

Decentralized Deep Reinforcement Learning for Cooperative Multi-Agent Flight Trajectory Planning in Adverse Weather

Extended Abstract

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ABSTRACT

Adverse weather, especially thunderstorms, disrupts air traffic operations and requires real-time trajectory adjustments to ensure aircraft safety. Existing methods often rely on centralized or single-agent approaches, lacking the coordination and robustness needed for scalable solutions. This paper presents a decentralized multi-agent method for cooperative trajectory planning, where each aircraft operates as an autonomous agent. The problem is modeled as a Decentralized Markov Decision Process (DEC-MDP) and solved with a proposed Independent Deep Deterministic Policy Gradient (IDDPG) algorithm. Experimental results show that the proposed method outperforms the state-of-the-art baselines in maintaining safe separation and optimizing rerouting efficiency under dynamically evolving thunderstorm cells.

KEYWORDS

Multi-Agent Systems; Cooperative Path Planning; Deep Reinforcement Learning; Air Traffic Management; Thunderstorm Weather

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1 INTRODUCTION

Thunderstorms pose significant challenges to air traffic management (ATM), leading to loss of separation between aircraft and

increased delays [6]. Effective trajectory planning for multiple aircraft in dynamic thunderstorms is essential to mitigate these risks and improve operational efficiency [2, 10]. The primary challenge lies in adjusting trajectories cooperatively in real-time, particularly in areas with limited air traffic control coverage, such as oceanic airspace [17], where timely and effective coordination is crucial.

Traditional trajectory planning under thunderstorms has utilized geometry [8], optimization [24], and heuristics methods [19]. Early works [7] emphasized iterative approach, while studies applied dynamic programming [16] and constrained optimization [14] for aircraft rerouting. Methods addressing uncertainties, such as [13, 18, 22], lacked real-time applicability or coordination in thunderstorm conditions. Optimal control approaches [9, 20, 25] improved robustness but still faced scalability challenges in complex and evolving environments. Heuristic methods [2, 11] showed effectiveness in trajectory planning but struggled with dependency and scalability, limiting large-scale and real-time applications.

Recent advancements in reinforcement learning (RL) have contributed to trajectory planning [27]. Proximal Policy Optimization (PPO) [4, 5] has been used for conflict resolution in air traffic. Deep Deterministic Policy Gradient (DDPG) [23] has optimized aircraft vectoring under uncertainties. Models [1, 28] incorporating physics-based knowledge provide explainable solutions, while studies [12, 21] validated multi-agent RL models in simulations, emphasizing the need for alignment with air traffic control procedures. Despite these advancements, existing RL approaches still struggle to ensure coordination and scalability, especially when adapting to dynamic and unpredictable weather, such as thunderstorms.

This paper proposes a cooperative and scalable multi-agent RL method for trajectory planning problem under dynamic thunderstorms. The problem is modeled as a decentralized Markov Decision Process (DEC-MDP) and solved using the proposed Independent Deep Deterministic Policy Gradient (IDDPG) algorithm. The experimental results show that our method outperforms the baseline algorithms in maintaining safe separation and improving scalability in diverse evaluation scenarios.



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2 PROBLEM AND METHODS

We model the problem as a Decentralized Markov Decision Process (DEC-MDP) [3], where each aircraft operates as an independent agent making decisions to optimize a joint reward while ensuring safe separations. For n agents, the DEC-MDP is defined by the joint state space $S = S_1 \times S_2 \times \dots \times S_n$, joint action space $A = A_1 \times A_2 \times \dots \times A_n$, joint reward function $R(s_1, \dots, s_n, a_1, \dots, a_n)$, and state transition probabilities $P = (P_1, P_2, \dots, P_n)$. The state space for aircraft agent i at t includes its position $p_i(t)$, velocity $v_i(t)$, thunderstorm cell information $O^W(t)$, and the remaining distance to the exit waypoint $d_t^{i, \text{Exit}}$. The action space consists of the heading change $a_t^i = \Delta h_i(t)$, a continuous variable within $[-30, 30]$ degrees. The reward function includes separation assurance, dynamic thunderstorm avoidance, heading change minimization, and distance minimization, all of which assign negative rewards for undesirable actions. The only positive reward is goal reaching. The total system reward is the weighted sum of these individual components, with the weights fine-tuned to reflect task priorities.

