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Comparative Analysis of Transfer-Learning-Enhanced PIO and Alliance-Based Formation Control in Multi-UAV Swarms

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Abstract:

This paper provides a comparative study of two state-of-the-art methods for coordinated control and swarm formation of unmanned aerial vehicles (UAVs). The first method uses a transfer learning-based, multi-objective optimization approach. In this approach, a hybrid Pigeon-Inspired Optimization (PIO) algorithm, combined with transfer learning (TL), enables dynamic UAV clusters to perform intelligent path planning, agent swapping, and global synchronization in complex 3D environments. The second approach is based on an alliance-based formation control strategy. It offers swarm robustness by dividing the UAV network into versatile subgroups driven by consensus laws and thus ensuring resilience in partial communication failures and dynamic topologies. Both methods are compared in this study in various aspects such as system modeling, communication strategy, fault tolerance, reconfiguration ability, optimization performance, and computational complexity. The analysis not only identifies the merits and limitations of each approach but also places them in the general research agenda of collective motion in multi-agent systems. The work concludes with the potential to integrate transfer learning and alliance-based resilience mechanisms into next-generation adaptive control architectures.

Keywords: *Comparative Analysis, Transfer Learning, Pigeon-Inspired Optimization.*

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have seen explosive growth in both military and civilian use, undertaking missions ranging from aerial photography and infrastructure inspection to search and rescue and environmental monitoring [1]. As UAV platforms have miniaturized and become less expensive, focus has shifted from single-vehicle operations to cooperative fleets, or swarms, of UAVs as multi-agent systems (MAS) [2]. By sharing information regarding detecting, routing, and mobility coordination with its neighbors, each UAV in a swarm helps achieve a common objective. Despite MAS's built-in benefits—redundancy, parallelism, and enhanced resilience-control, interaction, and real-time decision-making encounter challenging difficulties due to shifting environmental constraints.

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Intelligent path planning, which addresses multiple objectives at once, such as lowering journey duration, conserving energy, avoiding collisions and obstructions, and maintaining formation integrity, is a major difficulty in UAV swarm management [3-4]. To solve the aforementioned problems, many researchers have turned their attention to bio-inspired algorithms such as Ant Colony Optimization, Particle Swarm Optimization, and, most notably, Pigeon-Inspired Optimization (PIO). These algorithms are modeled after real collective behaviors like fish schools and bird flocks [5]. Despite its immense potential, PIO currently confronts issues with limited adaptability and sluggish convergence, particularly when UAV swarms are operating in unknown or constantly changing surroundings.

To address these limitations, the first selected article, "Intelligent Planning of UAV Herds via Transfer Learning and Multi-objective Optimization," presents a hybrid technique (TL-PIO) that combines PIO and transfer learning (TL) [6]. In a three-dimensional urban setting with impediments, TL-PIO expedites the search for the best formations and trajectories by drawing on previous mission experiences. The system manages multi-cluster switching and synchronization by simulating pigeon flocking behavior, and assures quick convergence, avoidance of local minima, and inter- UAV cohesiveness in three difficult circumstances. TL-PIO achieves up to 25% improvement over traditional methods and is also better at avoiding obstacles.

In contrast, the second selected study for this comparative analysis, “Collective Motion of Multi-objective Dynamic Agents based on Alliance-Based UAV Formation Control,” addresses the communication and resilience side of swarm coordination [7]. Recognizing that full connectivity to a single leader or extensive global communication can be impractical or fragile in large-scale deployments, the authors introduce an alliance-based scheme. Here, the swarm is partitioned into dynamically formed subgroups called alliances, each selecting a small subset of UAVs to interface with a virtual leader. Within each alliance, consensus-based control laws guide UAVs to maintain desired relative positions, while a feedback mechanism enables local correction when link failures or topology changes occur.

Though both TL-PIO and alliance-based control address collective UAV autonomy, they frame the issue from complementary sides: TL-PIO centers around learning-augmented optimization and 3D path-planning, while alliance-based control addresses communication robustness, consensus processes, and reconfiguration under limited connectivity. Neither class exclusively addresses the mixed requirements of dynamic urban scenes, changing link quality, and multi-objective mission objectives. This disconnect stimulates a comparative study to extract their individual strengths, discern areas of hybridization opportunities, and map the way toward an integrated control framework that fuses learning, optimization, and consensus.

