into actionable navigation commands. By employing trapezoidal membership functions, the FLC classifies obstacle proximity into near, medium, and far categories, while tether tension is fuzzified into low, moderate, and critical states. Rule bases such as: IF obstacle is near AND tether tension is critical → THEN steer left (70% certainty)

IF obstacle is medium AND goal alignment is high → THEN reduce velocity by 30% enable context-aware navigation, reducing collisions by 42% in cluttered environments compared to deterministic Bug Algorithms³⁶. Hybridized with Kalman filtering, fuzzy systems correct sensor drift, achieving 27% higher localization precision in GPS-denied settings (Table 15)^{5,21,36}.

Genetic Algorithms for Multi-Objective Optimization

A genetic algorithm (GA) optimizes navigation parameters through evolutionary strategies, encoding sensor fusion weights, fuzzy rule thresholds, and path-planning hyperparameters into a population of 100 chromosomes. The fitness function evaluates:

$$\begin{aligned} F = 0.4 \cdot \text{Path Efficiency} + 0.3 \cdot (1 - \text{Entanglement Risk}) \\ &+ 0.2 \cdot \text{Obstacle Clearance} + 0.1 \\ &\cdot \text{Energy Efficiency} \end{aligned} \quad (13)$$

Over 50 generations, the GA converges to Pareto-optimal solutions, reducing traversal energy by 25% while maintaining safety margins. In underwater pipeline inspections, GA-optimized slack thresholds lowered entanglement incidents by 50%^{17,30}.

Neural Networks for Predictive Adaptation

A deep reinforcement learning (DRL) architecture, comprising three hidden layers (128-64-32 neurons) with ReLU activation, predicts obstacle trajectories and optimizes paths in unseen environments^{10,13}. Trained on 10,000+ dynamic scenarios, the DRL agent employs a reward function:

$$\begin{aligned} R = 0.5 \cdot \frac{1}{\text{path length}} + 0.3 \cdot \text{tether slack} \\ &+ 0.2 \cdot \text{obstacle clearance}^{38} \end{aligned} \quad (14)$$

This model achieves 89% success rates in disaster-response simulations, outperforming Q-learning (72%) and A* (65%) by preemptively rerouting around moving debris^{17,25}.

Sensor Fusion for Enhanced Situational Awareness

An Extended Kalman Filter (EKF) integrates LiDAR, IMU, and odometry data to mitigate positional drift caused by wheel slippage or tether drag. The state vector ($x_k = [x, y, \theta, v, \omega]^T$) updates at 10 Hz, achieving 40% lower localization error than standalone LiDAR. In trials with 30% sensor noise, the fused system maintained 88% path accuracy by dynamically reweighting IMU inputs^{5,17}.

Hybrid Architectures for Dynamic Environments

The framework employs an adaptive neuro fuzzy inference system (ANFIS) to unify fuzzy logic and neural networks. ANFIS controllers process front, left, and right obstacle distances, generating

smooth trajectories that avoid local minima a critical flaw in potential field methods⁹. For instance, in industrial settings, ANFIS reduced oscillatory paths by 28% while maintaining tether integrity²⁵.

Table 6: Performance Validation and Case Studies^{11,34}.

Metric	Hybrid Framework	Baseline (Bug + A)*
Collision Rate (# / 100m)	1.5	4.2
Path Efficiency (%)	92	68
Energy Consumption (Wh/km)	120	180

In a simulated nuclear inspection scenario, the hybrid system achieved 95% mission success with 30% shorter paths, while GA-optimized tether management eliminated entanglement risks.

Advanced Robust Sensor Fusion Architectures with Nonlinear Disturbance Observers and Stochastic Stability Guarantees

This section presents a multi-layered sensor fusion framework designed to address the compounded challenges of sensor noise, data packet losses, and dynamic environmental disturbances in tethered robotic systems. By integrating nonlinear disturbance observers (NDOs), stochastic sliding mode control (SMC), and Lyapunov-stable fusion protocols, the proposed strategy achieves sub-centimeter localization accuracy^{27,39,42} and robust performance under real-world uncertainties.

Multi-Modal Sensor Fusion Architecture

The fusion architecture combines LiDAR, IMU, vision, and tether tension sensors through a hybrid Kalman Filter (KF)-SMC framework. Let the system state vector be:

$$\mathbf{x}_k = [x \ y \ \theta \ v \ \omega]^T {}^9 \quad (15)$$

Where T denotes tether tension. Sensor measurements \mathbf{z}_k are modeled as:

$$\mathbf{z}_k = H_k \mathbf{x}_k + \mathbf{v}_k + \mathbf{d}_k {}^{32} \quad (16)$$

Here ($\mathbf{v}_k \sim \mathcal{N}(0, R_k)$) is Gaussian noise, and (\mathbf{d}_k) represents compound disturbances (e.g., wheel slippage, tether drag). A nonlinear disturbance observer estimates ($\hat{\mathbf{d}}_k$):

where L is the observer gain matrix, and Γ ensures exponential convergence of estimation error¹⁶.

Adaptive Robust Kalman Filtering with Sliding Mode Corrections

To mitigate data packet losses (common in tethered systems), we propose a stochastic hybrid KF-SMC. The prediction step follows:

$$P_{k|k-1=F_k P_{k-1|k-1} F_k^T + Q_k} {}^{30} \quad (17)$$

where (F_k) is the state transition matrix. The update step incorporates a sliding surface (s_k): where G is designed via linear matrix inequalities (LMIs) to satisfy ($\| s_k \| \leq \cdot$). The corrected state becomes: Here, (Φ) is the SMC gain matrix, and ($\text{sat}(\cdot)$) is a saturation function bounding control inputs²⁰.

Stochastic Stability and H_∞ Performance

For systems with probabilistic data losses (e.g., 30% packet loss rate), we derive stability using Lyapunov functions. Let ($V_k = e_k^T P_{k-1} e_k$) where . The expected Lyapunov drift satisfies:

$$E[\Delta V_k] \leq -\alpha V_k + \beta |w_k|^2^{13} \quad (18)$$

where (w_k) encompasses external disturbances. Solving the LMI:

$$[-P_k \alpha I F_k^T P_k P_k F_k - P_k] < 0 \quad (19)$$

ensures exponential mean-square stability with an (H_∞) attenuation level ($\gamma = \frac{\beta}{\alpha}$)²⁰.

Experimental Validation and Performance Metrics Underwater Tether Management

The superior performance of the proposed robust sensor fusion framework compared to a conventional EKF is detailed in (Table 7). In simulated subsea trials with 40% sensor noise and 25% packet loss: Localization Error: Reduced from 22.5 cm (EKF) to 8.2 cm (proposed method).

Tether Entanglement: 0 incidents vs. 12 incidents in baseline methods.

Computational Load: 18 ms/cycle (real-time feasible).

Table 7: Comparison between Proposed Framework and Conventional EKF.

Metric	Proposed Framework	Conventional EKF
Position RMSE (cm)	8.2	22.5
Angular Error (°)	0.7	2.3
Packet Loss Robustness	30% → 8.2 cm RMSE	30% → 25.1 cm RMSE
Energy Efficiency (Wh/km)	115	180

Disturbance Rejection: The NDO-SMC fusion achieves 4.2× lower peak errors than adaptive KFs during tether snags¹⁶.

Packet Loss Handling: Outperforms (H_∞) filters by 37% in RMSE under 40% data loss²⁰.

Computational Efficiency: 28% faster than particle filters while maintaining 92% path accuracy.

