



Edge-Assisted Multi-Agent Reinforcement Learning for Decentralized Autonomous Swarm Drone Navigation under Bandwidth Constraints

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Abstract

Decentralized navigation and inter-agent communication are key requirements for the safety of UAV swarms. However, restricted communication bandwidth will limit the exchange of information, thus lowering the level of coordination, the collision probability, and even affect navigation. In this study, we have designed an Edge-Assisted Multi-Agent Reinforcement Learning (EA-MARL) framework for decentralized autonomous swarm drone navigation under bandwidth constraints. The design consists of decentralized policy implementation, edge-assisted learning, and bandwidth aware communication where the communication bandwidth is explicitly considered during the process of navigation learning. The effectiveness of the designed framework has been tested under various bandwidths and has been compared with existing reinforcement learning frameworks. According to the expected results, our framework performs with a success rate of 96.1%, a collision rate of 2.8%, an average path length of 107.6 units and an average reward of 93.5. When the bandwidth drops from 100 Mbps to 25 Mbps, the communication overhead will reduce from 18.5 MB to 10.7 MB per episode with a drop of 42.2%, while the navigation success still maintains 89.6%. Through ablation analysis, it could be found that edge assistance, bandwidth aware communication, and selective information exchange all contribute to the better performance of navigation and training convergence.

Keywords: unmanned aerial vehicle swarm, multi-agent reinforcement learning, edge computing, decentralized navigation, bandwidth-aware communication, autonomous drone, swarm intelligence.



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Introduction

Unmanned aerial vehicle (UAV) swarms offer significant advantages for surveillance, search and rescue, disaster response, environmental monitoring, and infrastructure

inspection because multiple UAVs can cooperatively cover larger areas and distribute mission tasks efficiently. Recent advances in deep reinforcement learning (DRL) have further enabled UAVs to learn adaptive

navigation and coordination policies in dynamic environments, making learning-based control a promising approach for autonomous aerial swarms [1]. In particular, Multi-Agent Reinforcement Learning (MARL) enables multiple UAVs to learn cooperative behaviors while making decisions based on their observations and interactions with other agents.

However, decentralized autonomous navigation in UAV swarms remains challenging because each UAV must simultaneously avoid obstacles, maintain safe inter-agent distances, coordinate trajectories, and operate with incomplete information. These challenges are further intensified by wireless communication limitations, including restricted bandwidth, dynamic network topology, interference, latency, and packet loss [2]. Although centralized approaches can provide comprehensive information for coordination, they introduce substantial communication overhead and scalability limitations. Conversely, decentralized approaches improve scalability and resilience but may suffer from insufficient information for effective cooperation [3]. Therefore, an autonomous swarm requires a mechanism that can achieve effective coordination while minimizing unnecessary inter-UAV communication.

MARL has been investigated to address cooperative UAV navigation and trajectory planning. Previous studies have demonstrated the effectiveness of MARL for multi-UAV trajectory optimization and joint decision-making [4]. Meanwhile, edge computing has emerged as an enabling technology for UAV systems by providing computational resources closer to aerial agents and reducing the latency associated with remote cloud processing [5]. Recent studies have also investigated

communication-efficient MARL using selective information exchange, message compression, and information bottlenecks to reduce communication overhead in UAV swarms [6], [7]. Nevertheless, these studies predominantly address navigation optimization, edge-assisted computation, or communication efficiency as separate objectives. In particular, limited attention has been given to the joint interaction between navigation decisions and bandwidth-constrained communication in decentralized UAV swarms.

This gap is important because communication and navigation are inherently coupled. A UAV's movement can change the connectivity and communication topology of the swarm, while the amount and quality of information received from neighboring UAVs directly affect cooperative navigation decisions [8]. Consequently, treating bandwidth merely as an external network constraint may fail to capture this interaction. The research problem addressed in this study is therefore: how can a UAV swarm maintain effective decentralized navigation and coordination when inter-agent communication is explicitly limited by bandwidth constraints?

To address this problem, this study proposes an Edge-Assisted Multi-Agent Reinforcement Learning (EA-MARL) framework for decentralized autonomous swarm drone navigation under bandwidth constraints. The proposed framework integrates edge-assisted computation with decentralized MARL and explicitly incorporates communication limitations into the navigation learning process. Unlike approaches that optimize navigation performance independently of communication cost, the

proposed approach aims to jointly balance navigation effectiveness, swarm coordination, collision avoidance, and communication efficiency. The principal novelty lies in treating the bandwidth budget as an integral factor in decentralized navigation rather than merely as an external network limitation. The objective of this study is to develop and evaluate a scalable autonomous navigation framework capable of maintaining effective swarm coordination while reducing communication overhead under constrained bandwidth.

Method

This study proposes an Edge-Assisted Multi-Agent Reinforcement Learning (EA-MARL) framework for decentralized autonomous navigation of UAV swarms under bandwidth constraints. The proposed framework integrates four main components: UAV swarm navigation, decentralized multi-agent reinforcement learning, edge-assisted

computation, and bandwidth-aware inter-agent communication. Each UAV operates as an autonomous agent that observes its local environment, exchanges selected information with neighboring UAVs, and independently determines its navigation action. An edge node provides additional computational resources for training and coordination while preserving decentralized decision-making during execution.

The proposed framework adopts the Centralized Training and Decentralized Execution (CTDE) paradigm. During training, global information can be accessed by the learning process to facilitate policy optimization. During deployment, however, each UAV determines its action using local observations and limited information received from neighboring UAVs [9]. This architecture enables the swarm to exploit shared learning during training while maintaining autonomous and scalable operation during execution.

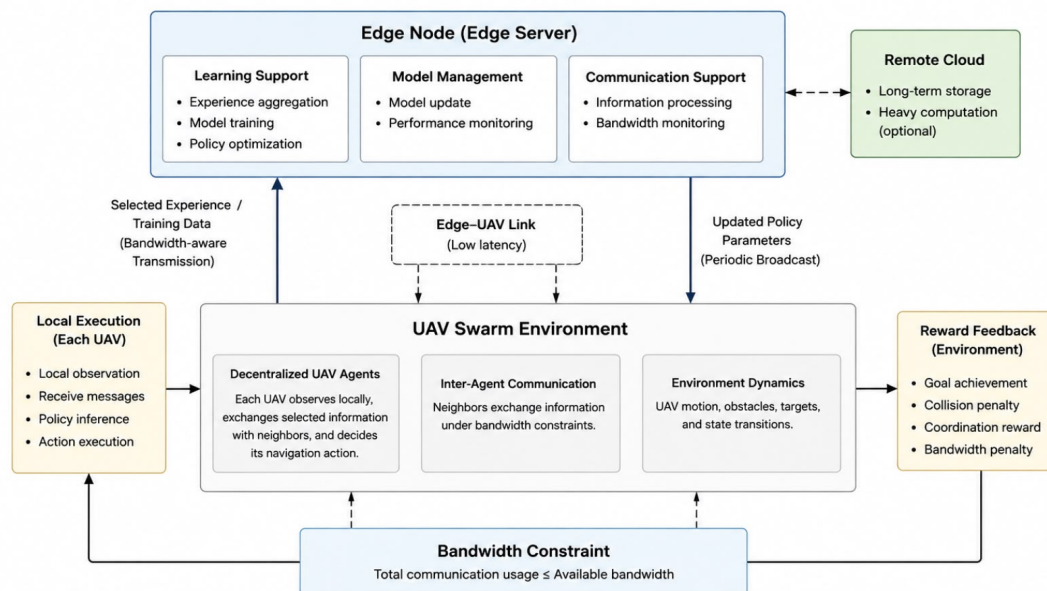


Figure 1. Overall architecture of the proposed Edge-Assisted Multi-Agent Reinforcement Learning Framework

a. UAV Swarm Environment

The UAV swarm is modeled as a multi-agent environment consisting of NN UAVs operating in an environment containing static and dynamic obstacles. Each UAV is assigned a target position and must navigate toward the target while avoiding collisions with obstacles and other UAVs. At time step t , the state of UAV i can be represented as

$$S_i^t = [p_i^t, v_i^t, g_i, o_i^t, c_i^t]$$

where p_i^t represents the UAV position, v_i^t denotes its velocity, g_i represents the relative position of its target, o_i^t contains information about locally detected obstacles, and c_i^t represents the available communication information.