The three contributions of this comparative study are as follows: firstly, it is a synthesis of the fundamental methodologies and performance measures of TL-PIO and alliance-based control within the larger body of bio-inspired and consensus-based MAS research. Secondly, it comparatively analyzes their scalability, fault tolerance, convergence rate, communication overhead, and adaptation in both 3D obstacle-filled and topologically changing environments. Third, it provides actionable insights into future work and describes how transfer learning can be used to enhance alliance formation strategies and how consensus mechanisms can help fortify learning-based planners against link failures.

The rest of this paper is structured as follows. Section 2 is a review of prior work in MAS, pigeon-inspired and transfer-learning optimizations, and alliance-based consensus control. Section 3 is an overview of methodologies and descriptions of the two chosen works. Section 4 provides a rigorous comparative analysis of the two selected works. Finally, Section 5 concludes with suggested directions for implementing and experimentally verifying hybrid strategies in the service of robust, adaptive multi-UAV coordination.

A. Related Work

The development of multi-agent systems (MAS) and swarm robotics has been a major driving force behind the rise of interest in decentralized coordination techniques for UAVs. Conventional techniques have used centralized planning or fixed formations, but they have scalability issues and are vulnerable to single points of failure. In order to combat this, distributed control systems that draw inspiration from natural flocking have begun to proliferate. Emergent global behavior and enhanced fault tolerance are the results of these systems, where each UAV behaves depending on information from its immediate neighbors. With its emphasis on position and velocity alignment using graph theory and Laplacian-based communication frameworks, consensus algorithms form the foundation of distributed coordination [8].

Path planning and optimization utilizing bio-inspired algorithms have been investigated more and more by researchers in an effort to improve distributed control with cognitive capabilities. Complex navigation problems are addressed by algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Pigeon-Inspired Optimization (PIO), which are inspired by natural phenomena. PIO specifically imitates how pigeons pick the best routes by using magnetic fields and environmental markers. PIO's simplicity and ability to avoid local minima have led to its use in multi-UAV missions. Though some PIO variants have issues like slow convergence and struggle in dynam- ically changing conditions, efforts have been made to hybridize them with adaptive or learning-based methods [9].

Transfer learning (TL) has also been investigated as a means to overcome the adaptability issues of bio-inspired techniques. TL can enable UAVs to leverage learned information from past experiences to speed up convergence in new settings, especially those with similar topologies to past missions. TL can be used to initialize swarm formations, optimize waypoints, or learn from unseen patterns of obstacles in multi-agent systems. TL has been used in conjunction with evolutionary algorithms in recent studies to reduce training time and enhance generalization. It is still challenging to implement TL in a distributed setting due to communication heterogeneity and real-time constraints [10].

Resilient formation control is one of the most important requirements for UAV swarms in hostile or uncertain environments. Alliance-based approaches divide the swarm into subsets (alliances) with fewer UAVs in direct communication with a virtual leader. This reduces the bandwidth requirements while ensuring group coherence through local consensus. Such approaches are applicable in partial link loss conditions, dynamic topologies, or jamming. Incorporation of second-order dynamics, leader adaptation through feedback, and dynamic alliance reconfiguration offers enhanced fault tolerance and system stability, even in dense or large-scale deployment [11].

More recently, researchers have started investigating hybrid control methods that combine the flexibility of learning-based methods with the resilience of distributed control. This includes, for instance, systems that employ TL to estimate routes at the mission planning phase and consensus-based approaches for real-time adaptation. Hybrid systems have the potential to leverage the strengths of both paradigms. Because of this hybridization, UAVs can adjust to local disruptions or deployment failures while also learning from past missions. For these immature systems, maintaining an equilibrium amongst real-time adaptability, communication latency, and processing complexity is crucial. Future UAV swarm operation designs must strike a compromise between these competing criteria to be intelligent, adaptable, and long-lasting

[12].

II. METHODOLOGICAL OVERVIEW

This section provides the methodological summary of the two selected studies. A cluster here means a group of more than one UAV, while a flock refers to a larger, networked group of clusters. An alliance means a dynamic, partially independent subgroup that is utilized in the alliance-based approach.

