LENS: Learning to Navigate with Active Search for Partially Observable MAPF in Unknown Environments

Anonymous authors
Paper under double-blind review

Abstract

Multi-Agent Path Finding (MAPF) is a fundamental challenge in autonomous robotics. While classical solvers guarantee collision-free coordination, their reliance on perfect global knowledge limits their applicability in strictly unknown environments. In response, modern learning-based approaches have diverged into a severe dichotomy. Decentralized reactive heuristics scale efficiently under partial observability but systematically fail at structured deadlocks due to myopic reasoning. Conversely, large-scale neural foundation models (e.g., MAPF-GPT) offer topological awareness but require pre-computed global heuristics, prohibitive training data, and operate as black boxes.

In this work, we bridge this dichotomy by introducing LENS (LEarning to Navigate with active Search), a hybrid architecture that explicitly decouples long-horizon topological guidance from rigorous local collision avoidance. To enable efficient navigation without myopic behavior, LENS employs a lightweight neural network that takes each agent's field of view (FOV) and goal direction vector as input to predict a dense local potential field, from which a multi-step local subpath is generated. When collisions are detected, agents aggregate their limited local observations into a consistent shared belief and project the endpoints of the neural proposals as local waypoints, then invoke a localized Conflict-Based Search (L-CBS) over bounded spatio-temporal windows to compute safe, collision-free refinements and dispatches them back to the agents. By partitioning anticipated collisions into disjoint conflict graphs, this integration resolves structural deadlocks through independent L-CBS instances. This ensures strict collision-free execution within a receding horizon window, avoiding the exponential overhead of global replanning and overcoming the myopia of purely reactive planners.

We evaluate our approach using a two-stage protocol. Assuming full global knowledge, LENS matches the solution quality of centralized algorithmic oracles, validating the efficiency of our hybrid search integration. Under this setting, it achieves competitive out-of-distribution generalization capabilities comparable to foundation models with up to 85M parameters (MAPF-GPT), while requiring less than 0.2% of their training trajectory data. In strictly unknown environments with online collaborative mapping, LENS leverages its collaborative inference to significantly outperform reactive baselines, improving the success rate by 41.5% in high-density maze configurations. Our results demonstrate that decoupling topological inference from local collision resolution provides a scalable, data-efficient, and collision-aware solution (locally collision-free within bounded windows) for complex autonomous navigation.

1 Introduction

Multi-Agent Path Finding (MAPF) serves as the algorithmic backbone for numerous large-scale robotic applications, ranging from automated warehousing (Li et al., 2021) to urban traffic management (Chen et al., 2024). While classical centralized algorithms, such as Conflict-Based Search (CBS) (Sharon et al., 2015; Boyarski et al., 2015) and LaCAM (Okumura, 2023), guarantee optimality or completeness(Surynek, 2010), they rely heavily on two assumptions: full observability of the environment and the availability of a

perfect global heuristic(Ma et al., 2021; Mac et al., 2016; Ferguson et al., 2005; Varambally et al., 2022) (e.g., pre-computed BFS). In realistic deployment scenarios like search-and-rescue, these assumptions collapse, defining the rigorous setting of navigation in strictly unknown environments under Partial Observability (POMAPF), where agents lack both a prior map and a global view of dynamic peers(Liu et al., 2020b; Wang et al., 2020; Skrynnik et al., 2024; Li et al., 2022b).

Recent MAPF scaling efforts present a severe dichotomy. *Decentralized reactive heuristics* (e.g., CS-PIBT (Veerapaneni et al., 2025; Okumura et al., 2022), LNS2-RL (Wang et al., 2025)) adapt well to partial observability but suffer from myopia, making them highly susceptible to *structured deadlocks* (e.g., U-shaped traps). Conversely, *neural foundation models* (e.g., MAPF-GPT (Andreychuk et al., 2025b)) provide topological foresight but rely on pre-computed global heuristics, which renders them inapplicable in unknown environments and demand prohibitive training data.

In this paper, we bridge the gap between myopic, efficient heuristics and data-hungry, global learners by proposing **LENS** (*LEarning to Navigate with Active Search*). We argue that learning and search should play complementary, rather than competitive roles(Veerapaneni et al., 2025). LENS treats learning as a mechanism for Heuristic Approximation(Pohl, 1970; Bander & White, 2002), which infers dense local potential fields conditioned on global intent from partial observations(Hwang et al., 1992; Aggarwal & Kumar, 2020), while delegating the rigorous logic of collision avoidance to a specialized search routine. By inverting the standard paradigm, we utilize learning for global guidance and search for local resolution. As a result, LENS achieves topology-aware coordination under partial observability while maintaining local collision-free within bounded spatio-temporal windows, without requiring large-scale end-to-end policy learning.

Our main contributions are summarized as follows:

Hierarchical Topo-metric Inference. We propose a guidance-conditioned Neural Proposer driven by an adaptive mechanism. Depending on the environmental scale, it dynamically generates directional condition vectors(either direct global goals or subgoals from a collaboratively updated Adaptive Region Graph (ARG)(Bai et al., 2020; Ardizzoni et al., 2023)) and injects them into a localized U-Net via Feature-wise Linear Modulation (FiLM). By regressing a dense cost-to-go potential field, agents extract multi-hop paths via greedy energy minimization in a single forward pass, mitigating reactive myopia.

Active Search Injection via Cascade. Second, we challenge the standard passive shielding paradigm by seamlessly coupling continuous neural heuristics with discrete combinatorial search. LENS incorporates a dynamic Cascade where the inferred potential field is utilized to project topology-aware local waypoints. This allows us to bound a L-CBS to strictly route agents toward these dynamic subgoals, efficiently resolving structured deadlocks. This architectural inversion guarantees the optimal resolution of structured deadlocks within localized spatio-temporal windows while strictly maintaining real-time execution frequencies.

Data-Efficient Generalization and Online Robustness. Finally, with a decoupled evaluation protocol, we demonstrate that LENS systematically resolves the aforementioned dichotomy. In unknown environments requiring online collaborative mapping, it improves the success rate over reactive baselines by 41.5% in high-density topologies. Furthermore, under global knowledge settings, it achieves competitive out-of-distribution robustness comparable to foundation models with up to 85M parameters (e.g., MAPF-GPT), while utilizing less than 0.2% of their training data, establishing a highly resource-efficient paradigm for swarm navigation.

2 Related Work

2.1 Decentralized Heuristics and Reactive Policies

Learning-based extensions like CS-PIBT (Veerapaneni et al., 2025) combine a lightweight policy with a collision shield (PIBT)(Okumura et al., 2022), while SCRIMP (Wang et al., 2023) uses Transformer-based communication for local tie-breaking. However, these reactive methods focus strictly on immediate 1-step collisions. Lacking global topological awareness, they often succumb to oscillatory failures in deep local minima (e.g., U-shaped traps or long corridor).

2.2 Learning-based Foundation Models

The success of large language models has inspired the development of "foundation models" for MAPF. MAPF-GPT (Andreychuk et al., 2025b) and its fine-tuned variant MAPF-GPT-DDG(Andreychuk et al., 2025a) demonstrate that scaling decision transformers on massive datasets (over 1 billion expert trajectories) can yield expert-level performance with zero-shot generalization capabilities. These models effectively learn to imitate the internal logic of centralized solvers like LaCAM entirely end-to-end.

However, these architectures inherently assume access to the full environment to compute global heuristics, rendering them unsuitable for navigation in unknown sectors. Furthermore, this paradigm faces a "scaling trap": implicitly learning the combinatorial logic of collision avoidance requires prohibitive amounts of data and compute. In contrast, LENS explicitly decouples the problem: we learn the *gradient* (via U-Net potential fields) but delegate the *validity* (collision avoidance) to a dedicated search kernel. This allows LENS to achieve comparable performance with less than 0.2% of the training data required by MAPF-GPT(1.3 million vs. >1 billion samples).

2.3 Potential-Field Learning for Navigation

Traditional artificial potential fields(Kim & Khosla, 1992; Daily & Bevly, 2008) guide agents via superimposed attractive and repulsive gradients, but are prone to local minima and offer no collision-free guarantees. Recent work embeds potential field optimization into neural architectures to address this(Rasekhipour et al., 2016; Lee & Chung, 2024). Notably, GPFNN (Lyu et al., 2025) unfolds potential field iterations as a deep feedforward network, guaranteeing monotonic potential flows over a fully known global graph with predefined boundary conditions. LENS takes a fundamentally different approach: rather than solving global Laplacian operators over a known topology, the Neural Proposer infers potential field gradients directly from partial ego-centric observations, enabling real-time guidance in strictly unknown environments.

2.4 Hybrid Search-Learning Frameworks

Hybrid approaches seek to combine the completeness of classical search algorithms with the computational speed of learning models(Veerapaneni et al., 2024; Liu et al., 2020a; Yan & Wu, 2024). For instance, LNS2+RL (Wang et al., 2025) integrates Multi-Agent Reinforcement Learning (MARL) into the Large Neighborhood Search (LNS) framework. In this paradigm, the global navigation framework remains search-based, while learning is utilized strictly as a local repair operator to resolve complex neighborhood conflicts. Similarly, Real-Time LaCAM (Liang et al., 2025) adapts centralized search for real-time execution but inherently relies on maintaining a global search tree to ensure completeness. LENS systematically inverts this conventional relationship: rather than searching globally and learning locally, it uses learning for global topological guidance and restricts search exclusively to local conflict resolution. This inversion yields two concrete advantages. First, classical global search requires perfect, pre-computed heuristics over a fully known graph, whereas neural networks robustly infer navigable gradients from partial observations. Second, while neural models generalize well over continuous navigation flows, they struggle with the discrete combinatorial logic required for collision avoidance in congested scenarios. By confining rigorous search (L-CBS (Sharon et al., 2015)) to small spatio-temporal windows, LENS enforces strict collision-free guarantees within these bounded scopes without incurring the overhead of global replanning.

2.5 Coordination in Unknown Environments versus Active Exploration

Our setting focuses on goal-directed navigation under partial observability, distinct from Multi-Robot Exploration (MRE) where maximizing map coverage is the primary objective(Tan et al., 2024; Bramblett et al., 2022; Chen et al., 2019). In LENS, map discovery is a passive byproduct of navigation. To isolate the fundamental challenge of structured deadlock resolution from the orthogonal complexities of SLAM and asynchronous map merging(Bailey et al., 2006; Burgard et al., 2000), we assume a synchronized, shared map ($\mathcal{M}_{shared}$). This abstraction, common in collaborative robotic deployments, ensures that evaluated performance disparities stem directly from topological reasoning and conflict resolution rather than map synchronization logic.