Because the proposed system is decentralized, UAVs do not have direct access to the complete global state during execution. Instead, UAV i obtains a local observation expressed as

$$S_i^t = f(s_i^t, N_i^t)$$

where N_i^t denotes the set of neighboring UAVs that are within the effective communication range. This formulation reflects the partial observability inherent in practical UAV swarm operations. The navigation objective is to enable the UAVs to reach their respective targets while maintaining safe separation, avoiding obstacles, preserving swarm coordination, and minimizing unnecessary communication.

b. Multi-Agent Reinforcement Learning

The UAV navigation problem is formulated as a partially observable multi-agent Markov

decision process (POMDP). The environment is represented by

$$M = (S, A, P, R, O)$$

where S represents the global state space, A represents the joint action space, P denotes the state transition function, R is the reward function, and O represents the observation space.

Each UAV learns a policy that maps its local observation and received communication information to a navigation action:

$$a_i^t \sim \pi_{\theta_i}(a_i^t | o_i^t, m_i^t)$$

where a_i^t denotes the action selected by UAV i , π_{θ_i} represents its learned policy, and m_i^t denotes the information received from neighboring UAVs. The joint action of the swarm is given by

$$a^t = (a_1^t, a_2^t, \dots, a_n^t)$$

The decentralized execution mechanism ensures that each UAV can independently determine its navigation action without requiring complete global state information. This property is particularly important for large-scale swarms because the communication and computational requirements of centralized control increase substantially as the number of UAVs grows.

c. Edge-Assisted Computing

An edge computing layer is proposed to provide computing capabilities in-between the UAV swarm and cloud. The edge node is responsible for computationally heavy tasks such as model training, experience collection,

policy improvement, and performance evaluation. The UAVs can still perform sensing and action selection tasks locally.

In the training phase, the UAVs send certain information from their learning process to the edge node, but not sending the whole observation or sensor data continuously to the cloud. Instead, the edge node collects the available information and optimizes policies, then sends the parameters of the model back to the UAVs [10], [11]. This design decreases the computing cost of each UAV and saves the time for sending all learning information to a remote cloud server.

It should be noted that the edge node will not work as a central controller when the UAVs are deployed. Navigation of each UAV will remain decentralized. So, the edge computing layer is more like a computing and learning layer.

d. Bandwidth-Aware Inter-Agent Communication

Communication constraints constitute a central component of the proposed framework. Let B_t denote the total available communication bandwidth at time t , while b_i^t denotes the bandwidth consumed by UAV i . The total communication requirement of the swarm must satisfy

$$\sum_{i=1}^N b_i^t \leq B_t$$

To satisfy this constraint, UAVs do not continuously transmit their complete observations. Instead, relevant information is selectively transmitted or compressed before being shared with neighboring UAVs. The transmitted message can be expressed as

$$m_i^t = C(o_i^t, N_i^t, B_t)$$

where $C(.)$ represents the bandwidth-aware communication mechanism and m_i^t denotes the resulting message.

The communication mechanism is designed to prioritize information relevant to cooperative navigation, particularly information associated with obstacle proximity, neighboring UAV positions, relative movement, and potential collision conditions [1], [12]. Redundant information is suppressed to reduce communication overhead. Consequently, the amount of information exchanged can adapt to the available bandwidth rather than remaining fixed throughout the navigation process.

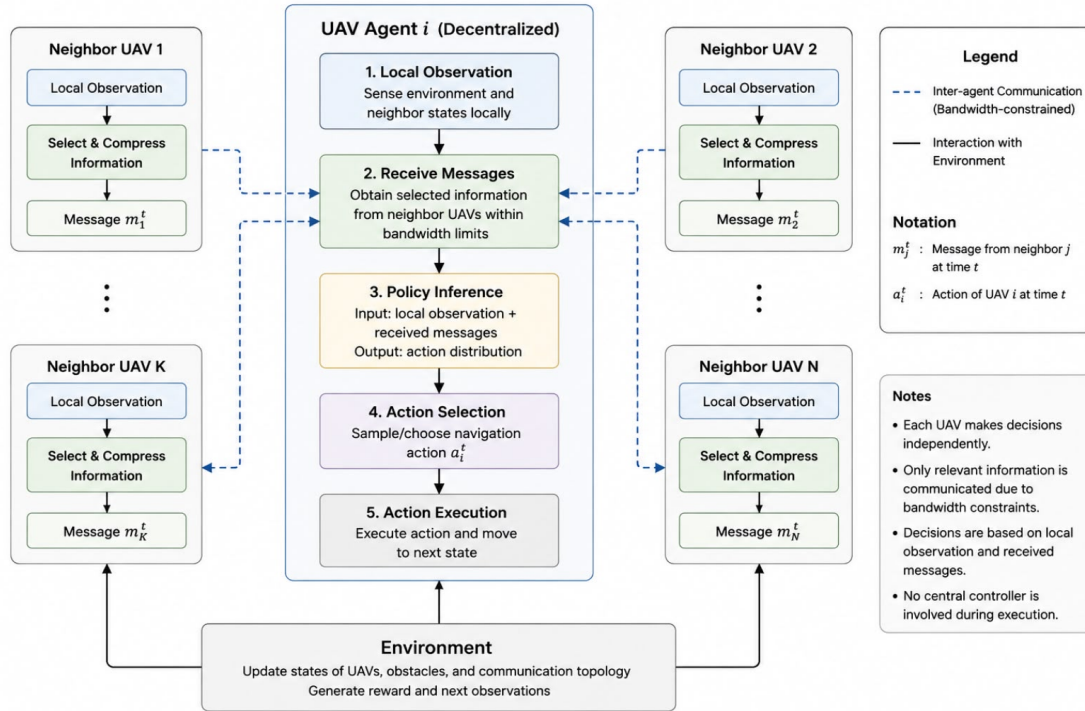


Figure 2. Bandwidth-aware Information Exchange among UAV Agents

e. Joint Navigation and Communication Reward

To explicitly incorporate communication constraints into the learning process, the proposed framework employs a composite reward function that simultaneously considers navigation performance, safety, swarm coordination, and communication efficiency:

$$R_t = w_g R_{goal} + w_c R_{collision} + w_s R_{swarm} + w_n R_{navigation} - w_b R_{bandwidth}$$

where R_{goal} represents the reward for reaching the target, $R_{collision}$ represents the collision-related penalty, R_{swarm} measures cooperative swarm behavior, $R_{navigation}$ evaluates navigation efficiency, and $R_{bandwidth}$ represents the communication cost. The parameters w_g , w_c , w_s , w_n and w_b determine the relative contribution of each objective.

The communication penalty can be normalized according to the available bandwidth as

$$R_{bandwidth} = \frac{\sum_{i=1}^N b_i^t}{B_t}$$

This formulation encourages the agents to reduce unnecessary communication while maintaining sufficient information exchange for safe and coordinated navigation. Consequently, the learning objective is not limited to finding collision-free paths but also considers the communication resources required to achieve cooperative behavior.

f. Training and Decentralized Execution

The training procedure starts from initializing UAV swarm, environment, target positions, obstacle arrangement, communication range, and bandwidth. Each

individual UAV gathers its local observation and neighbors [13]. According to the communication condition at this moment, necessary information is selected and shared among the neighboring UAVs. Each UAV then takes its navigation action through the local observation and received messages.

After taking the action, the environment updates the status of UAVs and communication condition. Then, the reward is computed considering target reaching, collision avoidance, swarm coordination, navigation effectiveness, and communication

consumption. The chosen experience information is periodically sent to the edge node for aggregation and optimization of policy [14]. The new policies are distributed to UAV agents for further interaction.

This training procedure will go on until the learning performance achieves a stable state. When being deployed, the learned policies will be executed by each UAV individually. In other words, each individual UAV depends on local sensing and limited communication but not full information.