A. Integrating Transfer Learning into Multi-objective Pigeon-Inspired Optimization

The first research [6] applies Pigeon-Inspired Optimization (PIO) with Transfer Learning (TL) to enable path planning and flocking for multi-UAVs. TL-PIO is a new approach that aims at enhanced efficiency, flexibility, and convergence speed of UAV swarms in dynamic and complex 3D city environments. The TL-PIO takes advantage of the natural homing and navigation abilities of pigeons, combined with transfer learning that learns from past completed missions.

The PIO algorithm models pigeon-like behaviors like landmark detection, map orientation, and compass orientation to guide agents through dense spaces. Its two main operators are the map and compass operator, which models the influence of the sun's position and the Earth's magnetic field for directional orientation, and the landmark operator, which utilizes environmental landmarks to minimize location updates in the search space.

Hybrid incorporates these agents with a Transfer Learning module that modifies agent action based on previous missions with similar characteristics. This enhances the swarm's capacity to respond to novel stimuli from the environment, accelerates convergence, and enables it to exit local minima. The TL module provides source and target domains from the former and current mission environments. A Kullback-Leibler divergence measure is used to compare domain similarity and determine when and how much to transfer. Population-level information (e.g., prior successful UAV locations and velocities) is used as input into the optimization loop to guide current trajectory generation. The transfer is dynamic, data-driven, and environment-dependent.

The UAVs use a Multi-Agent System (MAS) paradigm. The UAVs are independent intelligent agents with sensing, computing, and decision-making abilities. The agents are grouped into three clusters (A, B, and C), and each of them carries out path planning using TL-PIO initially, then the transfer of agents between clusters, and finally synchronization into one flock. They all share decentralized control but are synchronized with neighbors using local observations. The best UAVs from every group are automatically selected as leaders and used for flock formation and alignment during global synchronization.

The TL-PIO algorithm's general architecture is illustrated in Figure 1. The first steps in the process are to configure the agent's characteristics and load already trained data from prior missions. After that, each UAV's speed and position are dynamically modified according to nearby data and predefined optimization goals. Kullback-Leibler Divergence (KLD) is a vital aspect of the transfer learning paradigm since it assesses the degree of resemblance between source and target domains in order to manage knowledge transfer appropriately. The program uses iterative optimization cycles to maintain swarm stability and enhance trajectories while continuously evaluating convergence. This modular solution makes integration simple, provides real-time flexibility, and improves performance in dynamic and complicated environments.

B. Alliance-Based UAV Formation Control

The second study [7] is founded on dynamically breaking the UAV cluster into more adaptable and controllable groups known as cooperation agreements, each headed by a navigation-information UAV in proximity with a virtual commander. Furthermore, some of the alliance's non-navigation UAVs connect locally with their neighbors to keep their positions and speeds updated. By reducing congestion in the network and improving resistance to node failure or connection failures, a topology such as this enables global coordination with lower communication overhead.

The method represents UAVs as second-order dynamic agents, in which the position $x_i(t)$ and velocity $v_i(t)$ of each UAV change according to $\dot{x}_i(t)= v_i(t)$ and $\dot{v}_i(t) = a_i(t)$. Whereas, $a_i(t)$ is the control input (acceleration), and each UAV needs to stay within bounded velocity and acceleration constraints. UAVs communicate within a fixed radius, and the network topology is modeled using a time-varying graph **(t)**, where edges represent active communication links. Upon detecting a topology change, UAVs perform alliance reconfiguration via localized graph traversal.

In this methodology, two types of control laws govern the UAVs. The first is that the navigation-information UAVs use a composite control law that balances three things: velocity consensus with neighboring UAVs, velocity and position tracking of the virtual leader, and formation preservation using relative position offsets. The second control law is associated with non-navigation UAVs, which use a simplified consensus control based only on local alignment of velocity and position with neighbors. Moreover, if significant formation deviations are detected or a sub-alliance loses contact with the leader, a feedback process corrects the virtual leader's movement. The modulation of the velocity and acceleration of the leader is determined by the average navigation information of the UAV state so that overall formation coherence is maintained.