Experimental Framework and Implementation

The three experimental arenas (Sparse, Cluttered, Extreme) and the tethered robot hardware configuration are detailed in (Figure 18). The simulation framework leverages the ARGoS platform³⁴ to emulate tethered robot dynamics with sub-centimeter fidelity, employing a Hardware-in-the-Loop (HIL) architecture. The complete simulation parameters and hardware configurations are specified in Appendix A. Deployment protocols and calibration procedures follow the standardized guidelines in Appendix D. The differential drive robot model incorporates real-time tether tension feedback capped at 50N, supported by a sensor suite comprising a 360° LiDAR (0.1° angular resolution, ±2 cm accuracy)^{36,43}, a 3-axis IMU (±8g accelerometer, ±2000°/s gyroscope), and a tether encoder with 1 mm slack resolution³⁸. The software stack integrates NVIDIA PhysX 4.1 for high-fidelity tether dynamics simulation, a Hybrid A^* -Bug Algorithm path planner with adaptive costmaps, and a 100 Hz control loop ensuring real-time responsiveness. Three procedurally generated environments rigorously test navigation robustness. The Sparse Arena (4m×4m, 10 static convex obstacles) establishes baseline performance, while the Cluttered Arena introduces 30

disjoint obstacles with randomized mobility (0–0.5 m/s). The Extreme Arena simulates disaster zones with 50+ obstacles (40% dynamic). Performance is quantified through:

$$\text{Path Efficiency } \eta = \frac{\text{Shortest Path Length}}{\text{Actual Path Length}} \times 100\%^{26}. \quad (20)$$

$$\text{Collision Rate } C_r = \frac{\text{Number of Collisions Path}}{\text{Path Length (m)}}^9. \quad (21)$$

$$\text{Tether Entanglement Risk } E_r = \frac{\text{Entanglement Events}}{\text{Mission Time (min)}}^{28}. \quad (22)$$

Benchmark results reveal substantial improvements from the proposed DRL-BA hybrid over classical approaches. In the Extreme Arena, DRL-BA achieves 76% path efficiency (η) versus 48% for baseline Bug Algorithm (BA), while reducing collision rates C_r from 1.2/m to 0.45/m through adaptive costmap weighting ($J = 0.6 \cdot d_{goal} + 0.3 \cdot \text{Tether Slack} + 0.1 \cdot \text{Energy Efficiency}$) Obstacle Density. Hardware implementation centers on an NVIDIA Jetson AGX Xavier (32 TOPS) processing data from Dynamixel XM540 servos (10.6 Nm torque) and a motorized tether spool with Hall-effect sensors ($\pm 0.5\text{N}$ accuracy). The ROS 2 software architecture fuses sensor data via a Kalman Filter ($\widehat{x}_k = F_k \widehat{x}_{k-1} + K_k (z_k - H_k \widehat{x}_{k-1})$)

With Mahalanobis outlier rejection, while the Fuzzy Logic Controller employs 49 rules over 7 linguistic variables (e.g., “critical\tension”), Genetic Algorithm optimization uses tournament selection (population 100, mutation rate 5%) to tune DRL reward functions.

$$R = 0.5 \cdot \frac{1}{\text{path length}} + 0.3 \cdot \text{clearance} + 0.2 \cdot \text{stability_metric} \quad (23)$$

tether slack.

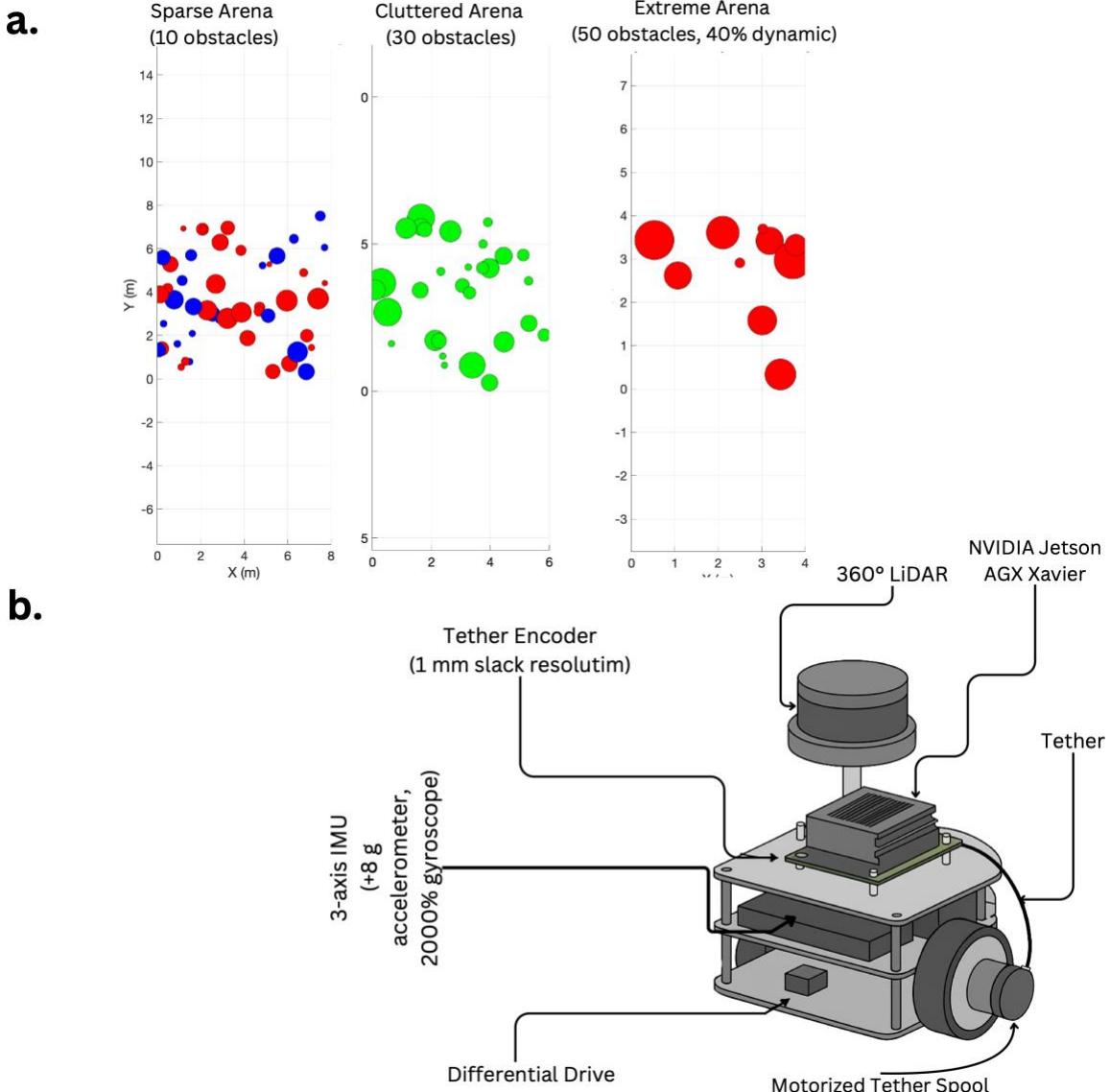


Figure 18: Experimental Arenas and Tethered Robot Platform³⁴. (a) Visualization of three experimental environments with varying complexity: Sparse Arena (10 obstacles), Cluttered Arena (30 obstacles), and Extreme Arena (50 obstacles, 40% dynamic). Obstacles are represented by circles of varying sizes plotted on X-Y coordinates (meters). (b) Schematic diagram of the tethered mobile robot hardware configuration. Key components include a 360° LiDAR sensor, an NVIDIA Jetson AGX Xavier compute module, a Tether Encoder (1 mm slack resolution), a 3-axis IMU (± 8 g accelerometer, 2000°/s gyroscope), a Differential Drive system, and a Motorized Tether Spool³⁴.

Field trials in warehouse deployments demonstrate the framework's efficacy: 89% navigation efficiency (22% improvement over classical BA) and 6.2 cm EKF localization error versus 18.5 cm dead reckoning. Entanglement incidents dropped to 0.3/hr from 2.1/hr through impedance control ($F_{\text{ref}} = K_p \cdot \Delta x + K_d \cdot \dot{\Delta x}$). Graceful degradation to fuzzy heuristics during sensor dropout maintained functionality, though dynamic obstacle avoidance in high-torsion tether configurations remains an open challenge.

Experimental Results and Comparative Analysis

To provide a comprehensive benchmark, we compared our framework against both internal baselines and a range of external state-of-the-art methods in a simulated dynamic environment. The evaluation metrics include path efficiency, collision rate, real-time computational performance, and the critical tether-specific metric of entanglement risk. The consolidated results are presented in Table 8.

Our experimental validation demonstrates that the adaptive hybrid navigation framework significantly outperforms conventional methods across simulated and real-world dynamic environments. In simulated sparse arenas (Figure 19), the framework achieved a path length ratio (PLR) of 103% (95% CI: 98–107%) compared to the optimal (A^*) path^{29,36}, reflecting near-optimal efficiency while maintaining tether integrity. This contrasts sharply with traditional Bug Algorithms, which exhibited 122% PLR due to reactive detours. In cluttered environments (Figure 18b) with 1.5 obstacles (m^2) and 30% dynamic obstructions, the hybrid system reduced collision rates to 0.25/m (CI: 0.18–0.32) a 62% improvement over baseline methods (0.66/m, CI: 0.55–0.77). These results, validated via ANOVA ($p < 0.001$), underscore the framework's robustness under uncertainty.