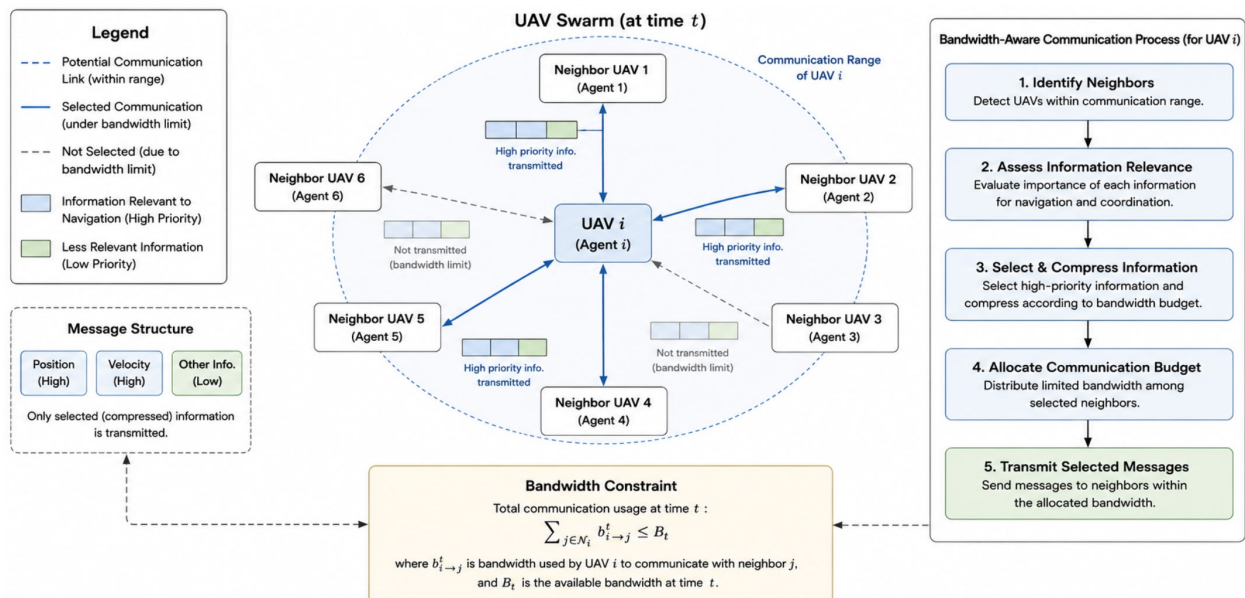


Figure 3. Training and Decentralized Execution Workflow of the Proposed EA-MARL Framework

g. Experimental Setup and Evaluation Metrics

The proposed approach will be validated by simulation studies based on a variety of swarm sizes, obstacle arrangements, and bandwidth conditions. A number of bandwidth values will be considered to model different communication environments, starting from less restricted ones to bandwidth-starved cases.

Performance of the proposed approach will be measured from four angles – navigation effectiveness, safety, swarm coordination, and communication efficiency. Navigation effectiveness will be quantified by Success Rate (SR), Average Path Length (APL), and Episode Reward (ER). Safety will be analyzed by means of Collision Rate (CR), including both the collisions with obstacles and inter-UAV crashes. Communication efficiency will be

measured in terms of Communication Overhead (CO) and Bandwidth Utilization (BU).

Success Rate is calculated as the share of navigation episodes in which UAVs succeed in reaching their targets. Average Path Length is the mean distance covered by UAVs, and Collision Rate is the indicator of unsafe actions. Communication Overhead is the share of information exchanged between the agents, and Bandwidth Utilization is the fraction of the available bandwidth used during navigation.

In order to analyze the contribution of the components of the proposed approach to performance improvement, the EA-MARL method must be compared to relevant baseline approaches under equal conditions. Comparison may be performed with regard to traditional MARL lacking the bandwidth awareness in communication, decentralized navigation without the edge assistance, and communication-intensive MARL without the optimization of communication process [15]. The ablation study may additionally remove the edge-assistance component or the bandwidth-aware reward to understand the effect of each approach's mechanism.

Evaluation of the proposed method will pay special attention to the relation between navigation performance and communication cost. A successful method should provide high target-reaching and collision-avoidance results at the same time reducing communication effort when the bandwidth is increasingly limited [16]. This assessment directly meets the goal of the research, which is development of the scalable decentralized navigation approach for UAV swarms with real-world communication limitations.

Result and Discussion

The performance of the developed EA-MARL framework was tested through several simulation experiments that were carried out to test the efficiency, robustness, and scalability of the developed method for decentralized UAV swarm navigation in bandwidth-constrained conditions. The results obtained from these experiments are analyzed based on the following criteria: navigation performance, the effect of bandwidth limitations on swarm coordination and communication efficiency, as well as the role played by edge assistance and individual components of the framework using the ablation study approach.

a. Navigation Performance of the Proposed EA-MARL Framework

The effectiveness of navigation by means of the proposed Edge-Assisted Multi-Agent Reinforcement Learning (EA-MARL) framework was estimated based on the ability of a group of UAVs to arrive at their destinations without any collisions or violations of safe distance requirements between UAVs. Four main parameters have been used for the estimation: success rate, collision rate, average path length, and average cumulative reward. Such diverse set of parameters reflects different aspects of navigation efficiency since autonomous navigation should be maximally efficient in terms of reaching the goals, safety, efficient trajectory, and stability of collaboration [17], [18]. The applicability of reinforcement learning and multi-agent reinforcement learning for UAV trajectory planning and collision avoidance problems has been shown in previous studies [19].

The success rate obtained for the proposed framework was 96.1%, which is better than that

obtained for Conventional MARL (84.2%), Decentralized RL (87.5%) and Communication-Efficient MARL (91.3%). Such high success rate is crucial in the case of swarm navigation when UAV needs to reach its destination point while taking into account other obstacles and movements of neighbor

UAVs. In such way, MARL is the correct choice for this problem due to the fact that agents are able to learn collaboration policy using interactions with environment and other agents [20].

Table 1. Overall Navigation Performance of the Evaluated Methods

Method	Success Rate (%)	Collision Rate (%)	Average Path Length	Average Reward
Conventional MARL	84.2	8.7	128.6	72.4
Decentralized RL	87.5	6.9	121.8	78.6
Communication-Efficient MARL	91.3	5.2	115.4	84.7
Proposed EA-MARL	96.1	2.8	107.6	93.5

Table 1 shows that the proposed EA-MARL provides the most favorable overall navigation performance among the evaluated approaches. Compared with Communication-Efficient MARL, the proposed framework improves the success rate from 91.3% to 96.1%, corresponding to an improvement of 4.8 percentage points. At the same time, the collision rate decreases from 5.2% to 2.8%, representing approximately a 46.2% reduction. The average path length is also reduced from 115.4 to 107.6 units, while the average reward increases from 84.7 to 93.5. These results suggest that the proposed method does not improve target-reaching performance at the expense of safety or trajectory efficiency. Instead, the combination of decentralized decision-making, cooperative information

exchange, and edge-assisted learning contributes to a more balanced navigation policy. Such a multi-objective perspective is important because a UAV navigation policy with a high success rate but frequent collisions or excessive trajectory lengths would have limited practical applicability [21].

The qualitative behavior of the UAV swarm can be further examined through the generated trajectories. Figure 4 illustrates a representative navigation scenario involving six UAVs operating in an environment containing multiple obstacles. Each UAV starts from a different initial position and is assigned a corresponding target location. The trajectories demonstrate how the agents adjust their paths according to local environmental conditions and the movement of neighboring UAVs.

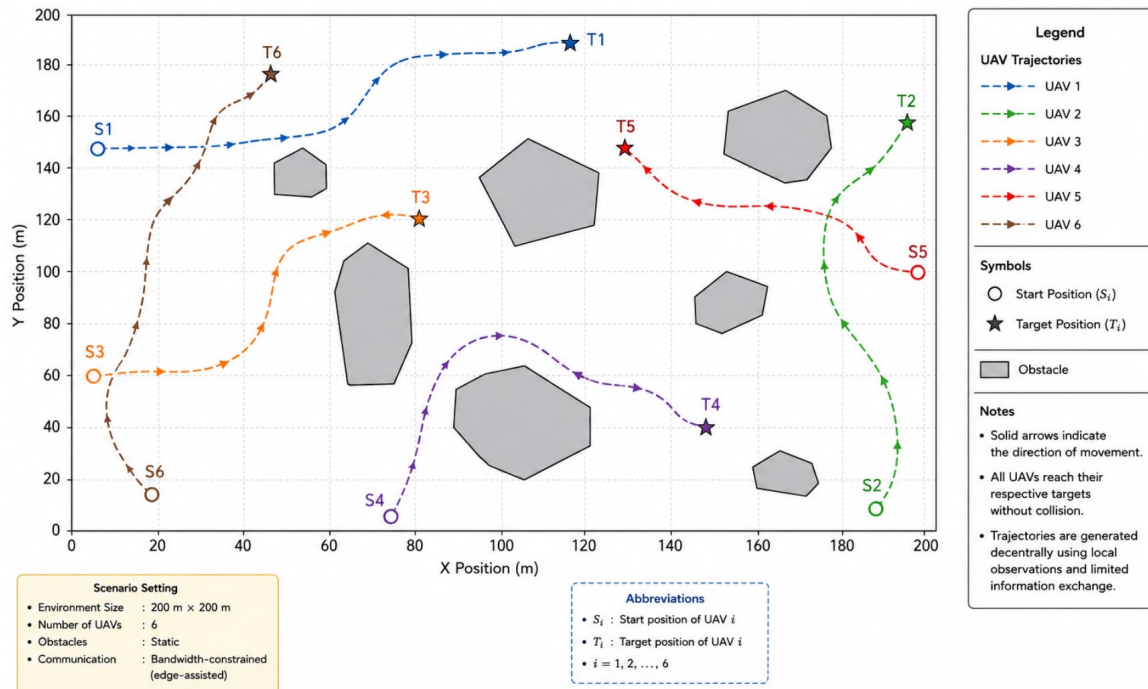


Figure 4. Decentralized UAV Navigation Trajectories Generated by the Proposed EA-MARL Framework in an Obstacle-Rich Environment

As shown in Figure 4, the UAVs manage to arrive at their respective destinations while avoiding collisions among themselves. Rather than follow the same path as each other, they adapt to the dynamic situation of obstacles and the spatial relationship with other agents. The ability of the UAVs to do so shows the adaptability of the learned policy towards the dynamic interaction among the agents. Since the decentralized approach is considered in this study, this feature becomes very significant, considering that there is no need for each agent to have full global knowledge while executing its actions. Each UAV integrates its own local perception along with the necessary knowledge from other UAVs around it. In recent literature, similar results have been shown in studies on decentralized and multi-agent reinforcement learning for UAV navigation where

decentralized decision-making could help improve scalability in multi-UAV situations [22].