3 Problem Formulation

We consider Multi-Agent Path Finding in unknown environments under partial observability, structured around an online centralized collaborative paradigm. The system consists of N agents $\mathcal{A} = \{a_1, \ldots, a_N\}$ navigating on an initially hidden grid graph. Rather than operating strictly distributedly, agents maintain a reliable connection to a central edge server. At each time step t, agents report their local observations O_t^i to incrementally update a shared map $\mathcal{M}_{shared}$. Action selection $u_t^i \in \mathcal{U}$ is jointly determined by local neural inference and server-side conflict resolution.

Dual Uncertainty (Map and Agents): Unlike classical MAPF where the static environment is pre-given, the global map M is initially completely unknown. Agent a_i relies strictly on a limited local field-of-view (FOV) of size $L \times L$ (11×11 in our experiments) to discover both static obstacles and dynamic peers online.

The Navigation Decomposition: The navigation framework π is a hierarchical decomposition of three sub-functions, designed to bridge local perception and centralized server-side coordination: **1. Global Guidance (f_{guide}):** Since local views lack topological context (e.g., U-shaped traps), a high-level function is needed to estimate the global gradient: $\mathbf{v}_{guide} = f_{guide}(\hat{M}_t^i, g^i)$. **2. Local Proposal ($f_{prop}$):** Agents must react to immediate dynamic obstacles. A reactive policy generates a motion intent: $\tilde{u}_t^i = f_{prop}(O_t^i, \mathbf{v}_{guide})$. **3. Conflict Resolution ($f_{defense}$):** Since myopic neural proposals are prone to deadlocks, the central server monitors proposed trajectories for anticipated conflicts. If structural deadlocks or collisions $\mathcal{S}_{dead}$ are detected, the server overrides local proposals with a coordinated centralized search: $\mathbf{u}_t = f_{defense}(\mathcal{M}_{shared}, \tilde{\mathbf{u}}_t)$, where $\tilde{\mathbf{u}}_t$ represents the joint neural proposals.

Our objective is to learn and engineer these three components to minimize the makespan enforcing local collision avoidance within the Defense Cascade's resolution scope, without access to a pre-computed global oracle. Note that LENS targets goal-directed navigation, not map exploration. Map discovery is a passive byproduct, not an objective. We abstract away SLAM and decentralized map merging via a synchronized shared map ($\mathcal{M}_{shared}$), isolating topology-aware conflict resolution as the core challenge.

4 Method: The LENS Framework

As illustrated in Figure 1, LENS implements a hierarchical decomposition of the navigation under dual uncertainty. The framework operates as a closed-loop control system: an *Adaptive Guidance Mechanism* provides high-level topological intuition, a *Neural Proposer* generates dense local motion gradients via heuristic approximation, and a *Defense Cascade* actively enforces coordination logic when reactive gradients fail.

4.1 The Neural Proposer: Heuristic Approximation via U-Net

The core decision-making module is the *Neural Proposer*. Unlike standard policies that classify discrete actions directly, which often discards spatial relativity, we formulate the learning task as **Heuristic Approximation**. The network learns to approximate the local crop of the ground-truth global potential field Φ^* within the agent's field-of-view.

We employ a U-Net architecture for three geometrically-motivated reasons: **1. Preservation of Spatial Topology:** Navigation is an inherently geometric problem. U-Net's skip connections preserve high-frequency spatial details (e.g., obstacle boundaries) that are essential for collision avoidance but often lost in the bottleneck layers of standard CNNs. **2. Dense Field Prediction:** The output is a *Cost-to-Go Potential Field* $\Phi \in \mathbb{R}^{L \times L}$. This scalar field provides a smooth gradient of descent, allowing agents to flow around obstacles by following the path of least resistance. **3. Context Fusion via Attention:** To effectively integrate heterogeneous inputs (static walls vs. dynamic agents), we enhance the U-Net encoder with **Squeeze-and-Excitation (SE) Blocks** (Hu et al., 2018), enabling adaptive channel-wise feature recalibration.

Goal Conditioning: The network input X comprises a 4-channel local spatial tensor (Obstacles, Dynamic Agents, Self-Position, Projected Local Target) and a non-spatial global guidance vector $\mathbf{v}_{guide}$. To effectively integrate the micro-scale spatial perception with the macro-scale topological intent, we utilize **Feature-wise Linear Modulation (FiLM)** (Brockschmidt, 2020) at the bottleneck. The non-spatial vector modulates

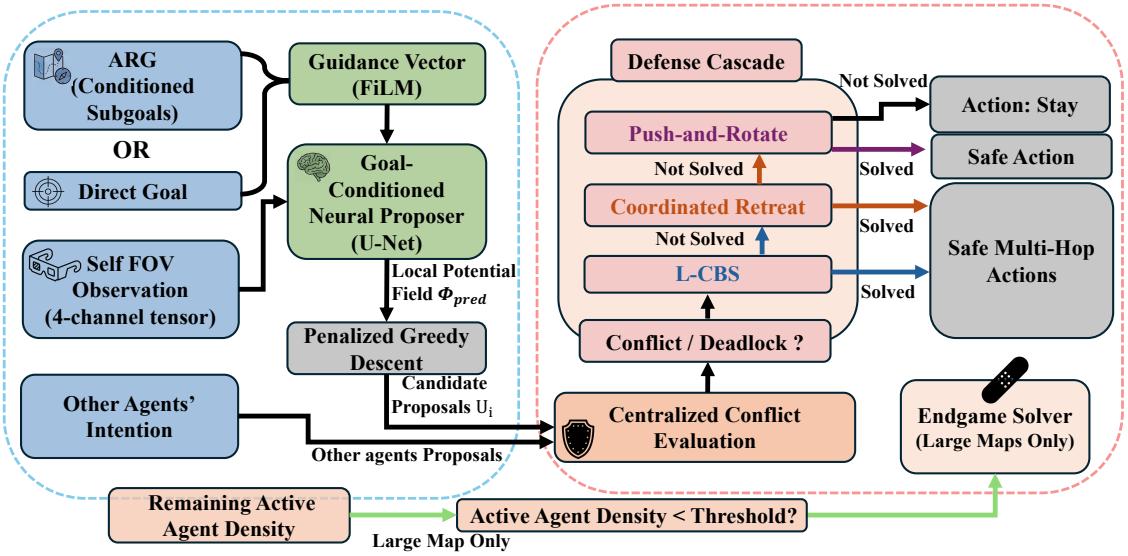

Figure 1: **The LENS Execution Flowchart.** The *Adaptive Guidance Mechanism* dynamically generates a directional condition vector (a direct goal or an ARG-based subgoal) based on the environmental scale. The *Neural Proposer* (U-Net) fuses this vector with local observations via FiLM to regress a dense potential field, from which a multi-hop neural proposal is extracted. These joint proposals are evaluated centrally; if collisions or structural deadlocks are anticipated, the system triggers the *Defense Cascade*, executing L-CBS on disjoint conflict groups or heuristic escapes to guarantee collision-free execution.

the feature maps via affine transformations, effectively conditioning the predicted potential field on the global navigation intent. The detailed architecture is provided in Appendix D.2.

Action Extraction: Discrete Potential Descent

Given the predicted local potential field Φ, the agent performs a masked greedy descent to identify a short-term waypoint (local subgoal) within the prediction horizon. Geometric obstacles act as hard constraints. For any valid transition $p' \in \mathcal{N}(s_t^i) \setminus \mathcal{O}_{local}$, the agent minimizes the adjusted potential $J(p')$: $J(p') = \Phi(p') + \psi(p', H_{local}) \quad \text{s.t.} \quad p' \notin \mathcal{O}_{local}$ where $\mathcal{O}_{local}$ represents the set of occupied cells in the current local field-of-view. The history-dependent term ψ acts as an anti-patterning regularizer to suppress oscillatory behavior:

$$\psi(p') = \begin{cases} \lambda_{visit} & \text{if } p' \in H_{local} \text{ (recently visited)} \\ \lambda_{stay} & \text{if } p' = s_t^i \text{ and } s_t^i \neq g^i \\ -\lambda_{mom} & \text{if } (p' - s_t^i) = v_{t-1}^i \text{ (momentum)} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Weights tuned via grid search on a hold-out validation set ($\lambda_{visit} = 0.5, \lambda_{stay} = 0.6, \lambda_{mom} = 0.2$) ensure smooth trajectories while discouraging local livelocks.

4.1.1 Data Generation and Training Strategy

We train the U-Net in a supervised manner, treating the problem as heuristic reconstruction: learning to predict the "ideal" navigation potential from local views, rather than cloning discrete actions from an expert policy. Training hyperparameters are comprehensively detailed in Appendix E).

Step 1. **Trajectory Simulation and Targeted Sampling:** We simulate MAPF episodes using **LaCAM** (Okumura, 2023) solely as a generative engine to produce diverse, valid agent configurations repre-

sentative of different scenarios, not as a policy to imitate. We apply event-based filtering to focus on two critical navigation phases: *initialization* (starting configuration) and *terminal approach* (within 5 steps of the goal), where the underlying topology is most distinct.

Step 2. **Ground Truth Potential Field Computation:** For each sampled state, we compute a global ground truth potential field via backward BFS from the agent's goal g_i on the fully known map. Each cell value encodes the true shortest distance to the goal, serving as the target geometric gradient.

Step 3. **Training Sample Assembly:** The input X is the agent's local FOV (obstacles, other agents, self-position) paired with a normalized goal vector injected into U-Net features via a **FiLM** layer. The target label Y is the corresponding FOV-sized patch of the global BFS potential field.

Composite Loss Function. To ensure the predicted potential field $\hat{P}$ captures both accurate distance values and the correct local gradient shape (which determines motion direction), we train the model using a composite loss function $\mathcal{L}_{total}$:

$$\mathcal{L}_{total} = \mathcal{L}_{MSE} + \lambda_{grad}\mathcal{L}_{grad} \tag{2}$$

The primary loss, $\mathcal{L}_{MSE}$, measures the pixel-wise Mean Squared Error between the prediction $\hat{P}$ and the target P_{target} (Hodson, 2022). The auxiliary gradient loss, $\mathcal{L}_{grad}$, penalizes discrepancies in spatial gradients (approximated via Sobel filters):

$$\mathcal{L}_{grad} = \|\nabla_x \hat{P} - \nabla_x P_{target}\|_1 + \|\nabla_y \hat{P} - \nabla_y P_{target}\|_1 \tag{3}$$

This gradient-aware objective (Chen et al., 2018) encourages the model to preserve the steepness and directionality of the potential field, which is critical for the subsequent greedy path extraction.

4.2 The Defense Cascade

While the Neural Proposer handles most steps efficiently, unguided local intent inevitably leads to multi-agent conflicts. LENS operates on a receding horizon control (RHC) scheme: proposing paths for k steps (e.g., $k = \min(d_{\text{subgoal}}, 10)$) but executing only the first n steps (e.g., $n = 3$ or $n = 6$). Before execution, the server constructs a Spatio-Temporal Conflict Graph from the joint proposals and extracts disjoint connected components. We introduce the **Defense Cascade**, applied independently to each disjoint conflict group. This isolation strictly prevents interference between overlapping resolution windows..