Figure 2 illustrates the alliance-based control process through a comprehensive flowchart that reflects the operations needed for formation stability in dynamic situations. The process starts with the initialization of UAV positions and dividing the swarm into alliances through local connectivity partitioning. In each alliance, a navigation-information UAV is chosen based on a weighted parameter that takes node degree and guide-link strength into consideration. These chosen UAVs are provided with virtual leader information and use a global control law, while the other agents use localized neighbor communication to stay together. The flow is also designed with a feedback mechanism that corrects the motion parameters of the leader according to deviances detected among navigation UAVs to ensure the formation modifies itself in the event of a communication disruption or topology. When the network changes, the system activates reconfiguration routines to redefine alliances and redistribute roles so that stability and adaptability can continue throughout the mission.

III. COMPARATIVE ANALYSIS

In this chapter, a detailed comparative analysis is given between the Transfer Learning Pigeon-Inspired Optimization (TL-PIO) approach and the alliance-based UAV Formation Control method. The comparison mainly analyzes each approach in terms of formation precision, obstacle evasion, convergence rate, adaptability, and overall robustness under different conditions.

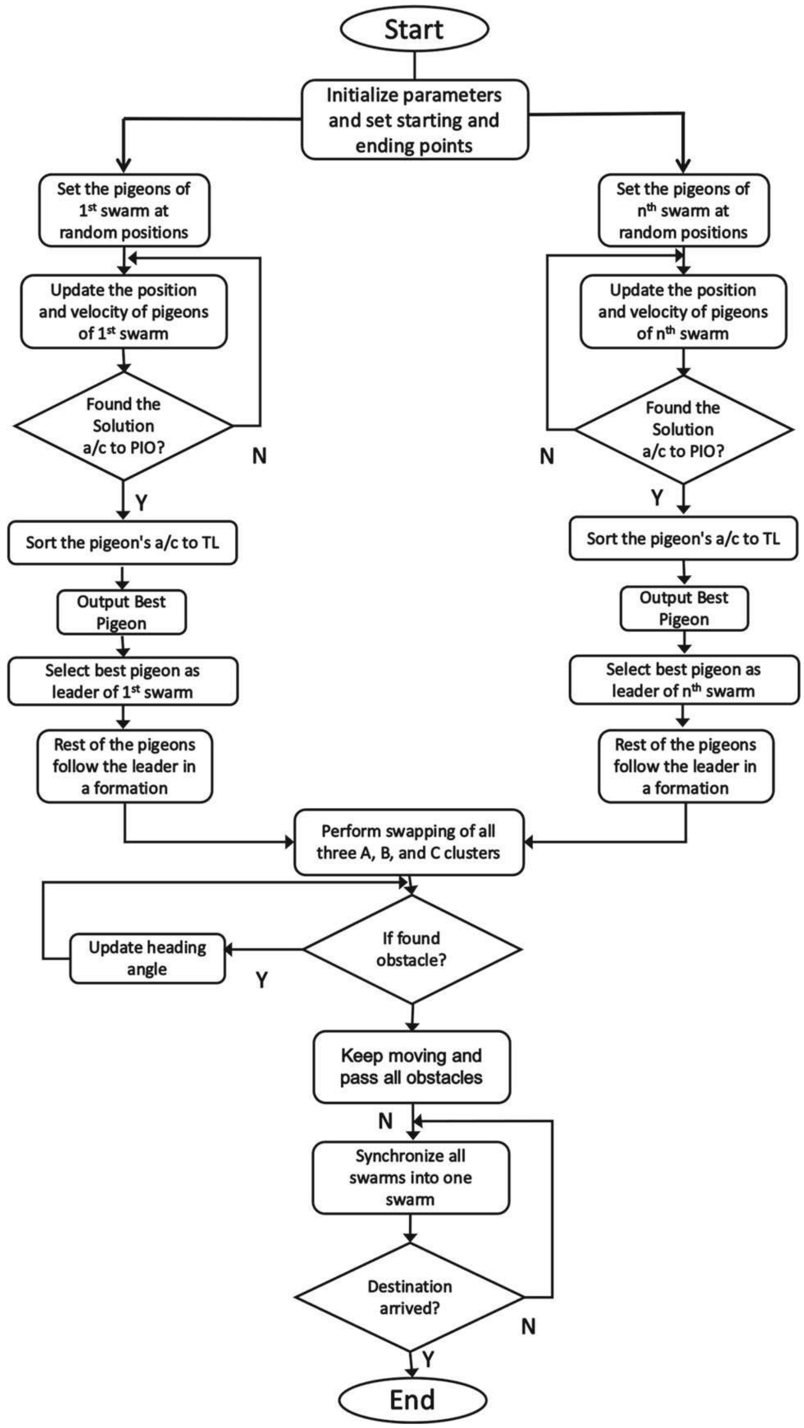

Figure 1: TL-PIO algorithm [6]

A. Comparison of Results

Transfer Learning with Multi-objective PIO: The first paper in consideration assesses the performance of Transfer Learning with Multi-Objective PIO (TL-PIO) with three scenarios. Figure 3 assesses the performance of the UAV flock in organizing into stable clusters and performing swapping manoeuvres in a 3D environment without obstructions. TL-PIO performed very well in reaching and sustaining stable formations, facilitating smooth swapping between clusters while moving towards the final targets.

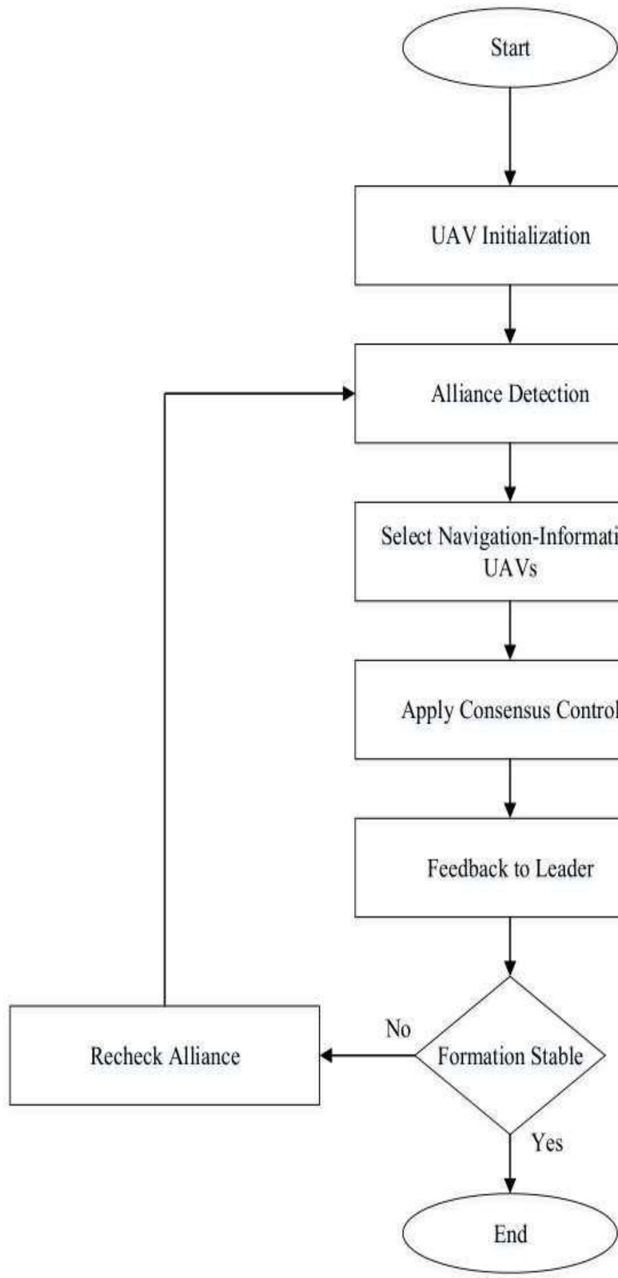

Figure 2: Alliance-based UAV formation control [7]