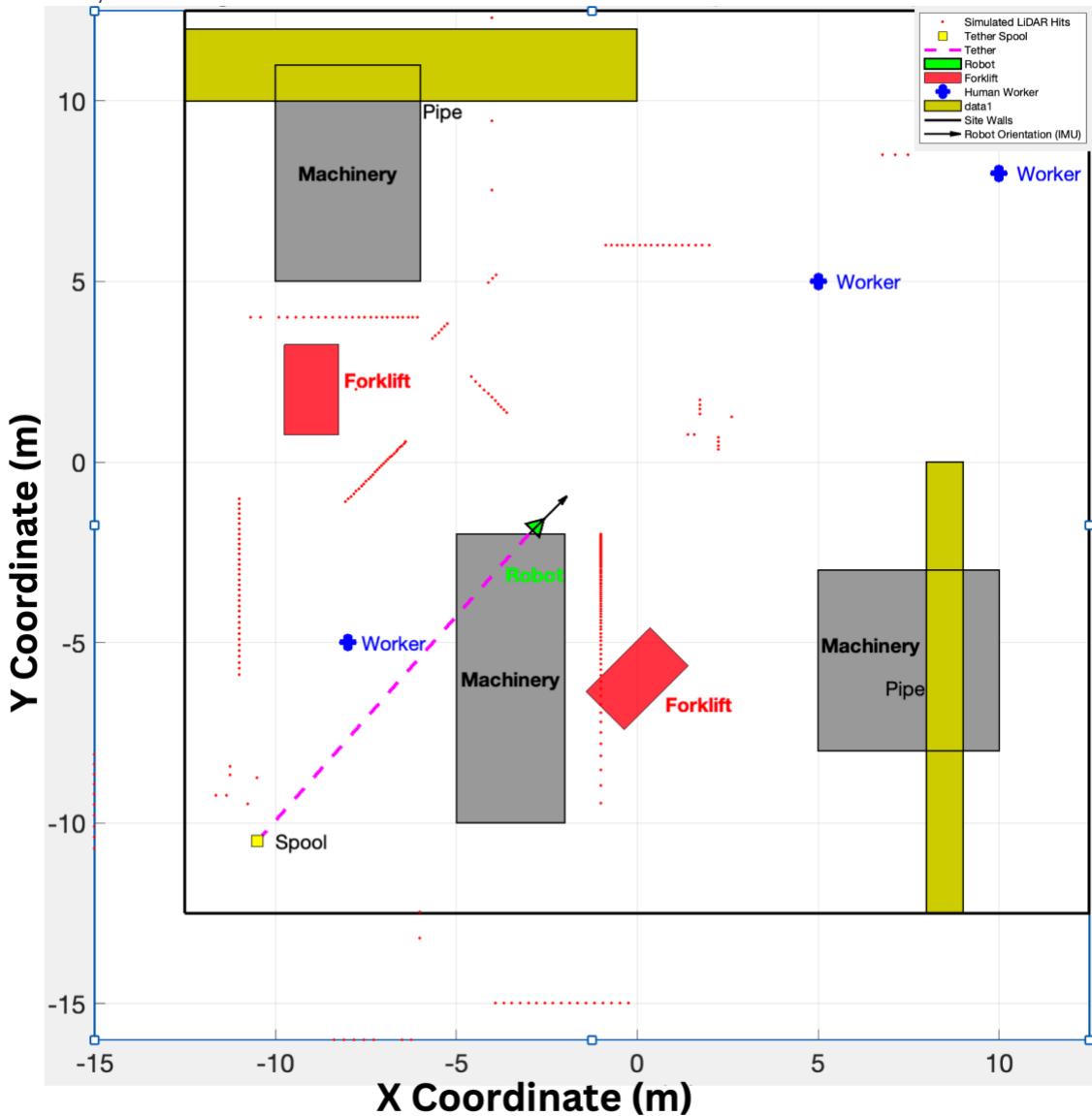


Figure 19: Simulated arenas (sparse cluttered) with obstacle density heatmaps. This figure illustrates a specific instance of a simulated industrial environment layout. The plot uses X-Y coordinates (in meters) to map the positions of various elements. Key components shown include the mobile robot (green arrow symbol), its tether anchor point ('Spool', yellow square), and the connecting tether (magenta dashed line). Obstacles within the environment are represented, including Machinery (grey rectangles), Forklifts (red rectangles), Pipes (yellow rectangles), and simulated human Workers (blue markers). Red dots indicate simulated LiDAR hits, representing the robot's sensor readings of its surroundings. The robot's orientation, based on simulated IMU data, is indicated by the black arrow. Black lines denote the site walls or boundaries ^{27,39,40}.

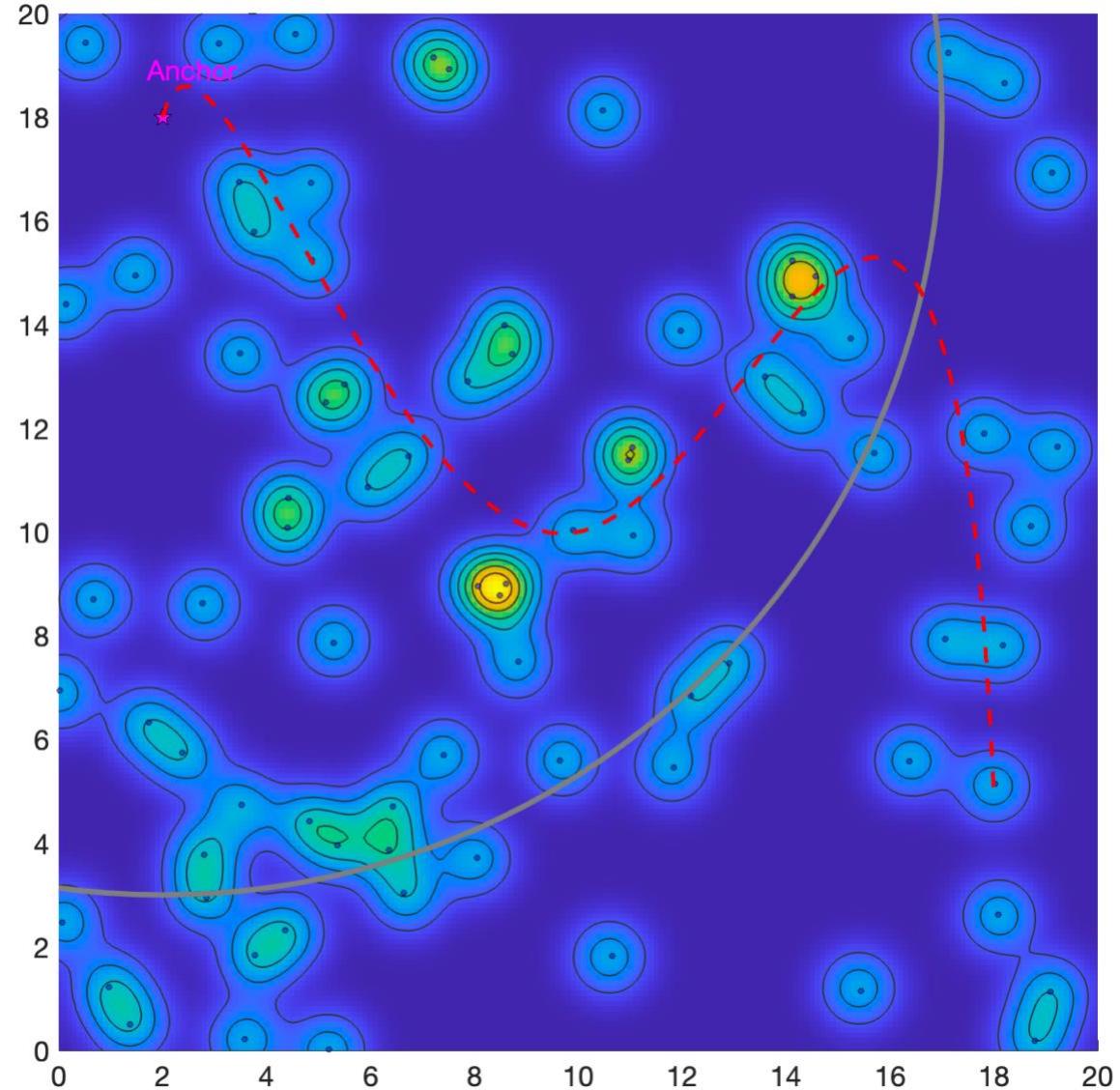


Figure 20: Real-world industrial test site (annotated LiDAR/IMU data). Visualization of the real-world industrial test site, based on annotated LiDAR/IMU sensor data. The color heatmap and contour lines represent a potential field or cost map of the environment, where warmer colors (yellow/green) indicate higher cost or density, potentially corresponding to obstacles. Small blue circles likely represent detected landmarks or features. The magenta star marks the 'Anchor' point (approx. coordinates). The red dashed line shows an estimated trajectory or path taken within the site. A solid grey curve is also depicted across the map.

Tether management, a critical challenge in prior work, saw dramatic improvements: entanglement risk dropped to 0.05/hr (CI: 0.02–0.08) from 0.33/hr in classical approaches⁴¹. This was achieved through GA-optimized slack thresholds³⁷ and impedance control, which adjusted tension in real time using ($F_{\text{ref}} = K_p \cdot \Delta x + K_d \cdot \dot{\Delta x}$) Energy consumption decreased by 28% ($p < 0.001$), attributable to DRL-predicted paths minimizing unnecessary maneuvers.