Deadlock Entry Zone Detector (DEZD): The DEZD module continuously monitors the agent's short-term positional history queue $H^i_{t-k:t}$ of length k. Rather than computing computationally expensive spatial bounding boxes or sequence overlaps, we employ a strict and lightweight entropy-based heuristic: a deadlock is flagged if the number of unique spatial coordinates visited within the history window falls below a critical threshold τ_{unique}. Mathematically, the intervention is triggered when $|\text{Set}(H^i_{t-k:t})| \leq \tau_{unique}$, effectively capturing both extreme positional stagnation and tight cyclic oscillations (e.g., $k = 10, \tau_{unique} = 3$).

The Hierarchy of Resolution: The cascade consists of strategies ordered by computational cost and "aggressiveness" (see Figure 1). Implementation details for each level are provided in Appendix F.

1. **L-CBS:** The foundational defense layer. It executes Conflict-Based Search strictly bounded by the k-step planning horizon and a predefined iteration timeout (refer to Appendix G for exact k/n horizons and timeout thresholds).Running concurrently on disjoint conflict groups, it mathematically guarantees collision-free execution for the n-step window.

2. **Coordinated Retreat via Distance-based Symmetry Breaking.** When L-CBS times out, agents are partitioned into two roles by heuristic distance: *Yielders* (furthest from their goals) run BFS to find the nearest free retreat cell, while *Movers* re-run L-CBS with Yielders' planned trajectories masked as dynamic constraints.

3. **Push-and-Rotate:** For small, tightly interlocked groups (e.g., a 2×2 cycle), this heuristic executes a synchronized rotation of agents into adjacent empty cells.

4. **Endgame Solver (Large-Scale Exclusive):** In massive environments like City maps, a few remaining agents (stragglers) may wander indefinitely after the majority reach their goals. When active agent density drops below a critical threshold (e.g., 15%), LENS triggers a globally coherent CBS exclusively for these stragglers to guarantee episode termination.

By prioritizing L-CBS, we maintain solution quality; by falling back to heuristic maneuvers (Evaporation/Retreat), we guarantee robustness against catastrophic deadlocks. Empirical profiling (detailed in Appendix C) validates this hierarchical design: standard L-CBS successfully resolves over 98.9% of conflict groups, confirming that the heuristic fallbacks act strictly as rare safety nets rather than the primary driver of resolution.

4.3 Collaborative Mapping and Adaptive Guidance

To overcome the myopia of local observations, LENS operates in a collaborative mapping and planning paradigm. Agents maintain a synchronized connection to an edge server via perfect broadcast communication, incrementally constructing a unified Persistent Known Map $\mathcal{M}_{shared}$ (Lajoie et al., 2022). While neural proposals can be generated efficiently using local views, the server acts as the central orchestrator for the Defense Cascade, executing L-CBS directly on the synchronized $\mathcal{M}_{shared}$ to untangle overlapping agent intents. This setup abstracts away communication latency and fully decentralized SLAM overheads, allowing us to strictly isolate the core algorithmic challenge: resolving structural deadlocks via online topological discovery rather than relying on pre-computed global oracles.

Based on $\mathcal{M}_{shared}$, the system maintains a global topological abstraction, the ARG $G_{ARG} = (V_{reg}, E_{reg})$. **Global Instance:** Unlike local graphs maintained individually, the ARG is a singleton instance shared across all agents. V_{reg} consists of fixed-size grid regions (e.g., 16×16 cells). **Dynamic Connectivity:** The connectivity set E_{reg} is updated incrementally. An edge e_{ij} between regions r_i and r_j is considered *traversable* only if the boundary cells in $\mathcal{M}_{shared}$ are effectively free. **Optimistic Assumption under Uncertainty:** For cells within $\mathcal{M}_{shared}$ marked as *Unknown*, the ARG adopts an optimistic assumption, treating them as traversable. While this encourages active exploration of frontier regions, it inherently risks guiding agents into large topological traps (e.g., deep dead-ends) as map discovery unfolds. LENS mitigates this structural vulnerability through a tight feedback loop with the DEZD.

Guidance Generation: As agents update $\mathcal{M}_{shared}$ with new observations O_t^i, the ARG re-evaluates connectivity. A high-level search on the ARG extracts a valid macroscopic subgoal. This subgoal (or its short guiding trajectory) is then directly projected into the agent's ego-centric FOV to form the fourth spatial input channel. This ensures that distant agents immediately benefit from structural discoveries (e.g., newly blocked corridors) made by their peers (Zhang et al., 2024).

5 Experimental Evaluation

Our evaluation strategy is designed to decouple the two core capabilities of the LENS framework: (1) the *architectural efficiency* of the potential-guided search when topological information is accurate, and (2) the *inference robustness* of the neural proposer when operating in unknown environments. To this end, we conduct experiments under two rigorously defined protocols: **Setting A (Architecture Validation)** and **Setting B (Unknown Environment Exploration)**.

5.1 Experimental Setup

Benchmark Environments: We utilize the POGEMA benchmark (Skrynnik et al., 2025), covering four distinct topologies: (1) **Random:** Unstructured clutter with 30% obstacle density. (2) **Mazes:** Procedurally generated corridors and dead-ends requiring long-horizon reasoning. (3) **Warehouse:** Structured logistics layouts testing extreme agent density. (4)**Cities:** Large-scale urban maps from MovingAI, testing scalability. Complete details regarding map configurations, hardware specifications, and all system hyperparameters (e.g., DEZD trigger thresholds) are provided in Appendices E, D and G.

Baselines & Adaptations: We compare LENS against state-of-the-art methods representing different paradigms. Baselines in Setting A: (1) **LaCAM** (Okumura, 2023): The centralized search oracle. (2) **SCRIMP** (Wang et al., 2023): A state-of-the-art communication-based MARL planner. (3) **LNS2-RL** (Li et al., 2022a): A hybrid solver where a MARL policy repairs local conflicts. *Training Data:* The model is trained via RL on Random maps with varying sizes (10×10 to 50×50) and obstacle densities (0% to 50%). (4) **CS-PIBT** (Veerapaneni et al., 2025): A reactive decentralized heuristic comprising a learned policy (SSIL) shielded by PIBT. *Training Data:* Unlike other baselines trained solely on random layouts, the underlying SSIL policy is trained on a diverse dataset derived from the MovingAI benchmark, covering structured topologies like cities and warehouses. (5) **MAPF-GPT** (Andreychuk et al., 2025b): A foundation model trained via large-scale imitation learning. *Training Data:* The model is pre-trained on a massive dataset of 1 billion expert observation-action pairs, generated predominantly from Maze-like maps (90%) and Random maps (10%) to encourage long-horizon reasoning.

To ensure a meaningful comparison in Setting B, the baseline methods were adapted to handle partial observability through integration with an *Incremental Map Discovery Framework*. Baselines in Setting B: (1) **SCRIMP** (Wang et al., 2023): It is naturally suitable for Setting B. (2) **Adapted LNS2-RL:** Granted access to $\mathcal{M}_{shared}$, but requires recomputing its global heuristic graph from scratch whenever new obstacles are revealed. (3) **Adapted CS-PIBT:** Similarly granted access to $\mathcal{M}_{shared}$ and adapted to dynamically recompute its heuristic graph upon obstacle updates. Note that MAPF-GPT is excluded from Setting B as its architecture fundamentally relies on pre-computed global cost-to-go maps Andreychuk et al. (2025b). DMCTS (Skrynnik et al., 2024) is also excluded: despite handling peer uncertainty, its neural policy (COSTTRACER) requires a pre-computed cost-to-go matrix over a fully known static map, the assumption incompatible with Setting B and not straightforwardly resolvable by online heuristic recomputation.

5.2 Setting A: Architecture Validation (Global Knowledge)

Objective: To evaluate the quality of the Neural Proposer's learned heuristic approximation against oracle-guided baselines. In this setting, all methods have access to the static global map. However, this setup is deliberately asymmetric: while the baseline methods receive pre-computed ground-truth cost-to-go maps (i.e., oracle heuristic guidance), LENS's U-Net performs learned inference from perception. This asymmetric setup places LENS at a relative disadvantage, as baselines are provided ground-truth heuristics while LENS relies entirely on its learned potential field approximation. We emphasize that the U-Net receives no ground-truth potential field in Setting A; all guidance is derived from learned inference. This distinguishes Setting A from a trivial oracle upper bound and validates the quality of the Neural Proposer as a heuristic approximator.

5.2.1 Results Analysis

Figure 2 presents a comprehensive comparison of Success Rate (SR), Runtime, and Sum of Costs (SoC). Detailed numerical results are provided in Tables 1 and 2 (Best in **Bold**, Second Best in *Underlined italic*).

Robustness in Structured Environments: In **Mazes** (Figure 2a), **LENS** achieves a **97.6% Success Rate** at 32 agents and **78.7%** at 64 agents. Remarkably, LENS achieves this competitive performance matching the centralized oracle LaCAM and significantly outperforming decentralized baselines such as CS-PIBT (37.2%) and LNS2-RL (32.0%), all of which rely on pre-computed global cost-to-go maps. This result confirms that even with global information available, reactive heuristics struggle with structured deadlocks, whereas the LENS Defense Cascade efficiently resolves them.

Efficiency at Scale: Regarding **Runtime** (Figure 2, Row 2), LENS exhibits superior scalability even while performing active neural inference rather than relying on pre-computed heuristics. In **Random** maps, **LENS** is approximately $2\times$ faster than LNS2-RL and $5\times$ faster than MAPF-GPT-85M. In the extreme density of the **Warehouse** (192 agents), LENS solves instances in 64s, whereas MAPF-GPT requires 242s. While LENS incurs higher total runtime in massive topologies like **Cities** (256 agents) compared to purely reactive heuristics, a granular computational profile (Appendix C) reveals this is an explicit engineering trade-off: the U-Net inference and L-CBS solver combined consume around 5% of the latency. The overhead stems primarily from the continuous synchronization of the global dynamic map across 256 agents, an aspect independent of the core decision-making efficiency.