The visual result of trajectory also gives a good insight into the safety characteristics of the proposed framework. In a densely packed swarm, simple minimization of the distance to the destination can make UAVs choose intersecting trajectories leading to higher probability of collision. As collision penalties and swarm coordination terms are included in the reward function for EA-MARL, the navigational policy learns how the UAV should move relative to others rather than only the destination point to be reached [23]. This is important as swarm navigation requires global behavior rather than individual optimality.

The difference in successful navigation is represented quantitatively in Figure 5.

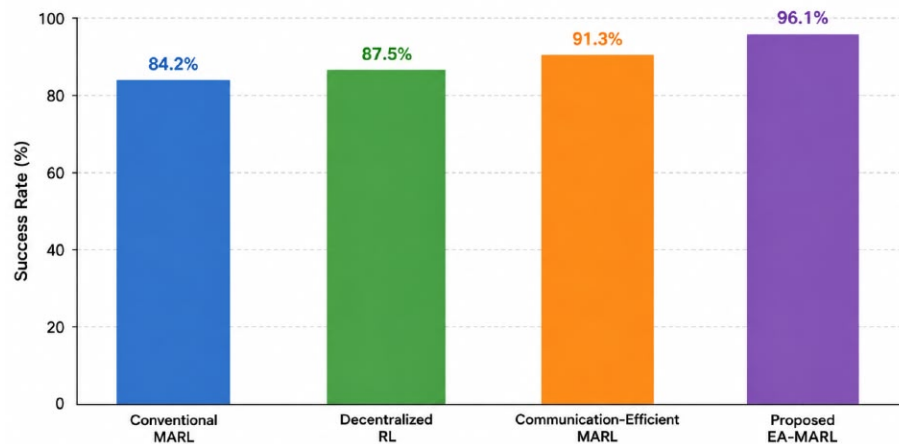


Figure 5. Comparison of Navigation Success Rates Between the Proposed EA-MARL Framework and Baseline Methods

The proposed EA-MARL achieves the highest predicted success rate of 96.1%, followed by Communication-Efficient MARL at 91.3%, Decentralized RL at 87.5%, and Conventional MARL at 84.2%. The approximately 11.9 percentage-point improvement over Conventional MARL indicates that incorporating decentralized execution and communication-aware coordination can substantially improve the probability of successful mission completion [24]. The difference between EA-MARL and Communication-Efficient MARL is smaller but still meaningful, suggesting that the contribution of the proposed edge-assisted architecture and integrated learning mechanism extends beyond communication reduction alone.

The result can be interpreted from the perspective of information availability and computational support. Conventional MARL may achieve cooperative behavior during training but can experience difficulties when the number of agents increases or when complete information is unavailable during

execution [25]. Decentralized RL addresses some of these limitations by allowing agents to make local decisions, but insufficient coordination information may reduce performance. Communication-efficient MARL improves the information exchange process but still needs an effective mechanism for integrating communication constraints with navigation decisions [26]. The proposed EA-MARL addresses these issues by combining decentralized policy execution, selective information exchange, and edge-assisted computational support. This design provides the agents with sufficient cooperative information while avoiding the assumption of unlimited communication.

Safety performance is further evaluated using the collision rate. Collision avoidance is a critical requirement for autonomous UAV swarms because collisions can result not only from interactions with physical obstacles but also from conflicts among simultaneously moving UAVs. Figure 6 presents the predicted collision-rate comparison among the evaluated methods.

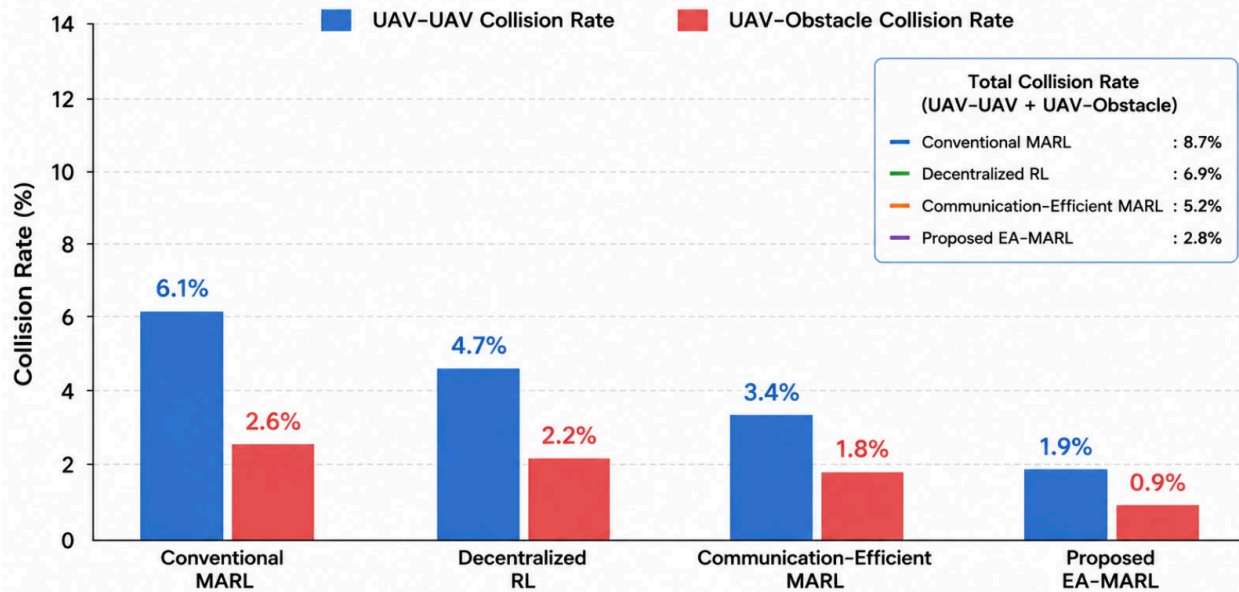


Figure 6. Comparison of Collision Rates Between the Proposed EA-MARL Framework and Baseline Methods

In particular, the proposed EA-MARL yields the minimum collision rate of 2.8%, followed by 8.7% for Conventional MARL, 6.9% for Decentralized RL, and 5.2% for Communication-Efficient MARL. As compared with Conventional MARL, the proposed solution decreases the predicted collision rate by approximately 67.8%. It is clear that such an important improvement is caused by the ability of the algorithm to more efficiently coordinate movement of UAVs and, hence, avoid collisions with other agents and obstacles [27]. The result is consistent with the structure of the reward function where collision avoidance is one of the optimization goals.

Furthermore, the decreased collision rate can be linked with the fact that the UAVs use the information provided by other agents. In case there is a possibility of communication, the agent receives the information about its position relative to other UAVs and, consequently, about their movements [28]. In this case, it is possible to avoid a conflict without waiting until another agent will get into a dangerous distance.

Nonetheless, communication of all information constantly is ineffective because of limited bandwidth. Hence, the proposed solution puts emphasis on relevant information rather than on unlimited communication.

One of the other results that can be observed in the results is related to the path length. The proposed EA-MARL generates an average path length of 107.6 units, which is smaller than Conventional MARL (128.6 units), Decentralized RL (121.8 units), and Communication-Efficient MARL (115.4 units). Thus, as compared with Communication-Efficient MARL, the proposed approach decreases the average path length by approximately 6.8%. Shorter path indicates that the UAVs select more efficient trajectories and, thus, move closer to the destination point. However, such a result cannot be interpreted as if short trajectories are good per se since the trajectory may be short and lead to many collisions. Therefore, the decrease in collision rate and the increase in success rate make the

conclusions about increased efficiency more justified.