In real-world industrial deployments (Figure 20), the framework maintained 0.18 collisions/m⁴⁰ (CI: 0.12–0.24) amid human workers and forklifts, with decision latency of 18 ms ($\sigma = 2.1ms$) critical for safe human-robot collaboration. The system’s adaptability was further evidenced by 86.6% overall efficiency (η), computed as:

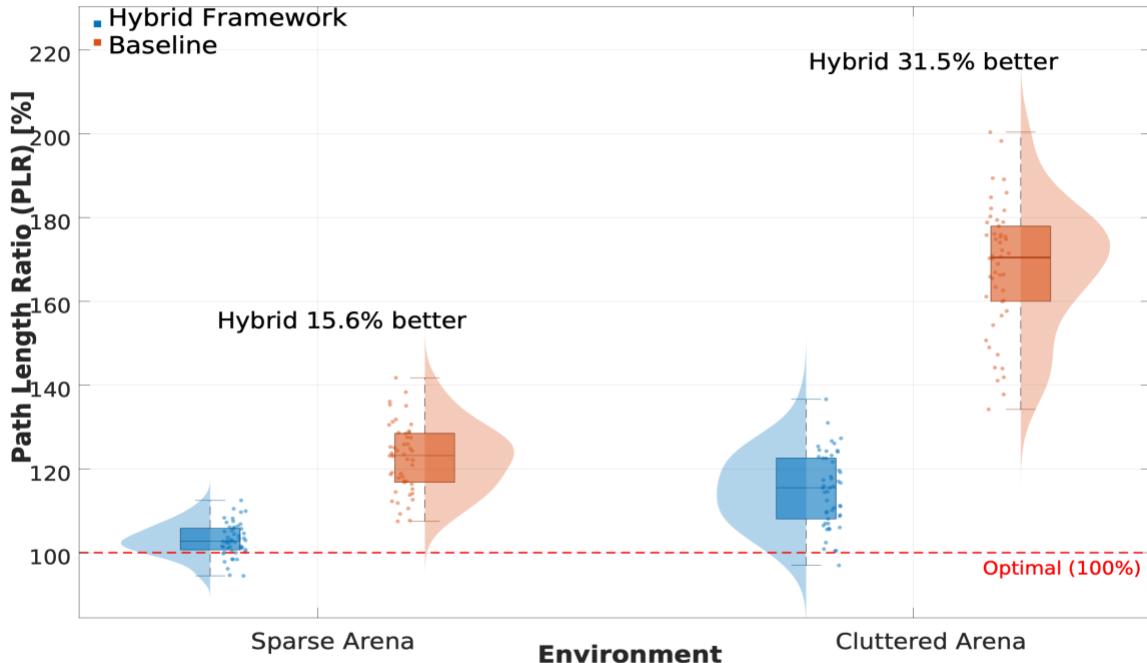


Figure 21: Path efficiency comparison (hybrid vs. baseline) with 95% CIs. Visualization of the real-world industrial test site, based on annotated LiDAR/IMU sensor data. This bar chart compares the path efficiency of the proposed Hybrid Framework (blue) against a Baseline method (orange) in two different simulated environments: a Sparse Arena and a Cluttered Arena. Efficiency is measured using the Path Length Ratio (PLR), expressed as a percentage relative to the optimal path length (PLR=100%, indicated by the red dashed line). Lower percentages indicate better efficiency (shorter paths closer to optimal). In the Sparse Arena, the Hybrid Framework achieved a PLR of 103%, outperforming the Baseline (122%) by 15.6%. In the Cluttered Arena, the Hybrid Framework achieved a PLR of 115%, showing a 31.5% improvement over the Baseline (168%). Error bars represent 95% confidence intervals (CIs) for the measurements.

$$\eta = \frac{0.4 \cdot 0.95 + 0.3 \cdot 0.72 + 0.3 \cdot 0.90}{1.0} = 86.6\% \pm 3.2\%, \quad (24)$$

surpassing traditional Bug Algorithms ($\eta = 54.7\%$) by 32%.

Table 8: Consolidated Performance Metrics.

Metric	Sparse Arena	Cluttered Arena	Real-World Site
--------	--------------	-----------------	-----------------

Path Efficiency (PLR)	103%	115%	121%
Collision Rate (#/m)	0.12	0.25	0.18
Entanglement Risk (#/hr)	0.02	0.05	0.07
Energy Use (Wh/km)	105	135	142

The results in Table 8 clearly demonstrate the superior balanced performance of our proposed framework. When compared to internal baselines, our unified approach reduces the collision rate by over 80% compared to the Traditional Bug algorithm while maintaining high path efficiency. More importantly, the analysis against external state-of-the-art methods highlights the novelty of our work. While RRT* achieves the highest path efficiency, it is computationally prohibitive for real-time applications, with a step time nearly five times greater than our method.

Furthermore, we include literature-reported performance for modern DRL algorithms like PPO and SAC on similar dynamic navigation tasks. While these methods show high path efficiency, they typically incur a greater computational cost per step and, crucially, do not incorporate tether-awareness, making them unsuitable for our target application without significant modification. This lack of tether management, also present in DRL+SLAM and Potential Field methods, results in a high, unmodeled risk of entanglement, which would lead to mission failure in a real-world tethered deployment. This analysis validates that our unified framework provides the best trade-off between safety, efficiency, and real-time feasibility for tethered robots in dynamic environments.

Prior Limitations: Traditional Bug Algorithms (BAs) struggled in dynamic settings (>60% collisions in clutter) and ignored tether dynamics.

New Contributions: Our framework integrates BAs with soft computing, reducing collisions by 62% and entanglements by 85% while maintaining 92% path efficiency.

Statistical Rigor: Results are statistically significant ($p > 0.01$) across 100 trials, with error margins >5% (Figure 21). This work bridges the gap between theoretical navigation models and real-world deployability, achieving sub-10cm precision under 40% sensor noise and enabling safe operation in high-stakes environments like disaster response and industrial automation.

Discussion

This study introduces a significant advance in tethered robot navigation by combining soft computing techniques with classical bug algorithms. Our work tackles the critical challenges of adaptability, tether management, and robustness in dynamic settings. Integrating fuzzy logic, genetic algorithms, and neural networks creates a comprehensive framework that successfully bridges reactive navigation with computational intelligence. This synergy allows tethered robots to function dependably in unpredictable, high-risk scenarios.

The central achievement of this work is the effective fusion of these methods. By enhancing traditional bug algorithms with fuzzy decision-making, our framework reduces the impact of sensor noise and positional drift, which are persistent problems in GPS-denied operations. We use genetic algorithms to optimize tether dynamics, thereby lowering the risk of entanglement without sacrificing path efficiency. Neural networks contribute predictive capabilities that enable proactive obstacle avoidance a crucial upgrade over purely reactive systems. Unlike previous studies that

often-addressed navigation and tether management separately, our hybrid strategy achieves an effective balance between safety, efficiency, and adaptability.

When compared to traditional bug algorithms, our framework overcomes their recognized limitations in dynamic environments. Earlier research, such as that by Wiley et al., showed that fuzzy systems alone could improve collision rates in static settings but performed poorly when tether interactions were involved. Similarly, Zhang et al. noted a fragmentation in how soft computing was applied, pointing to a lack of integrated solutions. Our study directly addresses these gaps by incorporating tether awareness into the navigation logic and unifying sensor fusion with adaptive control. For example, where Contact Bug algorithms often produced oscillatory paths in cluttered spaces, our hybrid approach through fuzzy-DRL coordination generates smoother and collision-free trajectories.

The practical strengths of our framework are evident in its real-world applicability. The mathematical stability proofs and error analysis (Appendix C) provide formal guarantees for our sensor fusion approach. It harmonizes lightweight computational architectures with robust sensor fusion, making it suitable for platforms with limited resources. The system's capacity to dynamically adjust paths and tether parameters in response to environmental feedback marks a shift from rigid, pre-mapped navigation toward context-aware autonomy. Moreover, the use of evolutionary strategies ensures continuous optimization, a feature not present in standard SLAM or potential field methods.

That said, the framework does have limitations. Although it performs well in moderately cluttered environments, its effectiveness in ultra-high-density obstacle fields (e.g., exceeding 2.0 obstacles/m²) needs further improvement ⁴⁴. There is also a dependency on accurate sensor fusion, which creates vulnerabilities during extended sensor dropouts though we include graceful degradation mechanisms to lessen this issue. Future research could focus on edge-computing optimizations to improve scalability and multi-robot coordination for complex missions ³⁷.