To solve the DEC-MDP, we propose an Independent Deep Deterministic Policy Gradient (IDDPG) method, leveraging a shared actor-critic architecture within a Centralized Training and Decentralized Execution framework [15]. During training, a centralized critic network $Q_i(s_t, a_t^i | \theta^{Q_i})$ evaluates actions for all agents using global state information s_t . This allows the critic to compute value functions that reflect the joint impact of actions, facilitating coordination across agents. Each agent maintains a decentralized actor network $\mu_i(s_t^i | \theta^{\mu_i})$, mapping its local observations s_t^i to actions a_t^i . In execution, each agent independently chooses actions based on its local state, ensuring scalability and real-time applicability.

3 EXPERIMENTAL RESULTS

The multi-agent decentralized IDDPG method is adapted for aircraft rerouting under dynamic thunderstorms. Training and evaluations were conducted in a self-built simulator. Multiple evaluations were performed to assess the effectiveness and scalability of the proposed method. Performance metrics include safety (loss of separation (LOS) rate) and efficiency (goal reach rate and flight distance ratio).

The effectiveness of the proposed method is demonstrated in Fig. 1, where all aircraft trajectories successfully avoid dynamic thunderstorm cells while maintaining safe separation over time. Scalability results in Table 1 reveal that as the number of aircraft increases from 4 to 8, the method’s performance remains robust, with Aircraft LOS rates consistently below 1% even in high-density scenarios. Baseline comparisons in Table 2 demonstrate that the proposed IDDPG method outperforms the state-of-the-art Fast Marching Tree (FMT) [11] and DDPG [23] methods with significant improvements, achieving a 98% goal reach rate compared to 87% for FMT and 90% for DDPG, while maintaining zero Aircraft LOS in contrast to 12% for FMT. These results show that the IDDPG enables superior coordination and efficiency in dynamic thunderstorm conditions.

4 CONCLUSIONS

This paper presents a decentralized multi-agent RL method for trajectory planning under dynamic thunderstorms. Simulations show a significant improvement in maintaining safe separation, with a reduction in conflict rates by up to 12% compared to baseline methods.

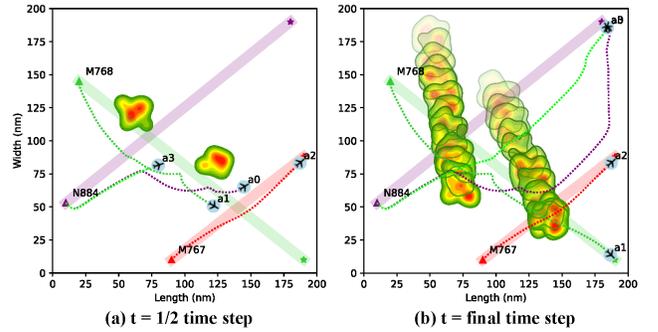


Figure 1: All aircraft successfully avoids dynamic thunderstorms (evolving contours) and maintains safe separation. Entry and exit waypoints are marked by solid triangles and stars, and dashed lines represent rerouted trajectories.

Table 1: Scalability analysis in 100 test scenarios.

Performance metrics	Number of aircraft				
	4	5	6	7	8
Aircraft LOS rate	0	0	0	1%	0
Thunderstorm LOS rate	0	2%	2%	3%	5%
Goal reach rate	100%	98%	98%	96%	95%
Distance ratio	(1.08	(1.17	(1.17	(1.16	(1.17
(Mean \pm S.D.)	± 0.06	± 0.15	± 0.16	± 0.17	± 0.17

Table 2: Comparisons of state-of-the-art methods in 100 diverse test scenarios with six aircraft.

Methods	Aircraft LOS rate	Thunderstorm LOS rate	Goal reach rate
FMT	12%	1%	87%
DDPG	2%	8%	90%
IDDPG (Ours)	0	2%	98%

The proposed IDDPG enables robust and scalable coordination between multiple aircraft trajectories during evolving thunderstorms, providing a promising method for real-time air traffic management in complex airspace affected by thunderstorms and other dynamic disruptions, such as space launch failures [26]. In future work, the method could be expanded to incorporate uncertainties in storm evolution and trajectory prediction.

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