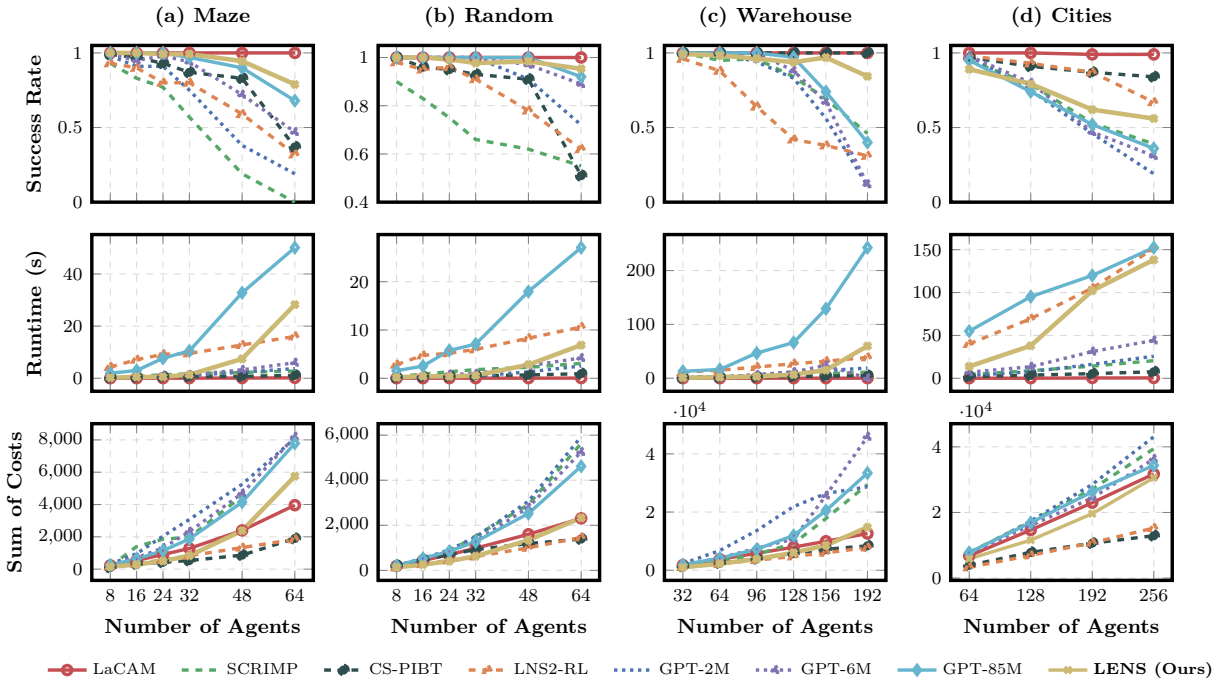

Figure 2: **Comprehensive Performance Analysis (Setting A).Top Row:** Success Rate (Higher is better). **Middle Row:** Runtime (Lower is better). **Bottom Row:** SoCs (Lower is better). **Legend:** LENS (Gold) demonstrates superior robustness in high-complexity maps (Maze/Warehouse) compared to reactive and learning-based baselines. Runtime is averaged over successful runs. SoCs is also computed only over successful instances. Points are omitted when an algorithm produces no successful runs in that setting; thus the SoCs is undefined rather than missing.

Table 1: **Small-scale Environments.** Individual Success Rate (ISR) and Makespan comparisons on Maze and Random maps.

	Maze Maps												Random Maps											
	ISR						Makespan						ISR						Makespan					
Agents	**8**	**16**	**24**	**32**	**48**	**64**	**8**	**16**	**24**	**32**	**48**	**64**	**8**	**16**	**24**	**32**	**48**	**64**	**8**	**16**	**24**	**32**	**48**	**64**
LaCAM	1.00	1.00	1.00	1.00	1.00	1.00	29.1	33.3	37.8	40.0	50.0	61.9	1.00	1.00	1.00	1.00	1.00	1.00	24.0	27.2	29.0	30.7	33.3	36.0
SCRIMP	0.98	0.88	0.82	0.68	0.50	0.37	42.7	64.5	109.3	99.2	114.2	-	0.97	0.90	0.80	0.71	0.67	0.64	43.4	74.2	104.1	132.7	121.7	123.2
CS-PIBT	**1.00**	**1.00**	0.99	0.99	**0.99**	**0.91**	34.0	35.0	**38.0**	**52.0**	101.0	101.6	**1.00**	**1.00**	0.99	0.99	0.99	**0.99**	26.7	31.5	36.1	42.4	57.9	89.9
LNS2-RL	0.98	0.99	0.98	0.98	0.94	0.83	39.7	51.6	62.0	66.4	**75.0**	**72.3**	0.99	0.99	**1.00**	0.99	0.98	0.95	31.7	36.8	42.3	45.6	53.7	**58.9**
GPT-2M	**1.00**	0.99	0.98	0.94	0.81	0.65	37.8	60.0	85.2	96.1	109.5	126.4	**1.00**	**1.00**	**1.00**	**1.00**	0.99	0.92	26.2	33.1	37.8	46.3	63.8	92.7
GPT-6M	**1.00**	**1.00**	**1.00**	0.99	0.94	0.83	33.6	44.1	54.7	72.6	97.7	128.1	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	0.96	**26.1**	31.4	36.6	40.7	58.2	82.1
GPT-85M	**1.00**	**1.00**	**1.00**	**1.00**	0.96	0.88	32.2	39.6	47.6	58.5	86.3	121.7	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	0.98	26.4	33.1	**35.2**	**39.8**	**52.5**	72.2
LENS	**1.00**	**1.00**	0.99	0.99	0.95	0.81	**31.0**	**33.4**	43.9	57.0	102.6	169.2	**1.00**	**1.00**	0.99	0.98	0.98	0.96	27.6	**29.4**	36.2	45.1	66.9	85.6

Solution Quality: The **SoC** results (Figure 2, Row 3) indicate that LENS generates paths of comparable quality to LaCAM. despite LENS receiving no oracle guidance. Notably, in Random maps, **LENS** achieves a lower SoC than other learning-based methods equipped with ground-truth BFS, suggesting that the learned potential field effectively approximates the true shortest path.

5.3 Setting B: Robustness in Unknown Environments (online collaborative mapping)

Objective: This setting mimics realistic deployments where pre-computation is impossible. Unlike Setting A, the global map is initially hidden. To rigorously evaluate our collaborative framework, we enforce an incremental map discovery protocol: agents navigate strictly using local FOVs without any prior map knowledge, while all valid observations are instantly merged into a shared dynamic map $\mathcal{M}_{shared}$ to progressively

Table 2: **Large-scale Environments.** ISR and Makespan comparisons on Warehouse and City maps.

	Warehouse												Cities							
	ISR						Makespan						ISR				Makespan			
Agents	**32**	**64**	**96**	**128**	**156**	**192**	**32**	**64**	**96**	**128**	**156**	**192**	**64**	**128**	**192**	**256**	**64**	**128**	**192**	**256**
LaCAM	1.00	1.00	1.00	1.00	1.00	1.00	55.2	58.9	60.7	62.0	63.9	65.7	1.00	1.00	0.99	0.99	105.7	114.4	119.7	123.9
SCRIMP	0.98	0.96	*0.99*	0.93	0.83	0.72	109.1	156.7	186.5	172.4	181.0	192.0	**1.00**	0.95	0.85	0.78	174.5	152.2	168.2	182.6
CS-PIBT	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	62.0	69.5	82.0	104.0	138.0	*164.0*	**1.00**	**1.00**	**0.99**	**0.99**	118.2	**123.6**	129.4	*134.6*
LNS2-RL	**1.00**	**1.00**	*0.99*	0.98	*0.98*	*0.98*	66.7	68.2	**72.5**	**73.2**	**76.6**	**79.0**	**1.00**	**1.00**	**0.99**	*0.98*	**115.6**	*124.1*	*128.6*	**130.0**
GPT-2M	**1.00**	**1.00**	0.97	0.80	0.68	0.42	70.3	105.7	142.0	171.0	214.5	236.2	*0.99*	*0.96*	0.89	0.80	*116.5*	135.8	148.7	168.3
GPT-6M	**1.00**	**1.00**	**1.00**	0.96	0.95	0.79	**57.2**	*64.9*	79.1	*83.8*	166.8	239.0	**1.00**	0.95	0.89	0.83	118.0	125.0	**127.3**	141.9
GPT-85M	**1.00**	**1.00**	**1.00**	*0.99*	0.87	0.78	*60.2*	**64.6**	*75.1*	93.4	*133.1*	174.0	*0.99*	0.95	0.87	0.88	122.0	132.1	136.9	143.1
LENS	*0.99*	*0.98*	0.96	0.94	0.97	0.87	63.3	89.3	116.6	154.7	182.1	233.0	0.97	0.95	*0.93*	0.89	243.1	224.1	253.2	293.1

reveal the topology. All methods in Setting B can access the synchronized shared map ($\mathcal{M}_{shared}$), updated identically via agents' collective observations.

5.3.1 Comprehensive Performance Analysis

Since all compared methods share identical map information in Setting B, the observed performance differences reflect purely algorithmic advantages in topological reasoning and deadlock resolution. Figure 3 visualizes performance in strictly unknown environments. Reactive schemes like CS-PIBT fundamentally lack the horizon to foresee structural deadlocks (e.g., entering a corridor that is blocked at the other end).

The Cost of Myopia: Without pre-computed flow guidance, **CS-PIBT** (Blue/Dashed) suffers significant performance degradation in structured environments. (1) **Maze (Figure 3a):** Success rate drops to **6.3%** at 64 agents (down from 37.2% in Setting A). Agents oscillate in dead-ends. (2) **Warehouse (Figure 3c):** The performance degradation is absolute. At 192 agents, SR drops from 100% (Known) to **0%** (Unknown). Local conflict resolution cannot handle massive congestion in narrow aisles without a global plan.

The Scalability Wall of Search: LNS2-RL (Orange/Dashed) performs reasonably in Random maps but hits a scalability wall in complex topologies. In **Cities** (Figure 3d), LNS2-RL performance drops to 59.8% at 256 agents with excessive runtime costs ($> 180s$), caused by the need to constantly re-plan as new obstacles are discovered.

LENS Stability: LENS (Gold/Solid) demonstrates remarkable stability. Its performance curves in Setting B show minimal degradation compared to Setting A, with success rate gaps consistently smaller than those of all baselines across almost all tested topologies. This empirically proves that LENS does not rely on map memorization but on generalized inference of topology from local views.

5.3.2 Gap Analysis: The Cost of Blindness

Table 3 quantifies the performance degradation (Δ) when switching from Setting A to Setting B.

Success Rate Gap: CS-PIBT suffers massive drops in structured maps ($\Delta_{SR} = -39.2\%$ in Random-64, -100% in Warehouse-192). LNS2-RL, while more robust, still degrades significantly in dense structured environments ($\Delta_{SR} = -4.4\%$ in Random-64, -20.3% in Warehouse 192), revealing the scalability limits of search-based repair under unknown topologies.

Runtime Gap: While LNS2-RL slows down significantly in Warehouse ($\Delta_{Time} = +34.4s$) due to deadlocks, LENS has a **negligible Gap** ($\Delta \approx 0$), as its architecture is inherently designed for exploration.

5.4 Ablation Study

To validate the contribution of each module within the unified LENS framework, we conducted ablation studies across two distinct regimes: high-density structured deadlocks (Maze, 64 agents) where the system operates in *Direct Guidance* mode, and large-scale navigation (City, 128 agents) where the system activates *Hierarchical Guidance* (ARG).