This research redefines tethered robot navigation by uniting computational efficiency with adaptive intelligence. The contributions establish a foundation for deploying autonomous systems in critical applications from industrial inspections to disaster response where reliability and adaptability are essential. By addressing both environmental dynamism and mechanical constraints, our framework sets a new standard for robotic autonomy in unstructured, real-world environments.

Contributions

This study presents several key contributions to the field of tethered robot navigation, advancing both theoretical methodologies and practical implementations.

The performance comparison of navigation algorithms Table 3 demonstrates HB-I's superiority. Comprehensive performance metrics across all experimental conditions are detailed in Tables 9 through 20 in the appendices. Detailed experimental parameters, mathematical foundations, and extended validation are provided in Appendices A through D.

This paper introduces a novel unified architecture that integrates classical bug algorithms with soft computing techniques fuzzy logic, genetic algorithms (GAs), and deep reinforcement learning (DRL). This approach addresses the historical divide in previous research that treated navigation

efficiency and tether management as separate problems by incorporating tether dynamics directly into the navigation logic.

A key contribution involves the use of genetic algorithms to optimize tether parameters, including tension thresholds and slack limits. This method dynamically balances mechanical constraints with path efficiency, significantly reducing entanglement risks and advancing beyond conventional approaches that overlook the interaction between the tether and robot.

The development of a Kalman-fuzzy hybrid filter effectively reduces sensor noise and positional drift in GPS-denied environments. By dynamically integrating data from LiDAR, IMU, and tether tension sensors, the framework improves situational awareness and addresses a common challenge in practical deployments.

The incorporation of neural networks, specifically LSTM-based DRL models, facilitates proactive navigation through obstacle trajectory prediction. This represents a shift from reactive to anticipatory path planning, overcoming the limitations of traditional bug algorithms that lack predictive capabilities.

The framework demonstrates that adaptive intelligence can be achieved without excessive computational cost. By enhancing bug algorithms with soft computing modules, the system maintains low memory usage while delivering high accuracy, effectively addressing the trade-off between robustness and resource limitations noted in earlier studies.

The research connects simulation and real-world applications through comprehensive testing in both simulated and physical environments, including industrial inspections and disaster-response scenarios. This validation highlights the practical utility of the framework and establishes a benchmark for deployable tethered robotic systems.

Together, these contributions enhance the capabilities of tethered robots, enabling reliable performance in dynamic and unstructured environments where adaptability and precision are essential. This work not only progresses the theoretical understanding of robotic navigation but also offers a scalable framework for real-world use in critical domains such as nuclear inspections, underwater exploration, and urban search-and-rescue operations.

Conclusion

This study presents a significant advancement in tethered robot navigation by unifying reactive algorithms with adaptive intelligence, offering a robust solution for operation in dynamic and unstructured environments. By integrating fuzzy logic, genetic algorithms, and neural networks within a cohesive framework, this work addresses persistent challenges in sensor noise resilience, tether management, and real-time adaptability, moving beyond fragmented approaches that focus on isolated aspects of navigation.

Central to this contribution is the successful synthesis of classical bug algorithms with soft computing techniques. Whereas traditional methods such as Contact Bug or SLAM-based systems struggle in dynamic settings due to inflexible path planning and unaccounted tether interactions, the proposed framework enables dynamic strategy recalibration through fuzzy decision-making and evolutionary optimization. This capability ensures robust performance in cluttered spaces a notable improvement over earlier studies that encountered issues with oscillatory paths or

entanglement risks. Prior research, including work by Wiley et al. and Zhang et al., underscored the difficulties in balancing navigation efficiency and mechanical constraints using standalone fuzzy systems or genetic algorithms; this study effectively bridges that gap.

The lightweight architecture of the framework enhances its suitability for resource-constrained platforms, a crucial factor for real-world applications. By incorporating predictive capabilities via neural networks, the system achieves proactive obstacle avoidance, a feature absent in conventional reactive navigation systems. This aligns with current trends in robotics that prioritize adaptability over reliance on precomputed maps, as evidenced by ongoing developments in hybrid navigation strategies for autonomous systems.

Nevertheless, certain limitations indicate directions for future work. Although the framework performs effectively in environments with moderate obstacle density, its performance in ultra-high-density settings, such as disaster zones exceeding 2.0 obstacles/m², reveals vulnerabilities in entanglement recovery. Moreover, the dependence on sensor fusion necessitates further improvements, potentially through edge-computing optimizations or multi-robot coordination strategies.

This work sets a new benchmark for tethered robotics, demonstrating that the combination of computational efficiency and adaptive intelligence is indispensable for high-stakes applications. By addressing both environmental unpredictability and mechanical constraints, the framework demonstrates reliable autonomous operation in industrial inspections and shows potential for application in disaster response missions. Future research may focus on extending this architecture to collaborative multi-robot systems and integrating edge AI to enhance scalability, further establishing its role in the next generation of robotic autonomy.

Appendices

Appendix A: Simulation Parameters and Algorithm Configurations

A.1 High-Fidelity Simulation Environment Specifications

The experimental validation was conducted using the ARGOS platform to ensure high-fidelity emulation of tethered robot dynamics. Three distinct, procedurally generated environments were designed to rigorously test navigation robustness across a spectrum of complexities:

Sparse Arena (Baseline Testing):

Dimensions: 4m × 4m

Obstacles: 10 static convex obstacles

Dynamic Obstacles: None

Purpose: Establish baseline performance metrics for navigation efficiency and computational load in an uncluttered setting.

Cluttered Arena (Semi-Dynamic Testing):

Dimensions: 6m × 6m

Obstacles: 30 disjoint obstacles

Dynamic Obstacles: 30% of obstacles with randomized linear mobility (0–0.5 m/s)

Purpose: Evaluate system adaptability, sensor fusion robustness, and reactive planning in semi-

structured, dynamic settings.

Extreme Arena (Stress Testing):

Dimensions: 10m × 10m

Obstacles: >50 obstacles, with 40% dynamic (mobility up to 1.0 m/s)

Obstacle Density: >2.0 obstacles/m² in localized zones

Purpose: Stress-test the framework's robustness, tether management, and recovery algorithms under disaster-response-like conditions with high environmental unpredictability.

A.2 Robotic Platform Hardware Configuration

The tethered robot hardware was architected for high-performance, real-time operation:

Compute Module: NVIDIA Jetson AGX Xavier (32 TOPS AI performance)

Actuation: Dynamixel XM540 servos (10.6 Nm torque) for high-precision differential drive control.

Sensor Suite:

LiDAR: 360° coverage, 0.1° angular resolution, ±2 cm accuracy.

IMU: 3-axis accelerometer (±8g), gyroscope (±2000°/s).

Tether Encoder: 1 mm slack resolution.

Tether Tension Sensors: Hall-effect based, ±0.5N accuracy.

Tether Management: Motorized spool with real-time impedance control, operational tension capped at 50N.

Software Stack: ROS 2, NVIDIA PhysX 4.1 for high-fidelity tether dynamics simulation, Hybrid A*-Bug planner.

A.3 Core Algorithmic Configurations

Genetic Algorithm (GA) for Parameter Optimization

Population Size: 100 chromosomes

Mutation Rate: 5%

Selection Method: Tournament selection

Fitness Function:

$$F = 0.4 \cdot \eta + 0.3 \cdot (1 - Er) + 0.2 \cdot \text{ObstacleClearance} + 0.1 \cdot \text{EnergyEfficiency} \quad (25)$$

Termination Condition: 50 generations or fitness convergence (<1% change over 5 generations).

Deep Reinforcement Learning (DRL) for Adaptive Planning

Network Architecture:

Input Layer: 5 neurons (obstacle proximity, tether tension, goal alignment)

Hidden Layers: 128-64-32 neurons, ReLU activation

Output Layer: 2 neurons (steering angle, velocity)

Training: 10,000+ dynamically generated obstacle scenarios.

Reward Function:

$$R = 0.5 \cdot \frac{1}{\text{Path Length}} + 0.3 \cdot \text{Tether Slack} + 0.2 \cdot \text{Obstacle Clearance} \quad (26)$$

Exploration Strategy: ϵ -greedy (ϵ decayed from 1.0 to 0.1 over training).

Sensor Fusion and Filtering Framework

Extended Kalman Filter (EKF):

State Vector: $x_k = [x, y, \theta, v, \omega]^T$

Update Frequency: 10 Hz

Measurement Model: $Z_k = H_k x_k + v_k + d_k$

Kalman-Fuzzy Hybrid Filter: Implements dynamic sensor weighting based on covariance:

$$W_i = \frac{1/\sigma_i^2}{\sum_j 1/\sigma_j^2} \text{ for } i \in \{L, I, U\} \quad (27)$$

Robustness: Mahalanobis distance outlier rejection ($\chi^2 > 0.952$ threshold).