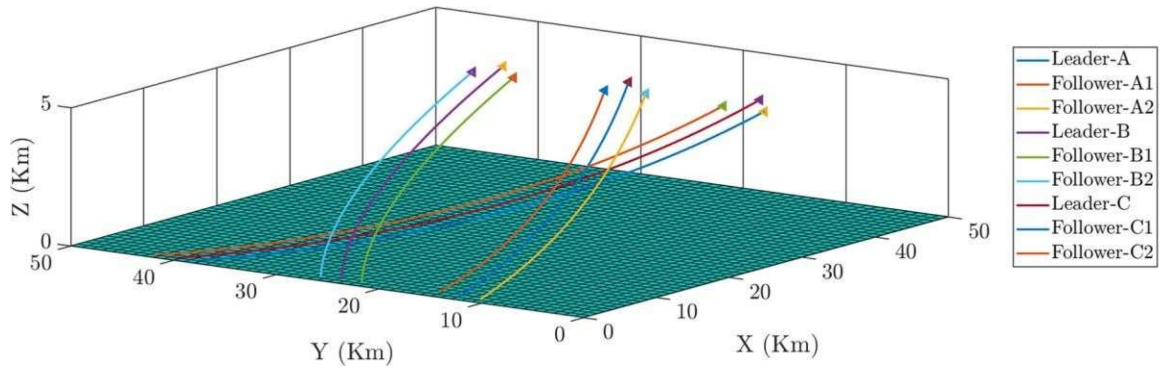

Figure 3: Scenario 1 of TL-PIO [6]

Figure 4 provided static obstacles, challenging the flock to be able to adaptively execute swaps and fly safely to targets. UAVs were able to maintain their formations and stay clear of collisions. The TL-PIO's endurance in dynamic, obstacle-filled surroundings is shown by this result, demonstrating its efficacy for missions in intricate urban settings**.**

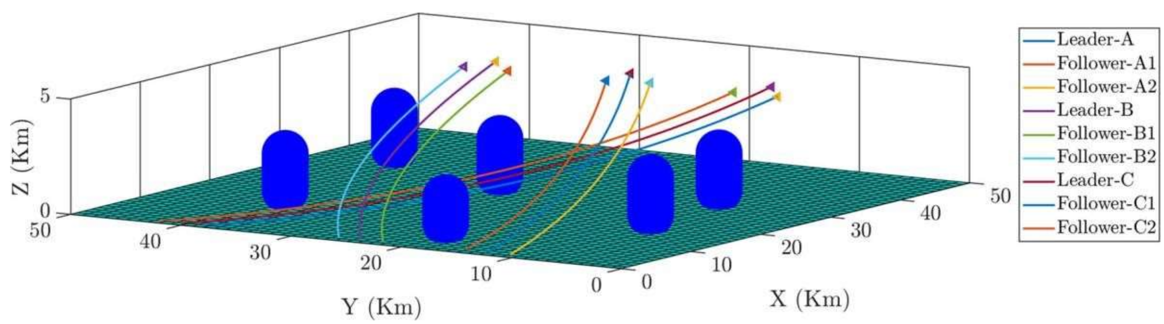

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Figure 4: Scenario 2 of TL-PIO [6]

Clusters have to switch and then synchronize into a single, cohesive flock while confronting static barriers in Figure 5. The best leader was chosen dynamically, ensuring that the formation remained together. TL-PIO completed sophisticated coordination tests, demonstrating its ability to synchronize and govern adaptive formations under difficult situations.

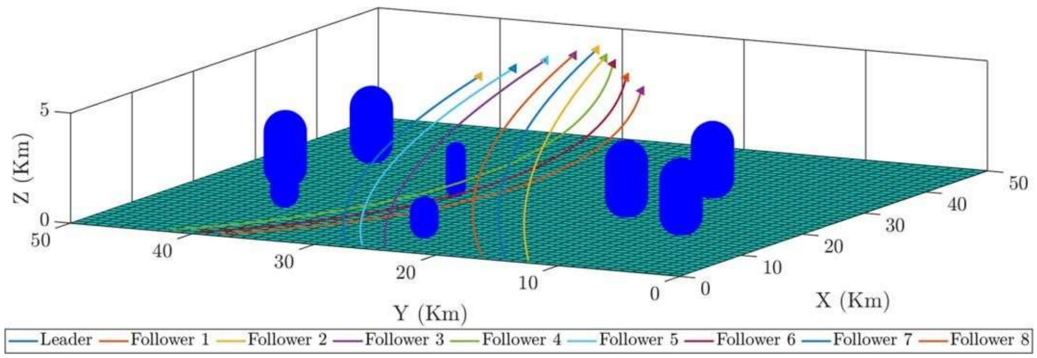

Figure 5: Scenario 3 of TL-PIO [6]

Alliance-Based UAV Formation Control: The second evaluated article examines the resilience of formation control by considering two completely separate operational scenarios.