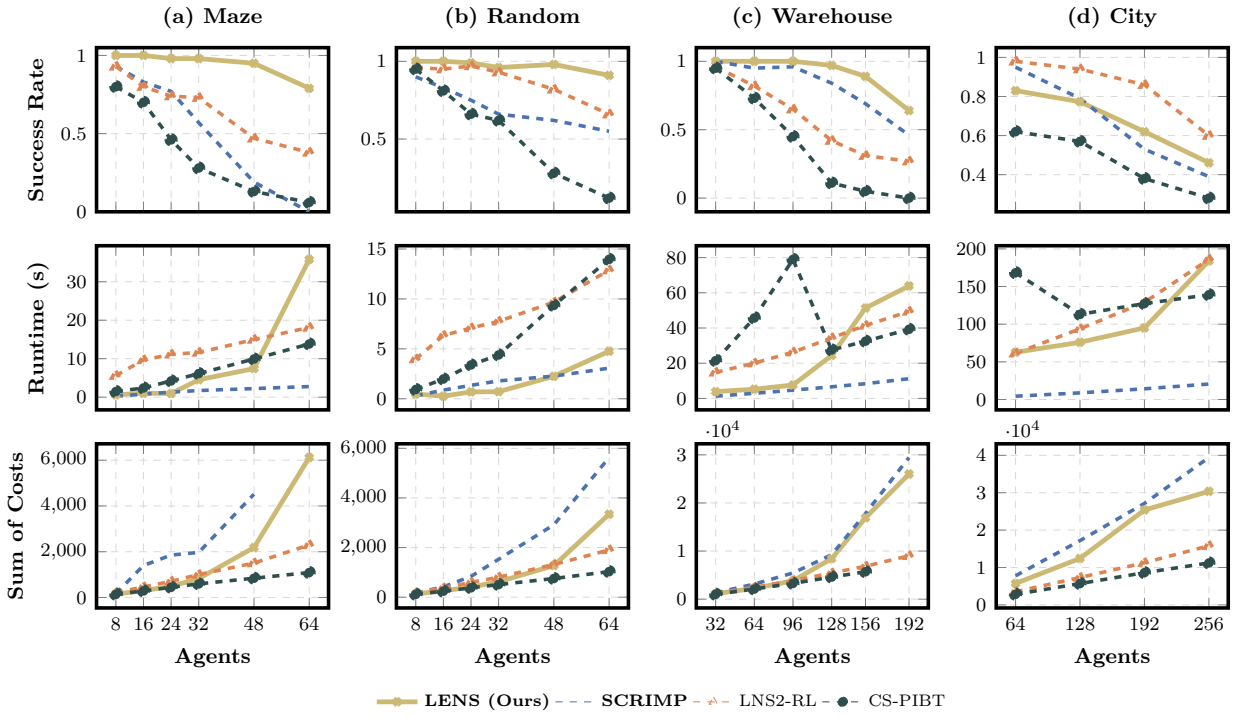

Figure 3: **Performance in Unknown Environments (Setting B).** Comparing LENS (Gold) against SCRIMP, LNS2-RL and CS-PIBT when the global map is unknown. **Top Row:** Success Rate. Note the dramatic collapse of CS-PIBT in Maze and Warehouse. **Middle Row:** Runtime. **Bottom Row:** SoCs. LENS maintains high success rates across all structured maps. Runtime is averaged over successful runs. SoCs is also computed only over successful instances. Points are omitted when an algorithm produces no successful runs in that setting; thus the SoCs is undefined rather than missing.

Table 3: **Gap Analysis (Setting B vs. Setting A).** The "Gap" represents $Value_{SettingB} - Value_{SettingA}$. A negative Gap in SR indicates performance loss due to unknown environments. LENS demonstrates robust performance with controlled degradation in runtime.

		CS-PIBT		LNS2-RL		LENS (Ours)	
Map	**Count**	**SR (Gap)**	**Time /s (Gap)**	**SR (Gap)**	**Time /s (Gap)**	**SR (Gap)**	**Time /s (Gap)**
Maze	8	79.5% (−19.5)	1.46 (+1.2)	92.9% (+0.0)	5.60 (+1.3)	100% (+0.0)	0.59 (+0.4)
	32	28.1% (−58.9)	6.13 (+5.5)	73.4% (−6.6)	11.61 (+2.1)	98.0% (−1.2)	4.53 (+3.2)
	64	6.3% (−30.7)	13.82 (+12.7)	38.3% (+6.3)	18.11 (+2.1)	79.0% (+0.1)	35.81 (+7.6)
Random	8	95.3% (−4.7)	0.93 (+0.8)	96.1% (−1.9)	3.98 (+1.1)	100% (+0.0)	0.48 (+0.3)
	32	61.7% (−31.3)	4.39 (+3.9)	93.0% (+2.0)	7.76 (+1.8)	96.0% (−1.7)	0.71 (+0.1)
	64	11.8% (−39.2)	13.96 (+13.0)	66.4% (+4.4)	12.88 (+2.3)	91.0% (−4.3)	4.76 (−2.1)
Warehouse	32	95.3% (−4.7)	21.47 (+20.6)	96.1% (+0.1)	14.79 (+3.4)	100% (+0.8)	3.84 (+3.1)
	128	10.9% (−89.1)	27.52 (+24.4)	42.2% (+0.2)	34.36 (+7.4)	97.0% (+3.2)	24.39 (+17.7)
	192	0.0% (−100.0)	39.27 (+34.4)	26.6% (−4.4)	49.42 (+10.8)	64.0% (−20.3)	63.93 (+4.0)
City	64	62.2% (−34.8)	168.28 (+166.3)	97.6% (−0.4)	61.33 (+21.3)	83.0% (−6.1)	30.71 (+17.1)
	128	56.7% (−34.3)	113.12 (+109.4)	93.7% (+0.7)	93.87 (+24.3)	77.3% (−1.8)	81.43 (+43.4)
	256	28.3% (−55.7)	139.09 (+131.5)	59.8% (−7.2)	186.01 (+34.5)	46.2% (−9.8)	184.1 (+27.03)

5.4.1 Impact of the Neural Proposer

A critical finding is the indispensability of the U-Net-based *Neural Proposer*. In the **Maze** environment (Table 4), replacing the U-Net with a standard A* solver ("w/o U-Net") degrades the success rate from **78.7**%

to 64.1%. This confirms that the learned potential field captures spatial features of dead-end structures better than generic heuristics.

More strikingly, in the **City** environment (Table 4), removing the U-Net results in a **0**% success rate. This is not an indictment of the A* algorithm itself, but a confirmation of the synergy within our framework. While the ARG provides a strategic subgoal, a naive A* planner—seeking the shortest path to this intermediate point—is blind to global context. It guides agents into geographic traps (e.g., entering a U-shaped obstacle from the wrong side). In contrast, the U-Net's potential field is conditioned on the global goal vector via FiLM, producing globally-aware local proposals.

5.4.2 Efficacy of the Defense Cascade

The *Defense Cascade* proves essential for resolving dense, multi-agent conflicts (Table 4). Disabling the entire cascade reduces the success rate to 65.6%, indicating that purely reactive policies are insufficient for structured deadlocks. Breakdown of the cascade levels reveals: **L-CBS:** Removing Local CBS causes the sharpest drop (63.4%), confirming its role as the primary solver for local gridlocks. **Push-and-Rotate:** Removing the randomized heuristic also degrades performance (62.5%), highlighting its importance in breaking symmetric livelocks. Removing the **Endgame Solver** causes the success rate to plummet to 3.9%. Without this final global coordination, a few remaining stragglers often fail to reliably converge over vast distances, leading to episode timeouts.

Table 4: **Ablation Study.** *Left:* Component analysis in Direct Mode on Maze maps with 64 agents. *Right:* Component analysis in Incremental Discovery Mode on City maps (64×64) with 128 agents.

Direct Mode (Maze, 64 agents)			**Incremental Discovery Mode (City, 128 agents)**			
Configuration	**SR**	**SoC (Runtime)**	**Configuration**	**SR**	**ISR**	**SoC**
LENS (Full)	**78.7%**	6117.55 (35.81s)	**LENS (Full)**	**77.1%**	**94.0%**	12440.32
Impact of Learning:						
w/o U-Net (using A*)	64.1%	3688.35 (21.06s)	w/o ARG	35.9%	82.9%	8830.35
Impact of Defense Cascade:						
w/o Defense Cascade (Full)	65.6%	3608.46 (20.74s)	w/o Heuristic Input	41.4%	84.4%	12051.43
w/o Local CBS	63.4%	3830.66 (21.32s)	w/o Endgame Solver	3.9%	90.3%	9635.60
w/o Coordinated Retreat	68.0%	3609.08 (20.51s)	w/o U-Net (using A*)	0.0%	26.2%	N/A
w/o Push-and-Rotate	62.5%	3592.60 (20.35s)				

6 Conclusion

LENS presents a scalable, hybrid framework for Partially Observable MAPF, resolving the dichotomy between data-intensive foundation models and myopic heuristics. By decoupling topological guidance from safety verification, LENS uses neural networks as heuristic estimators to infer topology-aware subgoals from partial observations. This guidance is grounded by the Defense Cascade, where L-CBS untangles structural deadlocks within bounded windows. Restricting combinatorial search to localized subgoals effectively circumvents the exponential overhead of classical global replanning. While LENS guarantees local collision avoidance within its receding execution windows by decoupling conflict groups, formally proving global, end-to-end completeness under partial observability remains an open challenge. Future theoretical work will focus on bounding the worst-case recovery time of the heuristic escape mechanisms. Future work will focus on three directions: (1) **Distributed Resolution:** Evolving the Defense Cascade into a hierarchical system where regional solvers handle local conflicts to further reduce reliance on centralized coordination; (2) **Socially Aware Learning:** Training the U-Net with soft penalties based on the predicted paths of other agents to generate proposals that are inherently less conflict-prone; and (3) **Long-Horizon Attention:** Augmenting the proposer with attention mechanisms to improve reasoning over larger spatial scales in real city-sized maps.

References

Shubhani Aggarwal and Neeraj Kumar. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. Computer communications, 149:270–299, 2020.

Anton Andreychuk, Konstantin Yakovlev, Aleksandr Panov, and Alexey Skrynnik. Advancing learnable multi-agent pathfinding solvers with active fine-tuning. In IROS, 2025a.

Anton Andreychuk, Konstantin Yakovlev, Aleksandr Panov, and Alexey Skrynnik. Mapf-gpt: Imitation learning for multi-agent pathfinding at scale. In AAAI, volume 39, pp. 23126–23134, 2025b.

Stefano Ardizzoni, Irene Saccani, Luca Consolini, and Marco Locatelli. Local optimization of mapf solutions on directed graphs. In CDC, pp. 8081–8086. IEEE, 2023.