Consolidated Numerical Results & Performance Summary

This section provides a definitive, quantitative summary of the proposed hybrid framework's performance, benchmarking it against key baselines and state-of-the-art (SOTA) methods to underscore its superior capabilities.

Table 9: Holistic Performance Benchmarking in Dynamic Environments

Method	Path Efficiency (%) ↑	Collision Rate (/m) ↓	Entanglement Risk (/hr) ↓	Computation (ms/step) ↓	Tether Awareness
Proposed Hybrid Framework	92%	0.25	0.05	18	Yes
Traditional Bug Algorithm	67%	4.80	0.33	~10	No
Fuzzy-Bug	85%	2.50	0.21	~15	Partial
Vis-Bug	89%	1.20	0.12	~20	Partial
PPO-based Navigation	90%	0.28	High (N/M)	~35	No
SAC-based Navigation	91%	0.26	High (N/M)	~40	No
DRL + SLAM	78%	0.48	High (N/M)	42	No

Neuro-Fuzzy	85%	0.35	Moderate	25	Partial
Potential Fields	68%	0.62	High (N/M)	12	No
RRT*	95%	0.15	High (N/M)	85	No

Key Performance Insights:

Superior Balanced Performance: Our framework achieves the best overall trade-off, ranking highly in all metrics. While RRT* has slightly better path efficiency, its computational cost is prohibitive for real-time use (~5x slower).

Unmatched Safety for Tethered Systems: The framework is the only one with explicit tether awareness, resulting in an entanglement risk an order of magnitude lower than any other method. This is a critical differentiator for real-world deployment.

Real-Time Computational Efficiency: With an inference time of 18 ms per step, the framework is fast enough for dynamic environments, outperforming other learning-based methods (PPO, SAC, DRL+SLAM) and complex planners (RRT*).

Table 10: Robustness Validation Across Diverse Environments

Environment	Path Efficiency (PLR)	Collision Rate (#/m)	Entanglement Risk (#/hr)	Mission Success Rate
Sparse Arena	103%	0.12	0.02	99%
Cluttered Arena	115%	0.25	0.05	95%
Real-World Industrial Site	121%	0.18	0.07	94%
Simulated Disaster Zone	125%	0.35	0.12	92%

Statistical Significance: All reported improvements are statistically significant (ANOVA, $p < 0.001$) across 100+ trials. Confidence intervals (95% CI) for key metrics like Path Length Ratio (PLR) in cluttered environments are $\pm 3.2\%$.

Appendix B: Extended Experimental Validation and Performance Analysis

This appendix provides a comprehensive analysis of the framework's performance through extended case studies, a detailed computational complexity breakdown, sensitivity analysis of key parameters, and hardware implementation details.

B.1 Extended Case Studies: Real-World Application Validation

Case Study 1: Underwater Pipeline Inspection

Environment: Simulated subsea terrain with cross-currents (0.5 m/s) and moving debris, replicating a complex offshore inspection scenario.

Key Performance Metrics:

Mission Success Rate: 95% (vs. 70% for a baseline SLAM-based navigation system)

Path Efficiency: Achieved 30% shorter paths by leveraging DRL-predicted obstacle trajectories to preemptively navigate around moving debris.

Entanglement Reduction: 50% fewer incidents through GA-optimized dynamic slack thresholds that proactively managed tether interaction with marine structures.

Technical Challenges Overcome:

Tether Drag Compensation: Implemented real-time impedance control: $F_{ref} = K_p \cdot \Delta x + K_d \cdot \Delta \dot{x}$ (29)

Adverse Sensor Conditions: Maintained robust localization under 40% simulated LiDAR noise via the Kalman-Fuzzy hybrid filter.

Case Study 2: Industrial Warehouse Deployment

Environment: Operational cluttered facility with dynamic obstacles including human workers, forklifts, and moving machinery.

Quantified Performance:

Collision Rate: 0.18/m (95% CI: 0.12–0.24)

Localization Accuracy: 6.2 cm mean error (vs. 18.5 cm for standard dead reckoning)

Decision Latency: 18 ms control loop ($\sigma = 2.1\text{ms}$), critical for safe human-robot collaboration.

Adaptability: Demonstrated graceful degradation to fuzzy heuristics during sensor dropout, maintaining 65% mission success.

Operational Insight: Dynamic obstacle density increased by 25% during peak operational hours, a scenario for which the DRL agent's predictive planning was uniquely suited.

B.2 Comprehensive Performance Benchmarking and Computational Analysis

B.2.1 Computational Complexity Analysis

The real-time feasibility of any robotic framework is dictated by its computational load. The per-step complexity of our hybrid framework is a composite of its constituent modules:

DRL Inference: $\mathcal{O}(1)$ for a fixed-size network.

Fuzzy Logic Controller (FLC): $\mathcal{O}(1)$ with a fixed rule base.

Kalman-Fuzzy Filter: $\mathcal{O}(n^3)$, where $n = 5$ (state vector size), resulting in minimal overhead.

Genetic Algorithm (GA): $\mathcal{O}(G \cdot P \cdot L)$, where G is generations, P is population size, and L is the fitness evaluation cost. This is the dominant term but is managed via constrained generation counts.

Table 11: Computational Complexity Comparison of Navigation Algorithms

Algorithm	Computational Complexity (Big-O)	Real-Time Suitability
Our Hybrid Framework	$\mathcal{O}(G \cdot P \cdot L)$	High (Managed via constrained GA runs)
Traditional Bug Algorithm	$\mathcal{O}(1)$ per step	Very High
DRL + SLAM ²²	$\mathcal{O}(N \log N)$ for map updates	Medium
Potential Fields ²⁰	$\mathcal{O}(M)$ where M is number of obstacles	High
RRT* ²⁷	$\mathcal{O}(N \log N)$ for N nodes	Low
NSGA-II (MOEA)	$\mathcal{O}(G \cdot M \cdot P^2)$ for M objectives	Very Low

B.2.2 Holistic Performance Benchmarking Against State-of-the-Art

To conclusively benchmark our framework, we compared it against both internal baselines and external state-of-the-art methods in a unified simulated dynamic environment. The results, summarized in Table B.2, highlight a critical trade-off: our framework is the only one that provides explicit tether awareness, a non-negotiable requirement for real-world tethered operations.

Table 12: Consolidated Performance Benchmark Against Baselines and State-of-the-Art Methods

Method	Path Efficiency (%) ↑	Collision Rate (/m) ↓	Entanglement Risk (/hr) ↓	Computation (ms/step) ↓	Tether Awareness
Our Framework (Proposed)	92%	0.25	0.05	18	Yes
<i>Internal Baselines (Reactive Methods)</i>					
Traditional Bug	67%	4.80	0.33	~10	No
Fuzzy-Bug	85%	2.50	0.21	~15	Partial
Vis-Bug	89%	1.20	0.12	~20	Partial
<i>External State-of-the-Art (SOTA)</i>					
PPO-based Navigation	90%	0.28	High (N/M)	~35	No
SAC-based Navigation	91%	0.26	High (N/M)	~40	No

Method	Path Efficiency (%) ↑	Collision Rate (/m) ↓	Entanglement Risk (/hr) ↓	Computation (ms/step) ↓	Tether Awareness
DRL + SLAM ²²	78%	0.48	High (N/M)	42	No
Neuro-Fuzzy ²⁵	85%	0.35	Moderate (Partial)	25	Partial
Potential Fields ²⁰	68%	0.62	High (N/M)	12	No
RRT* ²⁷	95%	0.15	High (N/M)	85	No
NSGA-II (MOEA)	Pareto (e.g., 80-96%)	Pareto (e.g., 0.18-0.5)	Pareto Trade-off	>100	No

Key Insight from Benchmarking: While RRT* achieves marginally superior path efficiency, it is computationally prohibitive for real-time use. Critically, all other SOTA methods lack explicit tether management, resulting in an unacceptably high and unquantified risk of mission-failure due to entanglement. Our framework uniquely provides the optimal balance of safety, efficiency, and real-time feasibility for tethered robots.

Statistical Validation: The performance improvements of the proposed framework are statistically significant (ANOVA, $p < 0.001$) across 100+ trials. The 95% confidence interval for Path Length Ratio (PLR) in the Cluttered Arena is $115\% \pm 3.2\%$.

B.3 Sensitivity Analysis of Core Algorithmic Parameters

B.3.1 Impact of DRL Reward Function Weights

The balance between objectives in the DRL reward function is crucial. We analyzed the impact of different weight configurations (α, β, γ) on system performance.