Figure 6 shows randomly placed UAVs reorganizing into two parallel lines with uniform spacing, illustrating an efficient architecture for cooperative sensing operations and linear survey operations. Each UAV in this scenario deter- mines its relative position by evaluating local neighbor data, rather than relying on global positional awareness. This decentralized strategy reduces computational load and communication dependency, while still enabling the swarm to exhibit coordinated behavior. This example shows how the alliance-based control framework can result in orderly, linear formations, demonstrating the independence of each UAV's repositioning while preserving overall stability and local cohesion.

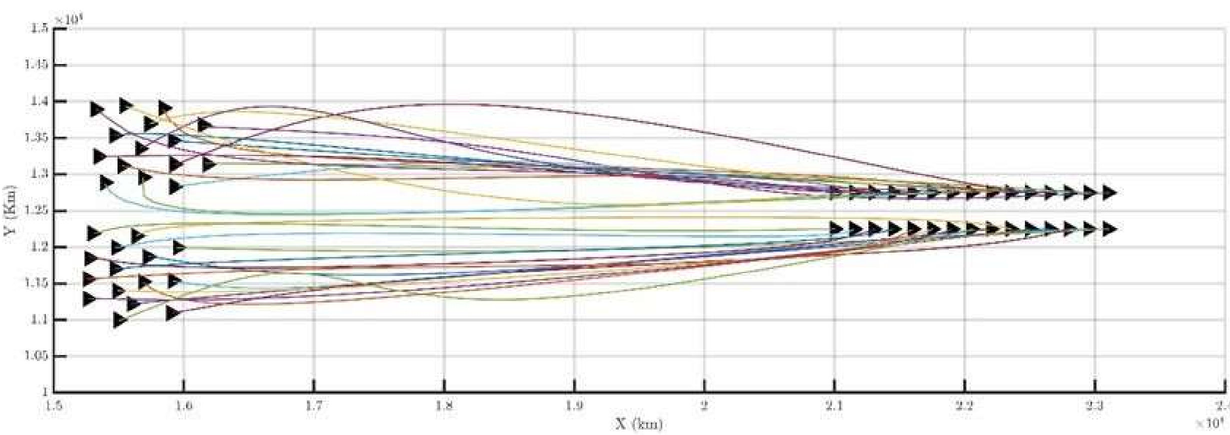

Figure 6: Scenario 1 of alliance-based Formation Control [7]

Figure 7 expands on the example in Figure 6 to show the system's adaptability and real-time reconfiguration capabil- ities by reorganizing the UAV formations from two parallel rows to a circular layout. The UAVs dynamically adjust their positions while maintaining local connectivity within alliances, and the transition occurs without any centralized instructions. This result demonstrates the alliance-based method's extraordinary adaptability, allowing it to smoothly reconstitute formations in the context of regional communication losses and dynamic topology changes. It demon- strates how well the framework works when rapid and flexible formation alterations are necessary.

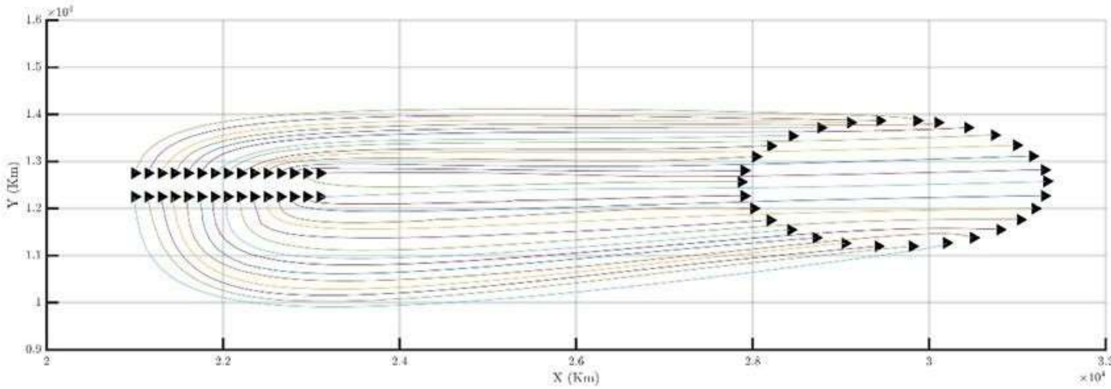

Figure 7: Scenario 2 of alliance-based Formation Control [7]