Lei Bai, Lina Yao, Can Li, Xianzhi Wang, and Can Wang. Adaptive graph convolutional recurrent network for traffic forecasting. Advances in neural information processing systems, 33:17804–17815, 2020.

Tim Bailey, Juan Nieto, Jose Guivant, Michael Stevens, and Eduardo Nebot. Consistency of the ekf-slam algorithm. In IROS, pp. 3562–3568, 2006.

James L Bander and Chelsea CIII White. A heuristic search algorithm for path determination with learning. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 28(1):131–134, 2002.

Eli Boyarski, Ariel Felner, Roni Stern, Guni Sharon, Oded Betzalel, David Tolpin, and Eyal Shimony. Icbs: The improved conflict-based search algorithm for multi-agent pathfinding. In SoCS, volume 6, pp. 223–225, 2015.

Lauren Bramblett, Rahul Peddi, and Nicola Bezzo. Coordinated multi-agent exploration, rendezvous, & task allocation in unknown environments with limited connectivity. IROS, pp. 12706–12712, 2022.

Marc Brockschmidt. Gnn-film: Graph neural networks with feature-wise linear modulation. In ICML, pp. 1144–1152, 2020.

W. Burgard, M. Moors, D. Fox, R. Simmons, and S. Thrun. Collaborative multi-robot exploration. In ICRA, volume 1, pp. 476–481 vol.1, 2000.

Fanfei Chen, Shi Bai, Tixiao Shan, and Brendan Englot. Self-learning exploration and mapping for mobile robots via deep reinforcement learning. AIAA Scitech 2019 Forum, 2019.

Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. GradNorm: Gradient normalization for adaptive loss balancing in deep multitask networks. In Jennifer Dy and Andreas Krause (eds.), ICML, volume 80, pp. 794–803, 2018.

Zhe Chen, Daniel Harabor, Jiaoyang Li, and Peter J Stuckey. Traffic flow optimisation for lifelong multi-agent path finding. In AAAI, volume 38, pp. 20674–20682, 2024.

Robert Daily and David M Bevly. Harmonic potential field path planning for high speed vehicles. In 2008 American Control Conference, pp. 4609–4614. IEEE, 2008.

Dave Ferguson, Maxim Likhachev, and Anthony Stentz. A guide to heuristic-based path planning. In Proceedings of the international workshop on planning under uncertainty for autonomous systems, ICAPS, pp. 9–18, 2005.

Timothy O Hodson. Root mean square error (rmse) or mean absolute error (mae): When to use them or not. Geoscientific Model Development Discussions, 2022:1–10, 2022.

Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In CVPR, pp. 7132–7141, 2018.

Yong Koo Hwang, Narendra Ahuja, et al. A potential field approach to path planning. IEEE transactions on robotics and automation, 8(1):23–32, 1992.

Jin-Oh Kim and Pradeep Khosla. Real-time obstacle avoidance using harmonic potential functions. 1992.

Pierre-Yves Lajoie, Benjamin Ramtoula, Fang Wu, and Giovanni Beltrame. Towards collaborative simultaneous localization and mapping: a survey of the current research landscape. Field Robotics, 2:971–1000, 2022.

Jinwon Lee and Woojin Chung. Effects of graph representation for multi-agent path finding. In ICCAS, pp. 1158–1159. IEEE, 2024.

Jiaoyang Li, Andrew Tinka, Scott Kiesel, Joseph W Durham, TK Satish Kumar, and Sven Koenig. Lifelong multi-agent path finding in large-scale warehouses. In AAAI, volume 35, pp. 11272–11281, 2021.

Jiaoyang Li, Zhe Chen, Daniel Harabor, Peter J Stuckey, and Sven Koenig. Mapf-lns2: Fast repairing for multi-agent path finding via large neighborhood search. In AAAI, volume 36, pp. 10256–10265, 2022a.

Wenhao Li, Hongjun Chen, Bo Jin, Wenzhe Tan, Hongyuan Zha, and Xiangfeng Wang. Multi-agent path finding with prioritized communication learning. In ICRA, pp. 10695–10701. IEEE, 2022b.

Runzhe Liang, Rishi Veerapaneni, Daniel Harabor, Jiaoyang Li, and Maxim Likhachev. Real-time lacam. arXiv preprint arXiv:2504.06091, 2025.

Yuan Liu, Min Wang, Zhou Su, Jun Luo, Shaorong Xie, Yan Peng, Huayan Pu, Jiajia Xie, and Rui Zhou. Multi-auvs cooperative target search based on autonomous cooperative search learning algorithm. Journal of Marine Science and Engineering, 8(11):843, 2020a.

Zuxin Liu, Baiming Chen, Hongyi Zhou, Guru Koushik, Martial Hebert, and Ding Zhao. Mapper: Multi-agent path planning with evolutionary reinforcement learning in mixed dynamic environments. In IROS, pp. 11748–11754. IEEE, 2020b.

Yueming Lyu, Xiaowei Zhou, Xingrui Yu, and Ivor Tsang. Graph potential field neural network for massive agents group-wise path planning. Transactions on Machine Learning Research, 2025. ISSN 2835-8856.

Ziyuan Ma, Yudong Luo, and Hang Ma. Distributed heuristic multi-agent path finding with communication. In ICRA, pp. 8699–8705. IEEE, 2021.

Thi Thoa Mac, Cosmin Copot, Duc Trung Tran, and Robin De Keyser. Heuristic approaches in robot path planning: A survey. Robotics and Autonomous Systems, 86:13–28, 2016.

Keisuke Okumura. Lacam: Search-based algorithm for quick multi-agent pathfinding. In AAAI, volume 37, pp. 11655–11662, 2023.

Keisuke Okumura, Manao Machida, Xavier Défago, and Yasumasa Tamura. Priority inheritance with backtracking for iterative multi-agent path finding. Artificial Intelligence, 310:103752, 2022.

Ira Pohl. Heuristic search viewed as path finding in a graph. Artificial intelligence, 1(3-4):193–204, 1970.

Yadollah Rasekhipour, Amir Khajepour, Shih-Ken Chen, and Bakhtiar Litkouhi. A potential field-based model predictive path-planning controller for autonomous road vehicles. IEEE Transactions on Intelligent Transportation Systems, 18(5):1255–1267, 2016.

Guni Sharon, Roni Stern, Ariel Felner, and Nathan R Sturtevant. Conflict-based search for optimal multi-agent pathfinding. Artificial intelligence, 219:40–66, 2015.

Alexey Skrynnik, Anton Andreychuk, Konstantin Yakovlev, and Aleksandr Panov. Decentralized monte carlo tree search for partially observable multi-agent pathfinding. In AAAI, volume 38, pp. 17531–17540, 2024.

Alexey Skrynnik, Anton Andreychuk, Anatolii Borzilov, Alexander Chernyavskiy, Konstantin Yakovlev, and Aleksandr Panov. POGEMA: A benchmark platform for cooperative multi-agent pathfinding. In ICLR, 2025.

Pavel Surynek. An optimization variant of multi-robot path planning is intractable. In AAAI, volume 24, pp. 1261–1263, 2010.

Derek Ming Siang Tan, Yixiao Ma, Jingsong Liang, Yi Cheng Chng, Yuhong Cao, and Guillaume Adrien Sartoretti. Ir2: Implicit rendezvous for robotic exploration teams under sparse intermittent connectivity. IROS, pp. 13245–13252, 2024.

Sumanth Varambally, Jiaoyang Li, and Sven Koenig. Which mapf model works best for automated warehousing? In SoCS, volume 15, pp. 190–198, 2022.

Rishi Veerapaneni, Qian Wang, Kevin Ren, Arthur Jakobsson, Jiaoyang Li, and Maxim Likhachev. Improving learnt local MAPF policies with heuristic search. In ICAPS, 2024.

Rishi Veerapaneni, Arthur Jakobsson, Kevin Ren, Samuel Kim, Jiaoyang Li, and Maxim Likhachev. Work smarter not harder: Simple imitation learning with cs-pibt outperforms large-scale imitation learning for mapf. In ICRA, pp. 10229–10236. IEEE, 2025.

Binyu Wang, Zhe Liu, Qingbiao Li, and Amanda Prorok. Mobile robot path planning in dynamic environments through globally guided reinforcement learning. IEEE Robotics and Automation Letters, 5(4): 6932–6939, 2020.

Yutong Wang, Bairan Xiang, Shinan Huang, and Guillaume Sartoretti. Scrimp: Scalable communication for reinforcement-and imitation-learning-based multi-agent pathfinding. In IROS, pp. 9301–9308. IEEE, 2023.

Yutong Wang, Tanishq Duhan, Jiaoyang Li, and Guillaume Sartoretti. Lns2+ rl: Combining multi-agent reinforcement learning with large neighborhood search in multi-agent path finding. In AAAI, volume 39, pp. 23343–23350, 2025.

Zhongxia Yan and Cathy Wu. Neural neighborhood search for multi-agent path finding. In ICLR, 2024.

Yulun Zhang, He Jiang, Varun Bhatt, Stefanos Nikolaidis, and Jiaoyang Li. Guidance graph optimization for lifelong multi-agent path finding. arXiv preprint arXiv:2402.01446, 2024.

A Additional Evaluation: Puzzles Benchmark

To specifically test fine-grained coordination and deadlock resolution in highly constrained spaces, we evaluated LENS in Setting A on the **Puzzles** benchmark from POGEMA. These small, hand-crafted maps require multi-step, sliding-tile-puzzle-like maneuvers that defeat greedy policies.

As shown in Tables 5 and 6, LENS achieves a **100% Success Rate**, matching the centralized oracle (LaCAM) and the large-scale model (MAPF-GPT). Notably, our Sum of Costs (SoC) is significantly lower than MAPF-GPT (e.g., 20.94 vs 97.43 for 4 agents), indicating that our L-CBS component finds much more efficient solutions in these tight logical puzzles than pure learned policies.

Table 5: Puzzles Benchmark (4 agents)

Configuration	SR (%)	Avg. SoC
LENS	**100**	**20.94**
LaCAM	100	28.68
MAPF-GPT-85m	100	97.43

Table 6: Puzzles Benchmark (3 agents)

Configuration	SR (%)	Avg. SoC
LENS	**100**	**14.94**
LaCAM	100	23.83
MAPF-GPT-85m	100	40.50

B Limitations

While LENS demonstrates strong performance, we acknowledge limitations:

- **Centralization Bottleneck:** The Defense Cascade is centralized. Although triggered locally for small groups, extreme congestion merging multiple groups could create a computational bottleneck requiring reliable communication.
- **Dependence on Exploration:** The search-based resolver relies on the shared global map $\hat{M}$. If critical paths remain unexplored (marked UNKNOWN), the resolver may fail even if a path exists.
- **OOD Generalization:** The U-Net proposer, trained on smaller maps, may struggle with unseen complex obstacle textures in OOD maps (e.g., Cities), necessitating more frequent cascade interventions.