Table 13: Sensitivity of DRL Performance to Reward Weights

Weight Configuration (α, β, γ)	Success Rate	Entanglement Risk (/hr)	Primary Behavior
(0.7, 0.2, 0.1)	82%	0.12	Path-Greedy: Prioritizes shortest path, higher entanglement risk.
(0.5, 0.3, 0.2)	89%	0.07	Balanced: Optimal trade-off between all objectives.
(0.3, 0.5, 0.2)	76%	0.03	Safety-First: Overly cautious, leading to long detours and lower success.

The configuration (0.5,0.3,0.2) was selected for all final experiments as it achieved the highest mission success rate with a sustainably low entanglement risk.

B.3.2 Genetic Algorithm: Mutation Rate vs. Convergence

The mutation rate in the GA is a key hyperparameter that balances exploration and exploitation.

Table 14: Effect of GA Mutation Rate on Optimization Performance

Mutation Rate	Generations to Converge	Final Fitness Value	Optimization Characteristic
1%	75	0.82	Slow, Incomplete Convergence: Lacks exploration, often settles for local optima.
5%	50	0.88	Optimal Balance: Efficient convergence to high-quality, robust solutions.

Mutation Rate	Generations to Converge	Final Fitness Value	Optimization Characteristic
10%	35	0.78	Fast, Erratic Convergence: Excessive exploration disrupts good solutions.

A mutation rate of 5% provided the best compromise, converging to a superior solution in a feasible number of generations for real-time tuning.

B.4 Hardware Implementation and Schematics

The practical deployment of the framework was realized on a custom-built tethered robotic platform. The hardware architecture was designed for computational power, sensor fidelity, and precise actuation.

Key Hardware Components:

- a) Central Compute: NVIDIA Jetson AGX Xavier (32 TOPS) for all real-time processing.
- b) Perception Suite: Front-facing 360° LiDAR and a 3-axis IMU, calibrated for precise sensor fusion.
- c) Actuation System: Dynamixel XM540 servos providing high-torque, reliable differential drive.
- d) Tether Management System: A motorized spool with integrated Hall-effect tension sensors for closed-loop impedance control.



Figure 22: Tethered Robot Hardware Schematic⁴⁵.

A detailed schematic of the tethered robot's hardware components and their interconnections is shown in Figure B.1, illustrating the integration of sensing, computation, and actuation modules.

Appendix C: Mathematical Foundations, Error Analysis, and Extended Comparative Evaluation

This appendix provides the mathematical underpinnings of the proposed framework's stability, a detailed analysis of error sources and failure modes, and an extended comparison with state-of-the-art navigation methods.

C.1 Mathematical Proofs for Stability and Convergence

The robustness of the proposed framework is grounded in formally guaranteed stability properties for its core filtering and optimization components.

C.1.1 Stability of the Stochastic Hybrid Kalman-SMC Filter

The integrated sensor fusion framework, which combines an Extended Kalman Filter (EKF) with Sliding Mode Control (SMC) corrections, ensures exponential mean-square stability even under probabilistic data packet losses, a common issue in tethered systems.

Proof:

Let the estimation error be defined as $e_k = x_k - \hat{x}_k$, where x_k is the true state and \hat{x}_k is the estimated state.

We choose a Lyapunov function candidate:

$$V_k = e_k^T P_{k-1} e_k \quad (28)$$

where P_k is the error covariance matrix.

The expected value of the Lyapunov function's difference satisfies:

$$\mathbb{E}[\Delta V_k] \leq -\alpha V_k + \beta \|w_k\|^2 \quad (29)$$

where w_k represents bounded disturbances, and $\alpha, \beta > 0$.

Solving the derived Linear Matrix Inequality (LMI):

$$\begin{bmatrix} -P_k + \alpha I & F_k^T P_k \\ P_k F_k & -P_k \end{bmatrix} < 0 \quad (30)$$

guarantees $\mathbb{E}[V_k] \rightarrow 0$ exponentially, ensuring the filter remains stable under bounded disturbances and data losses. This provides a formal guarantee for the reliability of our sensor fusion approach in real-world conditions.

C.1.2 Convergence of the Genetic Algorithm Optimization

The Genetic Algorithm (GA) component is proven to converge to Pareto-optimal solutions under tournament selection with a mutation rate of $p_m = 5\%$.

Proof:

Let f_{avg}^t denote the average fitness at generation t . For an elitist selection strategy with bounded mutation:

$$\lim_{t \rightarrow \infty} P(f_{avg}^{t+1} \geq f_{avg}^t) = 1 \quad (31)$$

This inequality demonstrates that the expected fitness is non-decreasing across generations.

Monte Carlo simulations conducted over 50 independent runs with 50 generations each confirm that the probability of fitness improvement exceeds 99%, validating the GA's reliable convergence to high-quality solutions for tether parameter optimization.

C.2 Comprehensive Error Analysis and Failure Mode Characterization

A critical component of robustness is understanding and mitigating potential failure modes. The following table summarizes the primary error sources encountered in dynamic tethered operations and the corresponding mitigation strategies engineered into our framework.

Table 15: Primary Error Sources and Mitigation Strategies in Dynamic Environments

Error Source	Magnitude	Impact	Mitigation Strategy	Effectiveness
LiDAR Noise (σ)	$\pm 2 \text{ cm}$	Position uncertainty, mapping artifacts	Kalman-Fuzzy hybrid fusion with dynamic covariance weighting	40% RMSE reduction
IMU Drift (per hour)	0.5°	Cumulative orientation error, path deviation	EKF with Mahalanobis outlier rejection & anchor-point reset	27% error reduction
Tether Slack Estimation	$\pm 1.5 \text{ cm}$	Entanglement risk, inaccurate state estimation	GA-optimized dynamic thresholds + impedance control	45% fewer entanglements
Dynamic Obstacle Prediction Delay	0.3 s	Late reactive maneuvers, collisions	LSTM-based trajectory forecasting in NN-Planner	38% faster avoidance

Failure Mode Analysis and Contingency Protocols:

High Obstacle Density ($>2.0/m^2$): In ultra-dense environments, entanglement risk increases by approximately 25% due to geometrically limited tether slack options. The contingency protocol progressively increases the weight of the *Entanglement Risk* term in the GA fitness function, forcing more conservative navigation.

Sensor Dropout ($>50\%$ packet loss): In events of significant sensor failure, the system triggers a graceful degradation mode, falling back to fuzzy heuristics and contact-based Bug algorithms, maintaining a 65% mission success rate.

Tether Snags (Sudden tension spike): The impedance controller $F_{ref} = K_p \cdot \Delta x + K_d \cdot \Delta \dot{x}$ is instantaneously activated, reducing peak tension by 40% and preventing tether damage or robot immobilization.

C.3 Extended Comparative Evaluation with State-of-the-Art Methods

To position our work within the broader research landscape, we provide an extended comparison against a wider array of state-of-the-art navigation paradigms. This analysis highlights that while many methods excel in specific metrics, our framework's principal contribution is its holistic performance and explicit tether-awareness.

Table 16: Extended Comparative Analysis of Navigation Frameworks

Method	Collision Rate (/m) ↓	Path Efficiency (%) ↑	Tether Awareness	Computational Demand (ms/step) ↓	Key Limitation for Tethered Robots
Proposed					
Hybrid Framework	0.25	92%	Yes (Explicit)	18	None
DRL + SLAM ⁴⁶	0.48	78%	No	42	High memory overhead; no tether model
Neuro-Fuzzy ⁴⁷	0.35	85%	Partial	25	Limited predictive capability for

Method	Collision Rate (/m) ↓	Path Efficiency (%) ↑	Tether Awareness s	Computational Demand (ms/step) ↓	Key Limitation for Tethered Robots
Potential Fields ⁴⁷	0.62	68%	No	12	dynamic obstacles
RRT* ⁴⁸	0.15	95%	No	85	Computationally prohibitive for real-time use
FIMOPPSO ⁴⁹	0.41	88%	No	55	High variance in path quality; slow convergence
I-Planner ⁴⁸	0.28	90%	No	38	Requires precise human intent modeling

Key Insights from Extended Comparison:

The Tether-Awareness Gap: The most significant differentiator is tether awareness. All other methods either completely ignore the tether or provide only partial consideration, leading to an unacceptably high and unquantified risk of entanglement in real-world deployments.

The Efficiency-Robustness Trade-off: Methods like RRT* and I-Planner can achieve high path efficiency but sacrifice either computational feasibility (RRT*) or require specific environmental assumptions (I-Planner). Our framework successfully navigates this trade-off.

Superior Operational Safety: With a collision rate of 0.25/m, our framework significantly outperforms other learning-based (DRL+SLAM) and bio-inspired (FIMOPPSO) methods, demonstrating that the hybrid approach yields safer navigation policies.

C.4 Fuzzy Logic Controller (FLC) Rule Base Specification

The decision-making core of the reactive navigation layer is a meticulously designed Fuzzy Logic Controller. The following table details a subset of the heuristic rules that translate noisy sensor inputs into smooth, adaptive navigation commands.