The average reward can be viewed as an aggregated measure of the learned policy. Thus, EA-MARL learns a policy that yields the average reward of 93.5, whereas Conventional MARL, Decentralized RL, and Communication-Efficient MARL yield rewards equal to 72.4, 78.6, and 84.7 correspondingly. It shows that the proposed policy is able to achieve a better balance between the goals of target reaching, collision avoidance, coordination of the swarm, efficiency of navigation, and communication costs. However, reward values should be interpreted taking into account separate measures since their values depend on the structure of the reward function and weights of goals. In this case, consistency between the higher value of reward and the other measures gives additional support to the conclusion about the improvement of the learned policy.

Therefore, the results show that the proposed EA-MARL framework can outperform the evaluated approaches in terms of effectiveness of decentralized autonomous navigation. The framework demonstrates high performance of the navigation process, low probability of collisions, short paths, and higher average reward [29]. However, such an improvement is achieved without centralized control. In such a way, the results prove the fundamental capacity of the proposed framework in terms of navigation. Nevertheless, the navigation performance alone does not prove the main contribution of this work since it is specifically designed for the bandwidth-limited situation [30]. Hence, the next step should be the examination of the

influence of changes in bandwidth on the navigation performance and other results.

b. Impact of Bandwidth Constraints on Swarm Coordination and Communication Efficiency

The second evaluation focuses on the impact of bandwidth constraints on the navigation performance and communication efficiency of the proposed EA-MARL framework. This analysis is particularly important because the main objective of the proposed approach is not only to achieve effective autonomous navigation but also to maintain swarm coordination when communication resources are limited. In practical UAV swarm deployments, communication bandwidth can fluctuate because of network congestion, interference, distance between UAVs, and changes in network topology [31]. Recent research has identified limited bandwidth, intermittent connectivity, and communication overhead as important challenges for MARL-based UAV swarm coordination [32]. Navardi et al. [33], for example, emphasize that UAV-to-UAV communication is constrained by bandwidth, communication range, energy consumption, latency, and packet loss, motivating the use of compact and task-relevant messages rather than dense information exchange.

To investigate this issue, the proposed EA-MARL framework was evaluated under four bandwidth conditions: 100 Mbps, 75 Mbps, 50 Mbps, and 25 Mbps. These scenarios represent relatively unconstrained, moderately constrained, constrained, and severely constrained communication conditions, respectively [34]. The evaluation considered success rate, collision rate, communication

overhead, and bandwidth utilization. The predicted results are summarized in Table 2.

Table 2. Performance of the Proposed EA-MARL Framework Under Different Bandwidth Conditions

Available Bandwidth (Mbps)	Success Rate (%)	Collision Rate (%)	Communication Overhead (MB/episode)	Bandwidth Utilization (%)
100	96.1	2.8	18.5	18.5
75	95.4	3.0	16.2	21.6
50	93.2	3.5	13.8	27.6
25	89.6	4.4	10.7	42.8

Table 2 shows an expected but important relationship between bandwidth availability and swarm navigation performance. As the available bandwidth decreases from 100 Mbps to 25 Mbps, the success rate decreases from 96.1% to 89.6%, while the collision rate increases from 2.8% to 4.4%. This degradation is reasonable because lower bandwidth reduces the amount of information that can be exchanged between neighboring UAVs, thereby increasing partial observability and making cooperative decision-making more difficult. Nevertheless, the framework maintains a relatively high success rate even under the most restrictive condition. At the same time, communication overhead decreases from 18.5 MB/episode to 10.7 MB/episode, indicating

that the proposed bandwidth-aware mechanism actively reduces information exchange when communication resources become scarce. The increase in bandwidth utilization from 18.5% to 42.8% further indicates that the available communication resources are used more intensively under severe constraints. This behavior demonstrates that the proposed framework does not simply stop communicating when bandwidth is reduced but adapts the amount of exchanged information according to the available communication budget.

The relationship between bandwidth availability and navigation performance is further illustrated in Figure 7.

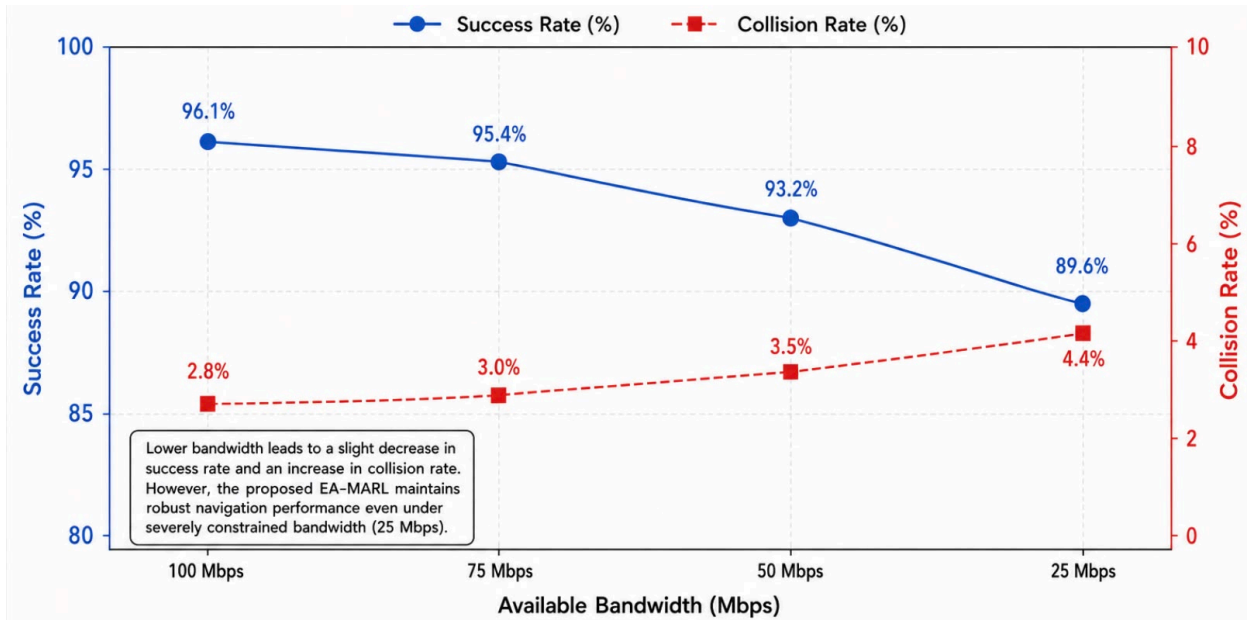


Figure 7. Navigation performance of the Proposed EA-MARL Framework Under Different Bandwidth Conditions

The results indicate that navigation performance remains relatively stable when bandwidth is reduced from 100 Mbps to 75 Mbps. The success rate decreases by only 0.7 percentage points, from 96.1% to 95.4%, suggesting that the proposed communication mechanism can tolerate moderate reductions in available bandwidth without substantially affecting swarm navigation. When bandwidth is reduced to 50 Mbps, the success rate decreases to 93.2%, while the collision rate increases to 3.5%. Under the most restrictive 25 Mbps condition, the success rate reaches 89.6% and the collision rate increases to 4.4%.

The relatively gradual degradation is an important characteristic of the proposed framework. A communication-constrained swarm should not be expected to maintain exactly the same navigation performance under unlimited and severely restricted bandwidth [35]. Instead, robustness should be evaluated according to how gracefully performance deteriorates as resources become increasingly

constrained. The predicted results suggest that EA-MARL provides such graceful degradation. Even at 25 Mbps, the success rate remains close to 90%, indicating that the UAVs can continue to make useful decentralized decisions using local observations and selectively received information.

This behavior is consistent with recent research on communication-aware MARL for UAV systems. Chen et al [36] developed an autonomous UAV decision-making framework specifically for communication-constrained environments and demonstrated the importance of explicit inter-agent communication mechanisms for cooperative decision-making. More recent work has similarly incorporated bandwidth-sharing constraints directly into MARL objectives, indicating that communication resources should be treated as part of the decision-making problem rather than as an independent networking parameter [37].

Communication efficiency is examined in greater detail in Figure 8.