C Computational Profiling and Defense Cascade Statistics

To transparently analyze the runtime characteristics and the internal behavior of the LENS framework, we present a granular computational profile based on our experiments in completely unknown environments (Setting B).

Defense Cascade Utilization. To validate the necessity and efficiency of our hierarchical conflict resolution, we logged the invocation frequency of each defense layer in highly constrained topologies (Maze maps with 64 agents). As shown in Table 7, out of 13,415 encountered conflict groups, the standard Local CBS (L1) successfully resolved 98.96% of them. This demonstrates that local search is highly capable of untangling congestion when guided by topology-aware potential fields. The heuristic fallbacks (L2-L4) are rarely invoked ($\approx 1\%$), confirming their role as strict extreme-case safety nets rather than primary planners.

Latency Breakdown in Massive Environments. In the City-scale maps (256 agents), LENS incurs a higher average runtime (184.04s) compared to purely reactive baselines. To identify the bottleneck, we profiled the per-step latency (Table 8). The analysis reveals that the core algorithmic components of LENS are extremely lightweight: the U-Net neural inference accounts for only 1.18% of the total time, and the L-CBS conflict resolution consumes merely 3.66%. The vast majority of the computational load (78.82%) is dedicated to the continuous updating of the global map ($\mathcal{M}_{shared}$) and pattern detection across 256 agents. This confirms that the observed runtime overhead in massive maps is an engineering artifact of centralized state synchronization, rather than a scalability limit of the hybrid learning-search architecture itself.

Table 7: Defense Cascade Usage Frequency (Maze, 64 Agents, Setting B)

Defense Layer	**Successful Invocations**	**Proportion (%)**
L1: Standard CBS (L-CBS)	13,276	98.96%
L2: Coordinated Retreat	72	0.54%
L3: Push-and-Rotate	66	0.50%
Total Conflict Groups	**13,415**	**100.00%**

Table 8: Computational Latency Profile (City Map, 256 Agents, Setting B)

Pipeline Component	**Total Time (s)**	**Proportion (%)**
1. Map Update	148.26	70.11%
2. High-Level Planning and ARG Guidance	50.93	24.08%
3. Conflict Resolution (L-CBS)	6.88	3.25%
4. U-Net Inference	2.82	1.33%
5. Path Execution	2.58	1.22%

D Implementation Details

Our LENS framework is implemented in Python, leveraging several key open-source libraries to ensure efficiency and robustness.

D.1 Core Technologies

The Neural Proposer, our U-Net model, is built using **PyTorch**. The environment for both expert trajectory generation and final evaluation is the **POGEMA** benchmark, which provides a flexible and standardized platform for MAPF research.

Algorithmic Components. The classical search components of our framework rely on well-established libraries. Graph-based operations, such as conflict group identification and the high-level planning in the ARG for LENS-H, are implemented using **NetworkX**. To accelerate computationally intensive, low-level functions such as heuristic calculations, we employ **Numba** for Just-In-Time (JIT) compilation, which significantly reduces the overhead of these frequently called routines. The core conflict resolution solver, local CBS, is a custom implementation optimized for small agent groups and limited planning horizons.

D.2 Neural Proposer Architecture

The Neural Proposer is implemented as a modified U-Net with the following specifications:

Inputs:

- **Spatial Tensor ($4 \times L \times L$):** Channel 0: Static Obstacles; Channel 1: Dynamic Agents; Channel 2: Ego-Agent Position; Channel 3: Projected Local Target (the subgoal coordinate or local guiding path).
- **Non-Spatial Vector (2×1):** Normalized vector $(\Delta x, \Delta y)$ pointing to the current subgoal.

Architecture:

- **Encoder:** 3 blocks of `DoubleConv` (Conv3x3 $\rightarrow$ BN $\rightarrow$ ReLU $\rightarrow$ Conv3x3 $\rightarrow$ BN $\rightarrow$ ReLU $\rightarrow$ **SEBlock**). Downsampling via MaxPool2d. Channels: $64 \rightarrow 128 \rightarrow 256 \rightarrow 512$.

- **Bottleneck & FiLM:** The bottleneck features are modulated by the **FiLM Layer**. The non-spatial vector is projected via an MLP to generate scale (γ) and shift (β) parameters.
- **Decoder:** 3 blocks of Transposed Convolution for upsampling followed by `DoubleConv`. Skip connections concatenate encoder features.
- **Output Head:** 1×1 Convolution to produce the $1 \times L \times L$ potential field.

E Data Generation and Training

E.1 Dataset Technical Details

To ensure our work is comparable to existing state-of-the-art models, we adopted a data generation strategy similar to that of MAPF-GPT, focusing on the same types of environments. Our dataset was generated exclusively on the **Mazes** and **Random** map types from the POGEMA benchmark (Table 9).

While MAPF-GPT generated over a billion samples, our targeted sampling strategy (focusing on initialization and terminal approach phases) resulted in a compact dataset of approximately **1.3 million samples**. This highlights the data efficiency of our hybrid learning approach compared to pure end-to-end imitation learning.

Table 9: Details of map sets from the POGEMA benchmark used for training and evaluation.

Set	Agents	Maps	Map Size	Seeds	Steps
Random / Mazes	8,16,32,48,64	128	17×17–21×21	1	128
Warehouse	32,64,128,156,192	1	33×46	128	128
Cities-tiles	64,128,192,256	128	64×64	1	512
Puzzles	2, 3, 4	16	5×5	10	128

E.2 Training Hyperparameters and Stability

The training was performed on a single NVIDIA A40 GPU. The key hyperparameters are detailed in Table 10. To demonstrate stability, Figure 4 illustrates the loss curves. The model converged smoothly, and training was halted early at epoch 93 via a patience mechanism, selecting the best model checkpoint at epoch 83 (validation loss = 0.2199).

Table 10: Key hyperparameters for U-Net training.

Parameter	Value
Training Setup	
Epochs	100
Batch Size	1024
Initial Learning Rate	5e-4
Optimizer	Adam
LR Scheduler	ReduceLROnPlateau (Patience 5, Factor 0.1)
Early Stopping Patience	10 epochs
Loss Function	
Primary Loss	MSE
Auxiliary Loss	Gradient L1 Loss ($\lambda_{grad} = 0.1$)

E.3 Qualitative Analysis of Neural Potential Fields

To validate that our Neural Proposer learns to infer global topology from local observations rather than merely memorizing maps, we visualize the predicted potential fields in distinct navigation scenarios. Figure

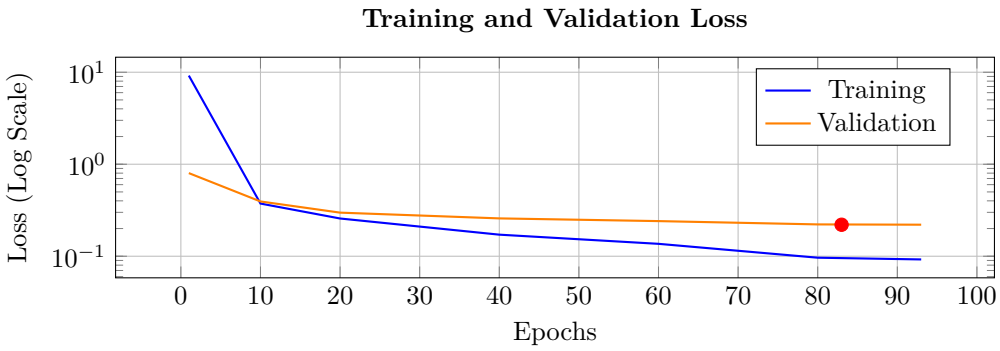

Figure 4: Training/Validation Loss. Training stopped early at epoch 93.

5 compares the local input, the ground-truth potential field (derived from global BFS), and the model's prediction.

As demonstrated in the **Dead End (Trap)** scenario (Middle Row), a naive Euclidean heuristic would assign a high value to the position inside the U-shape due to its proximity to the goal. However, our model, trained on global ground-truth potentials, correctly predicts a shadow of high cost (represented by dark pixels) inside the trap. This visualization confirms that the U-Net successfully reconstructs non-local constraints—recognizing that the path is blocked beyond the visual horizon—thereby enabling the agent to avoid structural local minima that plague reactive baselines like CS-PIBT.

F Defense Cascade Algorithms

This appendix provides the detailed algorithmic implementation of the multi-level Defense Cascade used in LENS. The cascade is triggered when the Deadlock Entry Zone Detector (DEZD) identifies agents in a non-progressive state.

F.1 Definitions and Notation

For clarity and consistency across the algorithms, we define the following mathematical notation:

Table 11: Mathematical Notation for Defense Cascade Algorithms

Symbol	Description
$\mathcal{A}_{conf}$	A subset of agents identified as being in a conflict group or deadlock.
a_i	An individual agent with index i.
$s_t^i = (x, y)$	The position of agent a_i at time step t.
g^i	The global goal position of agent a_i.
M_{local}	The local grid map representing static obstacles within the relevant area.
Φ^i	The learned local potential field for agent a_i (output of the U-Net).
$\mathcal{N}(s)$	The set of valid (traversable) neighboring cells of position s.
$h_{dist}(s_1, s_2)$	Heuristic distance function (e.g., Manhattan distance) between two points.
Ω	A set of spacetime constraints for CBS (e.g., (a_i, s, t) means a_i cannot be at s at time t).
k	The fixed short time horizon for the localized search (e.g., $\min(d_{\text{subgoal}}, 10)$ steps).
δ_{pad}	Spatial padding added to the bounding box of conflict agents.