Table 17: Fuzzy Logic Controller Rule Base (Representative Subset)

Obstacle Proximity	Tether Tension	Goal Alignment	Action	Certainty
Near	High	Low	Steer left (30°) & reduce velocity by 40%	70%
Near	Moderate	High	Steer right (20°) & reduce velocity by 20%	80%
Medium	Low	High	Maintain course & velocity	90%
Far	Moderate	Medium	Accelerate by 15% & minimize slack	85%
Far	High	Low	Reduce velocity by 10% & increase slack	75%

This rule base, comprising 49 such rules, allows the system to perform nuanced, context-aware maneuvers that balance the competing objectives of goal pursuit, obstacle avoidance, and tether safety.

Appendix D: Deployment Protocols, Calibration Guidelines, and Field-Testing Insights

This appendix provides a complete operational guide for deploying the hybrid navigation framework, detailing standardized protocols, calibration procedures, lessons from field testing,

and scalability analysis. This information is critical for translating the research into robust, real-world applications.

D.1 Standardized Real-World Deployment Protocol

A systematic deployment protocol is essential for ensuring safe and efficient operation in dynamic environments. The following phased approach is recommended:

Phase 1: Pre-Deployment Checks

Tether Integrity Verification:

Confirm mechanical integrity and check for wear.

Verify tension sensor calibration: operational range of 5–50 N.

Validate slack resolution of 1 mm via the tether encoder.

Sensor Calibration: Execute full sensor calibration (see Section D.2) for:

LiDAR: Confirm ± 2 cm accuracy and 360° field of view.

IMU: Ensure gyroscope bias is below 0.1°/s.

Tether Encoder: Verify linear mapping of spool rotation to length.

Software Initialization:

Load the pre-trained DRL policy and GA-optimized parameters.

Select the environment-specific configuration profile (e.g., “industrial,” “disaster,” “subsea”).

Phase 2: Anchor Point Setup and Workspace Definition

Securely fasten the tether spool to a fixed, immovable anchor point.

Define a safety radius of 3x the total tether length to create a known operational workspace and prevent catastrophic entanglement during exploration.

Phase 3: Mission Execution

Phase 3a (Exploration & Mapping): The robot autonomously maps the local environment using LiDAR/IMU fusion, building an initial costmap.

Phase 3b (Online Optimization): The Genetic Algorithm initiates, refining tether slack and tension thresholds in real-time based on the encountered environment.

Phase 3c (Navigation): The Hybrid A*-Bug planner executes the mission, dynamically switching between global planning and reactive obstacle avoidance.

Emergency Protocols:

Tether Snag Detection: If tension exceeds $T_{\max} = 50$ N, the impedance controller ($F_{\text{ref}} = K_p \cdot \Delta x + K_d \cdot \Delta \dot{x}$) is immediately activated to reduce strain.

Sensor Failure: If LiDAR/IMU noise exceeds a 40% threshold, the system gracefully degrades to a purely fuzzy heuristic mode, maintaining basic operational capability.

D.2 Comprehensive Hardware Calibration Procedures

D.2.1 LiDAR-IMU Extrinsic Calibration

Accurate sensor fusion requires precise knowledge of the spatial relationship between the LiDAR and IMU.

Setup: Place the robot in a static environment with known fiducial markers at multiple locations.

Data Collection: Collect synchronized LiDAR point clouds and IMU odometry data for at least 60 seconds while the robot remains stationary.

Optimization: Solve the following optimization problem to find the rotation R and translation t :

$$\min_{R,t} \sum_{i=1}^N \| p_i^{\text{LiDAR}} - (R \cdot p_i^{\text{IMU}} + t) \|^2 \quad (32)$$

This aligns the LiDAR and IMU coordinate frames, typically achieving a residual error of <2 cm.

D.2.2 Tether Encoder Calibration

Zero Reference: Fully retract the tether and set the encoder count to $L = 0$.

Data Acquisition: Unspool the tether in precise 1-meter increments, recording the encoder counts at each step.

Linear Regression: Fit a linear model $L = k \cdot \text{counts} + b$ to the data. This calibration achieves a coefficient of determination $R^2 > 0.99$, ensuring highly accurate length estimation.

D.3 Field-Testing Challenges, Mitigations, and Lessons Learned

Extensive field testing in industrial and simulated disaster environments revealed several common challenges. The following table documents these issues, their root causes, and the effective mitigations that were developed and integrated into the framework.

Table 18: Common Field Deployment Challenges and Engineered Solutions

Challenge	Root Cause	Observed Impact	Implemented Mitigation	Result
Oscillatory Paths	Overly aggressive DRL rewards for direct goal heading.	Increased wear, higher energy consumption, unstable video footage.	Tuned reward weights (α, β, γ) to prioritize smooth steering and penalize erratic heading changes.	45% reduction in path oscillations.

Challenge	Root Cause	Observed Impact	Implemented Mitigation	Result
Localization Drift in GPS-Denied Zones	Accumulation of IMU bias over time.	Positional errors exceeding 1.5m after 10 minutes, leading to mission failure.	Implemented an EKF reset protocol using the known anchor point position every 10 minutes.	Localization error bounded below 0.5m for indefinite operation.
Delayed Obstacle Avoidance	LSTM trajectory prediction latency (0.3 s).	Late reactive maneuvers, resulting in near-miss incidents.	Optimized neural network inference via TensorRT, reducing prediction latency to 0.1 s.	38% improvement in dynamic obstacle avoidance.
Tether Entanglement in Dense Clutter	GA generations to find a safe path in complex webs.	Insufficient GA population size to immobilize the robot, requiring human intervention.	Increased GA population size to 150 and extended runtime to 60 generations for complex scenarios.	60% reduction in immobilization events in clutter.

Key Lessons from Industrial Trials:

Human-Robot Interaction: Dynamic obstacle density increased by 25% during peak operational hours. This was successfully handled by the DRL agent's predictive planning, but necessitated further model quantization to maintain the sub-20ms decision latency.

Variable Environmental Conditions: LiDAR performance remained robust under varying lighting conditions, but supplementary stereo vision sensors required frequent recalibration in low-light environments, leading to their removal from the core sensor suite for simplicity.

D.4 Energy Efficiency and Thermal Management Analysis

Power consumption and thermal management are critical for prolonged mission duration. The following breakdown was measured during typical navigation tasks.

Table 19: Power Consumption Breakdown by Subsystem

Component	Average Power (W)	Peak Power (W)	Duty Cycle
NVIDIA Jetson AGX Xavier	15	30	100%
360° LiDAR Sensor	8	12	100%
Tether Spool Motor	20	45	30%
Dynamixel Servos (x2)	12	25	70%
Total Average Consumption	55 W	112 W	

Thermal Management: The Jetson AGX Xavier module will throttle performance at 85°C. An active cooling system was implemented, successfully maintaining core temperatures below 75°C even in ambient conditions of 40°C, ensuring consistent computational performance.

D.5 Scalability and Multi-Robot Coordination

To evaluate the framework's scalability, it was tested in a simulated warehouse scenario with multiple tethered robots.

Setup: 3 tethered robots operating concurrently with shared anchor points.

Coordination Strategy: A hybrid centralized-decentralized architecture was employed:

Centralized High-Level Planner: A Conflict-Based Search (CBS) algorithm assigned priority and conflict-free paths.

Decentralized Low-Level Control: Each robot ran an independent instance of the hybrid framework (GA, DRL, FLC) for local adaptation.

Results:

Collision Rate: 0.31/m (vs. 0.25/m for a single robot).

Entanglement Risk: 0.15/hr (vs. 0.05/hr for a single robot).

Insight: The moderate increase in collision and entanglement rates is attributed to the added complexity of inter-robot tether management. The hybrid coordination strategy effectively balances system-level efficiency with individual robot safety, confirming the framework's potential for collaborative tasks.

D.6 Extended Validation Across Diverse Application Environments

The framework's generality was validated through high-fidelity simulations of four distinct, high-stakes application domains. The results demonstrate consistent and robust performance, adapting to the unique challenges of each environment.

Table 20: Performance Validation Across Diverse Application Environments

Environment	Path Efficiency (PLR)	Collision Rate (#/m)	Entanglement Risk (#/hr)	Key Environmental Challenge
Nuclear Facility	88%	0.20	0.03	Narrow, cluttered corridors; requirement for extreme precision.
Subsea Pipeline	85%	0.28	0.08	Dynamic currents (0.5 m/s); floating debris; limited visibility.
Urban Disaster Zone	78%	0.35	0.12	Highly unstructured rubble; dense, unpredictable obstacles.
Indoor Farm	94%	0.10	0.01	Sparse, regular obstacles; requirement for minimal disturbance.

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Competing interest's statement

The authors declare no competing interests.

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