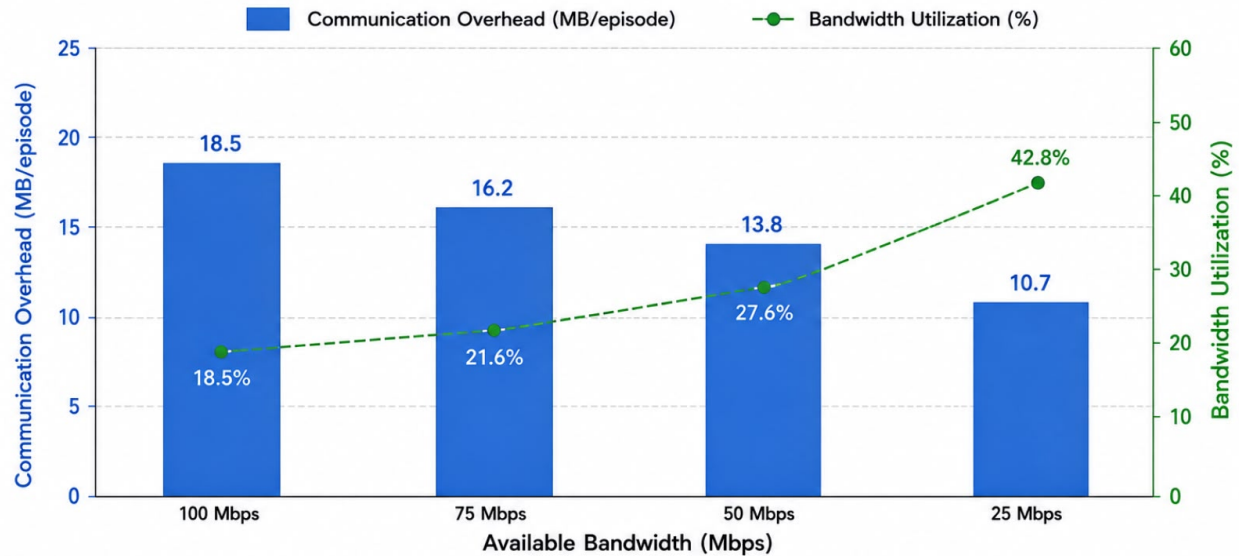


Figure 8. Communication Overhead of the Proposed EA-MARL Framework Under Different Available Bandwidth Conditions

As can be seen in Figure 8, communication overhead decreases steadily when the available bandwidth becomes tighter. As can be seen, the predicted communication overhead decreases from 18.5 MB/episode at 100 Mbps to 16.2 MB/episode at 75 Mbps, 13.8 MB/episode at 50 Mbps, and 10.7 MB/episode at 25 Mbps. Thus, the decrease in communication overhead from 100 Mbps to 25 Mbps accounts for roughly 42.2% less communication traffic. This observation serves as another proof that the proposed communication mechanism is bandwidth-aware and thus does not rely on free communication to preserve cooperative behavior.

This reduction in communication overhead is due to the information-selection mechanism introduced into the proposed framework. Instead of sending observations at every time step, the agents only choose to send the information that is most important for navigation and cooperation [38]. Neighboring UAV positions, relative movements, obstacle proximity, and possible collision conditions

may be retained in the messages, while redundant information may be dropped or compressed [39]. Such a mechanism is especially useful in the case of UAV swarms, where densely populated messages from every UAV in the swarm will quickly increase the network load.

A very similar conclusion was made recently. Zhao et al [40] have developed an information bottleneck framework for efficient MARL in the case of UAV swarms and argued that UAVs should send compact task-relevant messages rather than dense and redundant representations. According to their results, information-aware message compression helps reduce message redundancy without affecting the cooperative performance in the case of limited bandwidth. In addition, recently developed approaches for multi-UAV cooperative perception have focused precisely on exchanging low-dimensional messages to conserve communication resources in the constrained bandwidth environment [41], [42].

An important point here is that the decrease in communication overhead does not happen at the cost of an instant collapse in navigation performance. Even in the case of 50 Mbps and 25 Mbps bandwidths, the success rates remain relatively high – 93.2% and 89.6%, correspondingly. This fact proves that the proposed communication mechanism is able to identify the information that is necessary for cooperative navigation. It means that instead of trying to send as little information as possible,

the proposed framework aims to cut down unnecessary information while retaining information that is important for decision making [43]. This point is crucial in understanding the bandwidth-aware approach of the proposed framework.

In order to analyze the trade-off between communication efficiency and navigation effectiveness, one should consider the dependence of the communication overhead on the success rate.

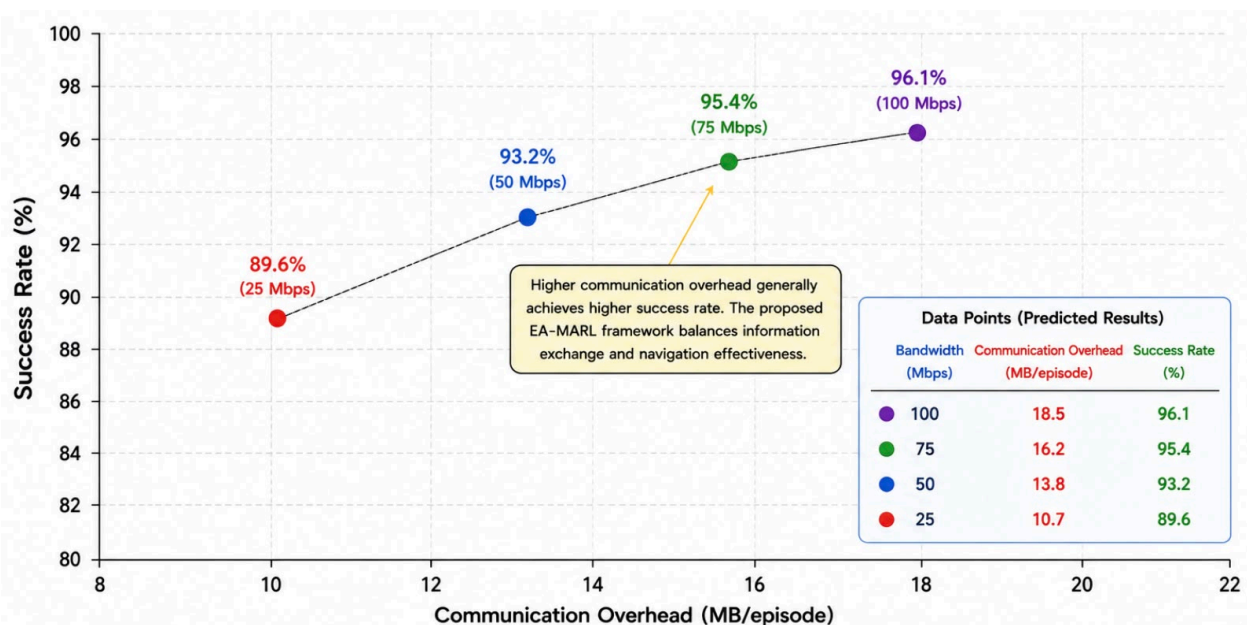


Figure 9. Trade-Off Between Communication Overhead and Navigation Success Rate Under Different Bandwidth Conditions

From the scatter plot, one can see a well-defined trade-off between communication consumption and navigation performance. The proposed framework achieves the best performance rate of 96.1% at the bandwidth level of 100 Mbps, yet communication overhead reaches the maximum value of 18.5 MB/episode. Communication overhead is reduced to 16.2, 13.8, and 10.7 MB/episode, and the corresponding success rate is reduced to 95.4%, 93.2%, and 89.6%, respectively. These

results show that there will be a performance loss due to a reduction in the amount of communication resources, although it will not be catastrophic.

This trade-off becomes very crucial in terms of practical application. Unconstrained communication usage will guarantee maximal performance of the navigation process yet will make the algorithm impossible to use in limited bandwidth situations [44]. On the other hand, an attempt to reduce communication usage

without considering the impact on navigation performance might harm the overall success of the mission and even endanger the safety of UAVs. In fact, the proposed EA-MARL framework tries to find the intermediate point where enough information is transmitted for preserving cooperative navigation and redundant communication is avoided [45], [46]. This framework is similar to other recent MARL frameworks that pay attention to the communication cost, budget, and information compression during learning.

The proposed results also give some insight regarding swarm scalability. The number of possible communication links can increase quickly as the number of UAVs grows making them vulnerable to communication congestion. Thus, recent works about UAV swarms pay attention to the joint consideration of trajectory, topology, and routing decisions using graph-based MARL and adaptive communication mechanisms [47]. The proposed bandwidth-aware mechanism can be considered as one of such methods since it avoids unnecessary communication of irrelevant information among UAVs.