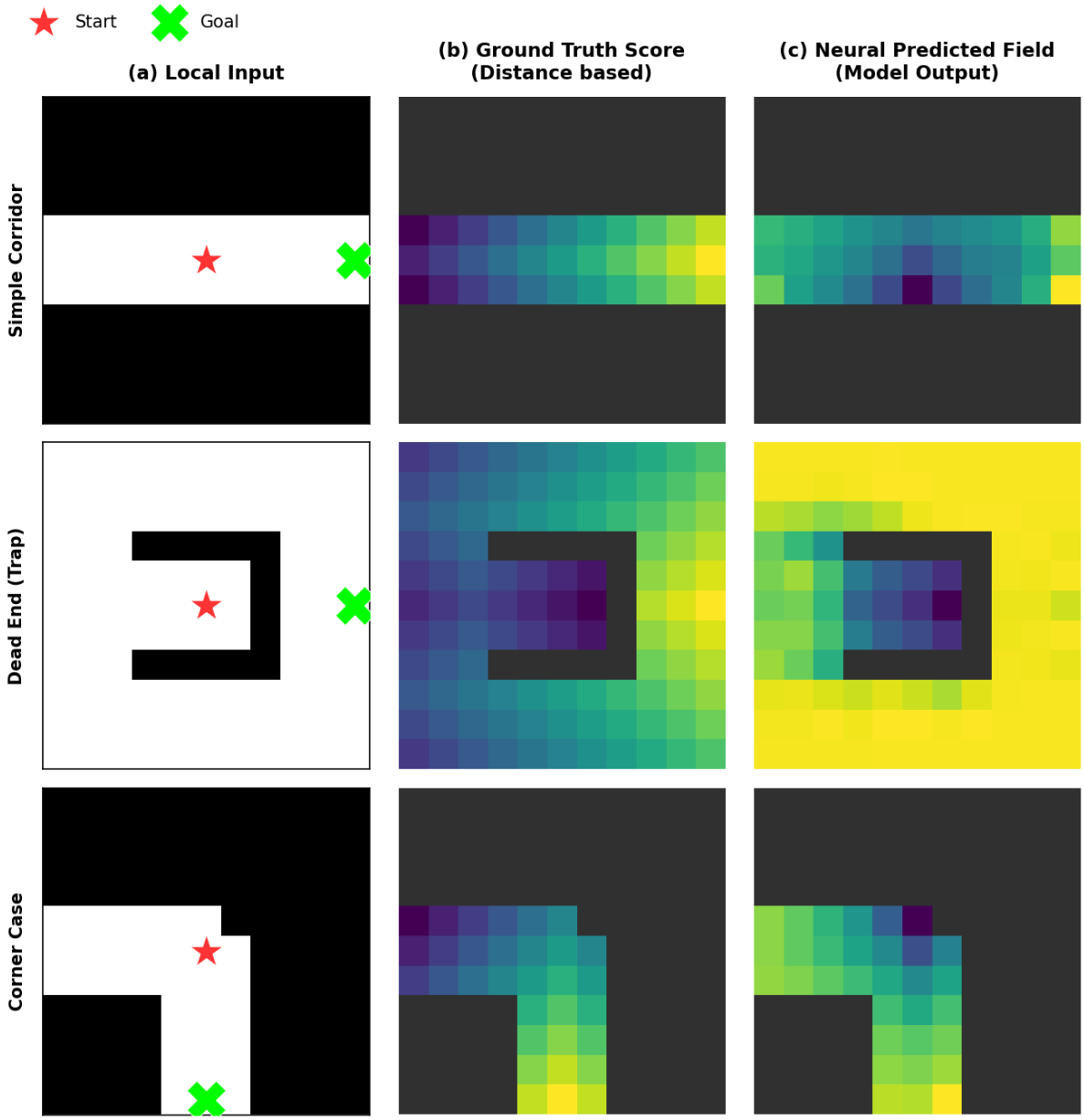

Figure 5: **Qualitative Comparison of Learned Potential Fields.** We visualize the Local Input (Left), the Global Ground Truth derived from BFS (Center), and the U-Net's Predicted Field (Right). **Top Row (Corridor):** The model correctly predicts a smooth gradient along the clear path. **Middle Row (Dead End/Trap):** This is the critical case. Although the goal (Green X) is geometrically close to the agent (Red Star), it is topologically distant due to the U-shaped wall. The Ground Truth reflects this with low scores (dark colors) inside the trap. Crucially, the Neural Proposer *reproduces this topological awareness*, predicting a low-value field inside the trap, effectively inhibiting the agent from entering the deadlock. **Bottom Row (Corner):** The model successfully infers the turning geometry.

F.2 Level 1: Localized Conflict-Based Search (L-CBS)

L-CBS is the primary execution kernel activated upon conflict detection. As implemented in our codebase, it differs from standard CBS in two critical ways: it is restricted to a small spacetime window, and its low-level search is actively guided by the neural potential field.

Algorithm 1 Level 1: Localized Conflict-Based Search (L-CBS)

Input: Conflict agents $\mathcal{A}_{conf}$, local map M_{local}, potential fields $\{\Phi^i\}_{i \in \mathcal{A}_{conf}}$, horizon k, padding δ_{pad}.
Output: Collision-free path segments $\mathcal{P} = \{P^i\}$ for $t \in [0, k]$ or `FAILURE`.
// Phase 1: Define Search Scope
Calculate spatial bounding box defined by $\{s_0^i\}$ and goals $\{g^i\}$ for all $a_i \in \mathcal{A}_{conf}$.
Define localized region R by expanding the bounding box by δ_{pad}.
Construct temporary map M_R by treating all cells outside R as obstacles.
// Phase 2: High-Level CBS
$Root.constraints \leftarrow \emptyset$
for each agent $a_i \in \mathcal{A}_{conf}$ **do**
  $Root.paths[i] \leftarrow$ `LowLevelSearch`$(a_i, s_0^i, M_R, \emptyset, \Phi^i)$
end for
$Root.cost \leftarrow \sum Cost(Root.paths[i])$
$OPEN \leftarrow \{Root\}$
while $OPEN$ is not empty **do**
  $N \leftarrow \arg\min_{Node \in OPEN} Node.cost$
  Pop N from $OPEN$.
  // Validate paths for vertex/edge conflicts within horizon k
  $C \leftarrow$ `FindFirstConflict`$(N.paths[0 \ldots k])$
  if C is `None` **then**
    return $N.paths$ {Optimal local solution found}
  end if
  // Branching on conflict $C = (a_i, a_j, s, t)$
  for each agent $a_k \in \{a_i, a_j\}$ **do**
    $NewNode \leftarrow$ copy of N
    Add constraint (a_k, s, t) to $NewNode.constraints$
    // Re-plan with potential-field guidance
    $NewNode.paths[k] \leftarrow$ `LowLevelSearch`$(a_k, s_0^k, M_R, NewNode.constraints, \Phi^k)$
    if $NewNode.paths[k]$ found **then**
      Update $NewNode.cost$ and insert into $OPEN$.
    end if
  end for
end while
return `FAILURE` {Trigger Level 2}

Procedure `LowLevelSearch`$(a_i, start, map, constraints, \Phi^i)$
Run Space-Time A* on map subject to $constraints$.
Crucially, define the heuristic cost $h(s)$ for state s using the neural potential field:
$h(s) = \Phi^i(s)$ {Leverage learned topological guidance}
return shortest path or `None`

F.3 Level 2: Coordinated Retreat

This module is triggered when L-CBS fails, typically due to structural deadlocks (e.g., a blocked narrow corridor) where no forward progress is possible within the search horizon. It resolves conflicts by explicitly breaking symmetry using a Yielder/Mover paradigm based on topological progress.

Algorithm 2 Level 2: Coordinated Retreat

Input: Conflict agents $\mathcal{A}_{conf}$, local map M_{local}, global goals $\{g^i\}$.
Output: Retreat paths for yielders, hold commands for movers.
// Phase 1: Classification
For each $a_i \in \mathcal{A}_{conf}$, calculate progress score $S_i = h_{dist}(s_t^i, g^i)$.
Sort $\mathcal{A}_{conf}$ in descending order of S_i (furthest from goal first).
Partition $\mathcal{A}_{conf}$ into $\mathcal{A}_{yielder}$ (top 50%) and $\mathcal{A}_{mover}$ (bottom 50%).
// Phase 2: Yielder Planning
Initialize plans $\mathcal{P} \leftarrow \emptyset$.
for each yielder $a_y \in \mathcal{A}_{yielder}$ **do**
  Determine retreat direction vector $\vec{d}_{retreat} = -1 \cdot \text{normalize}(g^y - s_t^y)$.
  Perform BFS starting from s_t^y in direction roughly matching $\vec{d}_{retreat}$ on M_{local}.
  Search for closest "junction" state s_{junc} (defined as a cell with > 2 free neighbors or an open area).
  if s_{junc} found **then**
    Plan path P^y from s_t^y to s_{junc} treating other agents as static obstacles.
    Add P^y to $\mathcal{P}$.
  else
    Add hold position command for a_y to $\mathcal{P}$.
  end if
end for
// Phase 3: Mover Planning
for each mover $a_m \in \mathcal{A}_{mover}$ **do**
  Add hold position command for a_m to $\mathcal{P}$ (waiting for yielders to clear).
end for
return $\mathcal{P}$

F.4 Level 3: Heuristic Agitation

This is the final fallback for tightly interlocked configurations (e.g., symmetric 2×2 cycles) where neither structured search nor retreat logic applies. It applies a randomized perturbation to break the symmetry of the deadlock.

Algorithm 3 Level 3: Heuristic Agitation (Push-and-Rotate)

Input: Conflict agents $\mathcal{A}_{conf}$, local map M_{local}.
Output: Single-step actions for $\mathcal{A}_{conf}$.
Assign random priorities to agents in $\mathcal{A}_{conf}$.
for each agent $a_i \in \mathcal{A}_{conf}$ in priority order **do**
  Identify set of valid unoccupied neighbors: $V_i = \{s' \in \mathcal{N}(s_t^i) \mid s' \text{ is free in } M_{local} \text{ and unoccupied}\}$.
  if V_i is not empty **then**
    Select a random neighbor $s_{next} \in V_i$.
    Assign action: move to s_{next}.
    Mark s_{next} as occupied for subsequent agents in this step.
  else
    Assign action: hold position (s_t^i).
  end if
end for
return Assigned actions.

F.5 Level 4: Endgame Solver

In massive scenarios (e.g., Cities), standard collision evaluation may timeout if disconnected stragglers indefinitely fail to converge. The Endgame Solver monitors the active agent density. Once this density drops

below a critical threshold (e.g., 15%), it explicitly disables localized spatio-temporal windows and transitions to a globally bounded CBS. This solver searches over the full $\mathcal{M}_{shared}$ with an extended iteration limit to guarantee the final sparse conflicts are optimally resolved, ensuring episode termination.

G System Hyperparameters

Table 12: Inference and System Hyperparameters.

Parameter	**Value**
Environment	
FOV Size (L)	11×11 (Radius 5)
Max Episode Steps	1024
Timeout	1000s
Adaptive Region Graph (ARG)	
Region Size	16×16
Update Frequency	Dynamic (on map discovery)
Defense Cascade	
Planning Horizon (k)	$\min(d_{\text{subgoal}}, 10)$ steps
Execution Window (n)	3(small map) or 6(large map) steps
L-CBS Time Limit	30s
L-CBS Max Iterations	100
DEZD Stagnation Window	10 steps
Stagnation BBox Size	8 cells
Evaporation Threshold	> 12 agents

H Future Work

Future research will focus on: (1) **Distributed Resolution:** Evolving the Defense Cascade into a hierarchical system where regional solvers handle local conflicts to improve scalability. (2) **Socially Aware Learning:** Training the U-Net with soft penalties based on predicted paths of other agents to generate proposals that are inherently less conflict-prone. (3) **Attention Mechanisms:** Augmenting the Neural Proposer with attention to improve long-range reasoning in large-scale maps.