B. Comparative Evaluation

Table 1 gives a comprehensive description of the comparison, highlighting the important aspects and differences of the two presented strategies:

Table 1: Comparative Summary

Aspect	TL-PIO Approach [6]	Alliance-Based Control Approach [7]
Domain Focus	Optimization & intelligent path planning (3D)	Resilient formation control (2D)
Environment	Dynamic 3D urban scenarios with obstacles	Dynamic 2D scenarios with formation changes
Core Mechanism	Transfer Learning hybrid with PIO	Consensus laws within local alliances
Communication Strat- egy	Centralized training disseminated via TL	Decentralized, localized communication
Formation Control	Cluster swapping, synchronization into flocks	Dynamic alliances with feedback-based cor- rections
Fault Tolerance	Moderate (assumes reliable info sharing)	High (stable under partial communication loss)
Scalability	Moderate (requires adjustment for com- plexity)	High (low overhead & localized control)
Computation Cost	High (due to TL overhead)	Moderate to low (local consensus, minimal updates)
Adaptability	Strong (mission adaptation via TL)	Strong (topology adaptation via alliances)
Best Use Case	Mission-critical tasks needing quick con- vergence	Networks susceptible to communication dis- ruptions

The comparative table indicates a number of key differences between the two approaches. Because of its exceptional performance in challenging route planning tasks and speedy convergence, TL-PIO is particularly beneficial in locations with a lot of information and barriers. In contrast, alliance-based control structures are more enduring in high-dynamic work contexts with little communication.

IV. CONCLUSION

This article conducted a thorough evaluation of two distinct cutting-edge UAV swarm management strategies: alli- ance-based UAV formation control design and transfer learning Pigeon-Inspired Optimization. TL-PIO demonstrated its edge in swift convergence as well as effective path planning in complex 3D environments by adaptively using its transfer learning architecture for dynamic obstacle avoidance and synchronization tasks. In contrast, the alliance- based technique displayed higher adaptability, flexibility, and resilience in dealing with intermittent interruptions in communication and frequent topological changes, making it ideal for applications that require rapid reconfiguration and fault tolerance.

The comparison analysis demonstrates that by emphasizing the complementary characteristics of both systems, a hy- brid integration can give synergistic benefits and increase overall performance. The distributed durability of alliance- based formation control, when paired with the adaptable optimization capabilities of TL-PIO, can produce a hybrid solution that increases endurance, performance, and flexibility in real time. Such a combined system may be capable of satisfying the complicated requirements of upcoming UAV uses via efficient coordination and control in a variety of challenging operating conditions.

While this study focuses on a methodological comparison, future research should concentrate on simulated and experimental verification, as well as real-world application, of the proposed integrated system. Such validation would provide critical insights into how communication disruptions, real-time adaptability, and optimization efficacy interact in dynamic multi-agent environments. More research into complicated processes of learning, as well as how they interact with distributed group consensus control mechanisms, is required for the development of long-lasting, adap- tive, and intelligent multi-UAV swarms.

A conceptual hybrid model would integrate the TL-PIO framework during the mission pre-planning phase to generate optimized initial trajectories and formations. During deployment, alliance-based consensus would be employed to ensure real-time reconfiguration and resilience to communication losses. This dual-phase system leverages historical mission data and learning, while adapting to present uncertainties through distributed control. Such validation would provide critical insights into how communication disruptions, real-time adaptability, and optimization efficacy interact in dynamic multi-agent environments. More research into complicated processes of learning as well as how they interact with distributed group consensus control mechanisms, is required for the development of long-lasting, adaptive, and intelligent multi-UAV swarms.

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