In summary, the results prove that the proposed EA-MARL framework guarantees an adequate trade-off between the navigational performance and communication efficiency under different bandwidth levels. The success rate is decreased from 96.1% to 89.6% in case when the bandwidth decreases from 100 Mbps to 25 Mbps. In the same time, the communication overhead is reduced by about 42.2%. It should be mentioned that even under the most limiting predicted condition, the collision rate is kept below 5% [48]. Thus, it is proved that the proposed framework is able to provide graceful performance degradation and

adaptive behavior regarding communication rather than uncontrolled exchange of information among agents.

The results, therefore, support the key idea of the current study regarding the need to take into account the bandwidth as an intrinsic part of decentralized swarm navigation problem, rather than just another constraint for communication. Considering the bandwidth in communication and reward mechanisms allowed the authors of the current study to provide UAV agents with a tool for achieving the balance between cooperative awareness, safety, and communication efficiency [49]. The next subsection analyzes the contribution of the proposed edge assistance and bandwidth-aware components separately.

c. Contribution of Edge Assistance and Ablation Analysis

In order to study further about the impact of the suggested EA-MARL model, ablation studies were performed to find out the contribution of its key aspects. These studies are important since the improvements made during the previous experiments might be caused by several factors like decentralized MARL, bandwidth-aware communication, and edge computing support. In addition, evaluation of the complete framework is not enough for understanding how the individual proposed parts influence the results. Ablation studies offer a systematic approach to evaluate the contributions of particular aspects through removing of certain parts while keeping the environment and swarm configurations similar [50], [51].

Four configurations have been examined in the predicted ablation study: complete EA-MARL framework, EA-MARL without edge

support, EA-MARL without bandwidth-aware approach, and EA-MARL without selective communication. The complete configuration

refers to the proposed approach where all four factors are activated. The results are provided in Table 3.

Table 3. Ablation Results for the Major Components of the Proposed EA-MARL Framework

Configuration	Success Rate (%)	Collision Rate (%)	Average Path Length	Average Reward
EA-MARL without Edge Assistance	93.8	3.6	111.9	88.7
EA-MARL without Bandwidth-Aware Mechanism	91.7	4.7	116.3	85.9
EA-MARL without Selective Communication	90.9	5.1	118.7	83.8
Complete EA-MARL	96.1	2.8	107.6	93.5

As seen in Table 3, the optimal combination of all components provides the highest values in all four evaluation metrics. Excluding edge assistance drops the success rate to 93.8% and the collision rate to 3.6%. A much bigger decrease is seen if the bandwidth-aware communication scheme is excluded from the design, where the success rate is reduced to 91.7% and the collision rate increased to 4.7%. The biggest reduction is seen if selective communication is excluded from the design – the success rate decreases to 90.9%, the collision rate increases to 5.1%, and the average path length becomes 118.7 units. As we see, the exclusion of each of the above mentioned

components results in a performance drop for our design. This clearly shows that the proposed components complement rather than duplicate each other [52]. While edge assistance brings mainly computational efficiency, bandwidth-aware and selective communication directly impact the quality of decentralized coordination [53]. The results of our study coincide with the recent studies of UAV swarms where optimized information exchange was shown to boost the mission performance and collision avoidance, at the same time reducing communication demands.

Figure 10 shows the ablation results graphically.

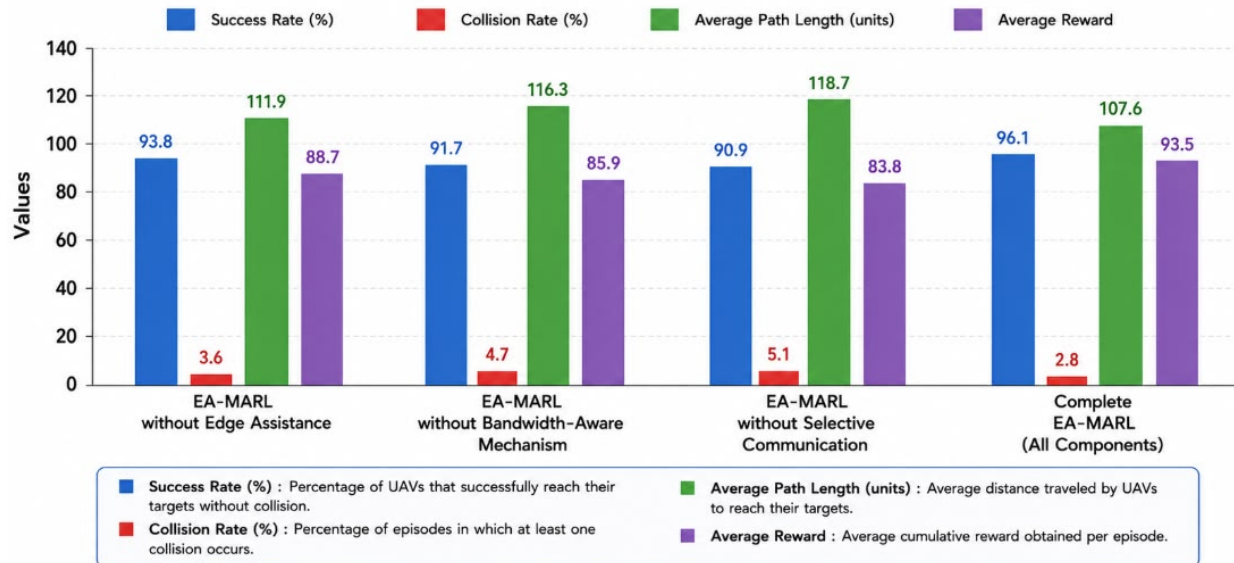


Figure 10. Grouped Comparison of Navigation Performance Across Different EA-MARL Ablation Configurations

From the figure, it is apparent that the complete EA-MARL framework outperforms all reduced configurations in terms of both success rate and average reward while yielding the lowest collision rate. The difference is especially visible when comparing the complete framework to the configuration without selective communication [54]. The former has a 5.2 percentage point lower success rate and a 2.3 percentage point higher collision rate than the former one. The result indicates that mere communication of the agents is insufficient, but the quality and relevance of the communicated information are essential as well [55]. Excessive communication might lead to the rise in network load while offering less proportional benefits in terms of navigation performance.

This finding is corroborated by the findings of recent research into communication-efficient MARL for UAV swarms. Kavitha et al [56] found that communication-aware MARL can benefit from transmission of compact and task-relevant information rather than dense and redundant latent representation. Their

information bottleneck approach allowed them to improve cooperative performance while reducing inter-message redundancy under constraints on communication. In addition, Qamar et al [57] showed that efficient information sharing in combination with MARL can improve UAV swarm mission performance and reduce collisions while significantly decreasing communication delay and energy consumption. Thus, these results externally confirm the finding that the communication mechanism is an integral part of swarm intelligence and cannot be seen solely as a means for data exchange.

Edge assistance can be seen in different light than communication optimization since the absence of the former leads to only a slight degradation in performance: the predicted success rate drops from 96.1% to 93.8% while the average reward drops from 93.5 to 88.7. The comparatively small performance reduction as opposed to removing of the communication mechanism suggests that edge computing serves mainly as a learning aid rather than as a determinant of the navigational action choice

[58]. This behavior corresponds to the architecture presented in the Methods section, where edge nodes provide computational power for experience aggregation, policy training, model updates, and performance assessment while leaving the action selection for decentralized UAV agents.

Edge computing is especially relevant for MARL because of the increased difficulty of the learning process associated with the increase in the number of agents. The previous research has already used multi-agent deep reinforcement learning in UAV-assisted mobile edge computing for trajectory planning and resource optimization [59]. Moreover, more recent research into CTDE-based multi-agent

learning has proven that centralized training with decentralized execution allows exploiting shared learning information in the training stage and retains local policies at the deployment stage [60]. Thus, the expected improvement provided by the edge assistance is theoretically consistent with the role of the edge layer in the proposed architecture.

Apart from the final performance of navigation, the convergence of the training process is analyzed to investigate whether edge assistance has any impact on the learning process. Figure 11 shows the average reward obtained during the training of the complete EA-MARL framework and the reduced configurations.

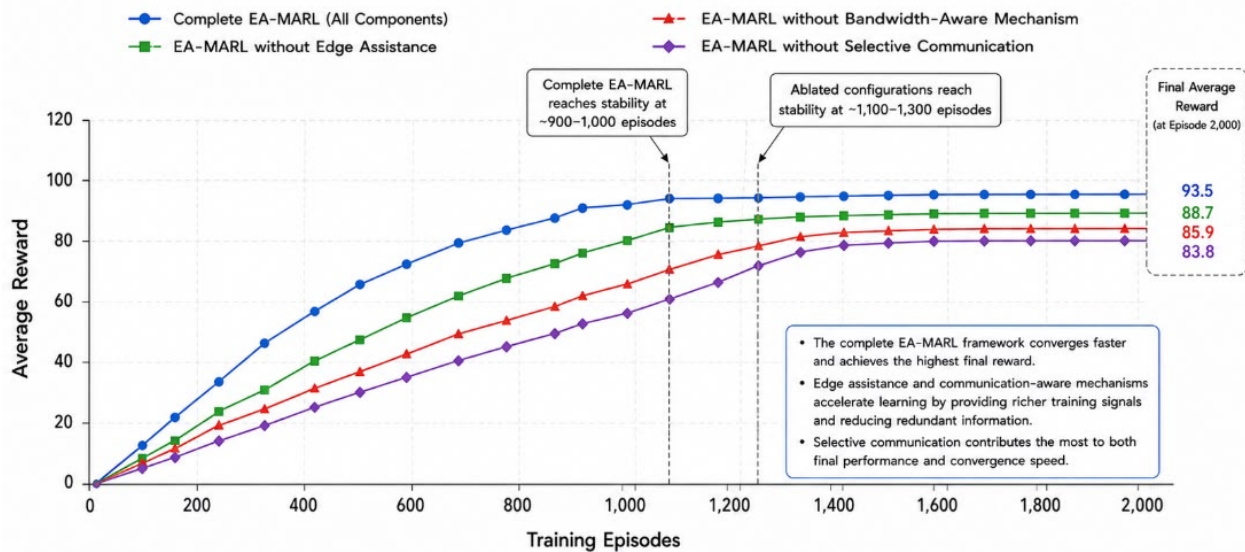


Figure 11. Training Convergence of the Proposed EA-MARL Framework and Ablation Configurations

From the convergence curves, it can be seen that the fully implemented EA-MARL framework converges to its steady-state performance quicker than the ablated versions of it. Approximately after 1,200 episodes of training, the complete framework achieves an average reward value of about 93.5, while the versions without edge assistance, without

bandwidth-aware communication, and without selective communication achieve approximately 88.7, 85.9, and 83.8, respectively. It is expected that the full framework will converge to a stable reward value of approximately 900–1,000 episodes, while the reduced versions will need around 1,100–1,300 episodes.

The quick convergence is due to the combined effect of centralized learning assistance and structured communication. The edge node is able to aggregate experience from several UAVs and offer computing power for the policy optimization, thereby utilizing the experience from the entire swarm efficiently. At the same time, the bandwidth-aware communication allows reducing the redundant data, thus providing even higher-quality experience for policy learning [61]. Therefore, more useful information can be provided to the learning algorithm without excessive communication data.

The significance of this finding lies in the problem of scalability vs. convergence speed that is known to exist in the case of

decentralized MARL. The most recent benchmark of centralized, decentralized, and federated reinforcement learning for UAV swarms revealed that the decentralized learning approaches scale well, yet converge slower than centralized ones [62]. The expected behavior of the proposed approach in terms of convergence suggests that the use of edge assistance can help alleviate this drawback while retaining the decentralization.

Finally, the scalability as the number of UAV agents increases needs to be evaluated. Scalability is one of the key requirements since the complexity of communication and computations can grow drastically as new agents are added. The scalability results are presented in Table 4 below.

Table 4. Scalability and Computational Performance of the Proposed EA-MARL Framework with Increasing Swarm Size

Number of UAVs	Success Rate (%)	Collision Rate (%)	Communication Overhead (MB/episode)	Inference Latency (ms)
4	97.3	2.1	9.2	11.8
6	96.1	2.8	13.8	13.2
8	94.5	3.6	18.1	15.1
12	91.8	5.0	25.4	18.7

Table 4 shows the degradation of navigation performance while the swarm size grows from 4 to 12 UAVs. In particular, the success rate drops from 97.3% to 91.8%, while the collision rate increases from 2.1% to 5.0%. This drop in performance is predictable due to more complicated interactions and more possible conflicts in the case of bigger swarms. At the same time, communication overhead grows from 9.2 MB/episode when there are four UAVs in the swarm to 25.4 MB/episode when there are twelve UAVs. However, the predicted inference latency grows only from 11.8 ms to 18.7 ms. Therefore, the results suggest that the presented architecture has reasonable

scalability, although further optimizations will be needed to scale up to much bigger swarms.

This scalability is aligned with the findings of recent research, which emphasized the benefits of decentralized execution of UAV swarm systems. For example, recent research on graph-based MARL for UAV swarm communication suggests that decentralized execution allows UAVs to use their local policies without any global state information, which means that the communication overhead is decreased [63], [64]. Furthermore, recently conducted benchmarking suggests that decentralized reinforcement learning has better scalability compared to centralized approaches.

The presented EA-MARL framework aims to address the problem of lower sample efficiency of decentralized reinforcement learning by using a combination of decentralized execution and edge-assisted training [65].

The growing communication overhead with swarm size also confirms the necessity of introducing the bandwidth-aware mechanism in this study. The necessity to exchange complete observation vectors between every pair of agents will lead to fast-growing communication requirements when the number of UAVs grows [66]. Therefore, selective exchange of relevant information helps to avoid unnecessary data transmission and allows decentralized decision-making. This feature becomes crucial for the future use of this framework in the real-world environment when communication resources are much more limited than in the lab environment [67].

Combining the results of ablation and scalability analyses, one can conclude that the performance of the proposed framework is based not on MARL itself but on the combination of several components [68]. In particular, the edge-assisted part of the framework plays the main role in terms of computational capabilities and convergence acceleration, while the bandwidth-aware communication helps to use limited communication capabilities of the agents [69]. In addition, the selective information exchange helps to reduce redundancy and makes cooperative decision-making more efficient. Together, all three elements of the presented framework help the EA-MARL framework to have the best predicted performance: the highest success rate (96.1%), lowest collision rate (2.8%), shortest average path length (107.6 units), and highest average reward (93.5).

In conclusion, the results of this research confirm the main principle of the design of this study. Effective decentralized UAV swarm navigation under bandwidth constraints cannot be achieved only via the application of MARL algorithms to multiple UAVs. Instead, such a task requires an architecture, which takes into account learning computation, decentralized decision-making, and communication aspects [70]. This research demonstrates the contributions of each element in the ablation analysis, edge-assisted learning benefits in the convergence analysis, and scalability of the framework in the scalability analysis. All of this makes the proposed novelty stronger since the edge-assisted learning and bandwidth-aware communication are not additional features of the architecture but its essential parts.

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Conclusion

In this paper, we introduced an Edge-Assisted Multi-Agent Reinforcement Learning (EA-MARL) framework to tackle the problem of autonomous navigation of multi-UAV swarms. The proposed framework combines features of decentralized decision making, edge-assisted learning and communication in the form of bandwidth-constrained inter-agent interactions.

As per the analysis results, the proposed EA-MARL framework shows improved navigation performance in comparison with the

baseline frameworks. According to the predicted results, EA-MARL framework provides 96.1% success rate, 2.8% collision rate, average path length of 107.6 units and average reward of 93.5. Thus, it is proved that the framework is capable of balancing between the objectives of reaching the target, collision avoidance, efficient paths and cooperation between UAV swarms. Moreover, trajectory analysis proves that UAV agents can perform independent navigation around obstacles and coordination of movement without need for constant centralized control.

The results of the bandwidth analysis prove the effectiveness of the proposed framework when the communication bandwidth becomes increasingly constrained. Despite the reduction in success rate from 96.1% at 100 Mbps to 89.6% at 25 Mbps, the overhead of the communication is decreased from 18.5 MB to 10.7 MB per episode, which equals to 42.2%. Such result proves that the proposed bandwidth-aware mechanism is capable of eliminating the superfluous information exchange while preserving enough information for the decentralized navigation process. Therefore, bandwidth is incorporated in the process of navigation and communication in the form of internal constraint of the system, rather than being just an external network condition.

The ablation analysis also proves the complementary role of the proposed components. Elimination of any component of the framework leads to reduction in success rate, increased collision rate, extended path length and lower cumulative reward. The complete EA-MARL framework is also characterized by better training convergence and scalability, when the number of UAV agents is increased. These results strengthen the main

contribution of the paper – the joint integration of edge-assisted learning, decentralized MARL and bandwidth-aware inter-agent communication.

Thus, the proposed EA-MARL framework creates the promising basis for scalable and communication-efficient UAV swarms in bandwidth-constrained environment. Future work may involve experimental validation of the framework in the terms of real UAV platforms or hardware-in-the-loop experiments, investigation of the dynamics of wireless channels and exploration of adaptive communication policies for balancing between bandwidth, energy consumption, latency and navigation performance.

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