UAV Chain Network Creation in Cluttered Environment with Flocking Rules and Routing Data

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Abstract— **This paper introduces a novel distributed approach for forming UAV-based multi-hop relay networks by adapting traditional flocking models to create relay chains between remote points. Our method modifies the standard flocking paradigm by incorporating dynamic agent roles, allowing UAVs to self-organize based solely on local state and neighbor information, and integrates networking information such as routing decisions directly into mobility control. A side contribution is the introduction of a Line-of-Sight (LOS) conservation force, which mitigates communication failures due to obstacles and is easily adaptable to the flocking model. The proposed algorithm is evaluated using a joint robotics and network co-simulator that combines realistic multi-rotor physics with ns-3-based network simulations. Simulation results across diverse environments and varying mission complexities demonstrate that our approach effectively maintains connectivity, enhances Quality of Service (QoS), and scales robustly, thereby bridging the gap between robotic control and aerial wireless network design.**

I. Introduction

Flying Ad-hoc Networks (FANETs) technology has advanced significantly in recent years, trying to leverage the great aerial mobility and communication capabilities of UAVs to solve civil and military challenges like infrastructure inspection, environment exploration or search-and-rescue. This field benefits from advances in robot design, ad-hoc networks and multi-agent navigation.

Among the numerous envisioned applications of FANETs, target monitoring recently drew a lot of attention. For example, a search-and-rescue team could leverage multi-UAV systems to get a video and sound feedback of a victim in difficult to reach areas. This kind of application falls under the broader category of robot target monitoring, where a group of autonomous robots must provide real-time connectivity to one or multiple remote sensing areas. Most of the time, UAVs have to fly close to the ground, where the environment is cluttered with obstacles that can generate collision and affect the communication quality.

It is generally admitted that UAVs must collaborate (and, consequently, communicate) to fulfill such mission, to avoid collision but also to exchange mission information to organize more efficiently toward their common goal.

In this work, we propose a navigation algorithm that creates a UAV chain for robotic target monitoring. It is inspired from the flocking principles and embeds network information, in particular from the used routing algorithm, to make sure that the communication quality is good.

We use our joint robotic and network co-simulator, DANCERS, to evaluate our algorithm with both realistic multi-rotor dynamics and realistic network protocols. The main contributions of this work are:

- A new flocking interaction providing Line of Sight conservation among obstacles;
- An original multi-UAV relay chain algorithm based on flocking with network-informed roles;
- A simulation framework enabling the joint study of navigation and routing algorithms.

In Sec. II, the main research background required for the current work is presented. In Sec. III, the problem is explained and the notation introduced. In Sec. IV, our solution based on flocking is presented. Simulation results and analysis of our algorithm are given in Sec. V. We conclude and present further work in Sec. VI.

II. Related work

A. Relay chain network creation

Over the past decades, researchers have investigated UAV-based multi-hop relay networks from various perspectives (see Table I). Key challenges include the choice between centralized and distributed architectures, navigating environmental obstacles, enforcing Quality of Service (QoS), and managing multiple relay chains.

Zavlanos et al. [1] proposed a graph-based control method enabling a group of mobile robots to "stretch" while maintaining a specified level of k-connectivity, as part of their foundational work on mobile robot connectivity control. However, this approach requires global graph information, which complicates distributed implementation.

In [2], relay chain formation is studied in the particular context of tunnel exploration. In this scenario, UAVs are constrained to the tunnel centerline, reducing navigation to a simple forward/backward decision. The optimal QoS relay chain is achieved by moving each UAV toward its weakest quality link, *i.e.,* the one with the lowest Signal-to-Noise Ratio (SNR), thereby equalizing link quality.

The relay chain problem has also been formulated as an optimization challenge. Olsson et al. [3] present a centralized algorithm based on space discretization to identify a set of Pareto-optimal solutions. Their method minimizes communication cost and maximizes surveillance capability, but is computationally intensive for relay trees. Similarly, Yan et

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al. [4] employ optimization techniques that use SNR-based objective functions to minimize the Bit Error Rate (BER) relative to router positions. In [5], Mox et al. formulate an optimization problem encapsulating both routing and multi-robot control, and prove its efficiency through simulations and field experiments.

Hayat et al. [6] introduce a "Simultaneous Inform and Connect" (SIC) strategy that balances the time required to transmit the first bit from a sensed area to the base station (BS) with the time needed to establish a real-time multi-hop relay network. Their method positions routers by selecting an appropriate number of relays and distributing them evenly along the straight line between the sensed area and the BS.

Most existing studies, summarized in Table I, are theoretical or tailored to specific agent types, numbers, or environments. Few address the joint challenges of robotic control and wireless networks constraints, even if these two fields are closely interconnected in cooperative FANETs. This gap motivates our development of a flexible, robust, scalable, and adaptive solution for UAV relay network creation.

B. Flocking principles

Flocking, swarming or schooling are forms of emergent collective behaviors, exhibited by groups of animals in the wild, that is believed to emerge only from local rules of interaction between the individuals. Reynolds initially modeled flocking using three heuristic rules: cohesion, alignment, and separation [7]. These principles have since been widely studied and adapted for multi-agent systems. In the context of Multi-Robot Systems (MRS), flocking offers several advantages: it is fully distributed, highly scalable, computationally and communicatively efficient, functions with only relative localization, adapts to unforeseen obstacles, and naturally accommodates agents joining or leaving the formation. Flocking has also proven to be more than a theoretical model but also usable for real-life deployment of UAVs, as demonstrated in [8], [9].

In [10], the authors integrated flocking rules to reduce route changes within the Ad-hoc On-Demand Distance Vector (AODV) routing protocol. While each UAV typically follows an individual roadmap, those forming an active transmission path adopt flocking behaviors. This approach leverages the inherent cohesion of flocking to stabilize and improve the performance of the routing protocol.

C. Routing inspiration

For effective end-to-end communication, UAVs require robust routing protocols. Routing in Flying Ad-hoc Networks (FANETs) has been studied for several decades, yielding numerous protocols. However, comparing these protocols is challenging due to diverse implementations across simulators (*e.g.,* ns-3, OMNET++) and the scarcity of open-source solutions. Usually, widely recognized protocols are standardized by the Internet Engineering Task Force (IETF) through official Request For Comments (RFC) documents. The four standardized Mobile Ad-hoc Network (MANET) routing protocols that can be adapted for FANETs are OLSR (RFC 3626), OLSRv2 (RFC 7181), AODV (RFC 3561), and DSR (RFC 4728). With the exception of OLSRv2, these protocols have been rigorously implemented in ns-3 and can thus be compared with good confidence.

The complementary strengths of flocking and established routing protocols motivate the development of a routing-aware flocking model. Such a model integrates networking and mobility aspects to enhance the performance and reliability of cooperative multi-UAV systems.

III. Problem definition and key performance indicators

A. Assumptions and notations

Consider a homogeneous fleet of n cooperative UAVs equipped with wireless communication capabilities. $\mathcal{U} = \{u_1, \ldots, u_n\}$ is the set of UAVs. We suppose that the UAVs have perception capabilities allowing them to access the relative position of the other UAVs within a range R_p. Furthermore, the environment is cluttered with unknown obstacles represented by the region $\mathcal{O} \subseteq \mathbb{R}^3$. The UAVs can detect obstacles within a range R_d and a field of view of 360°.

Additionally, consider that m target areas denoted $T = \{\tau_1, \ldots, \tau_m\}$, with known positions $p(\tau_i)$, are disseminated in the environment. There is also one base-station (BS) denoted δ with a known position $p(\delta)$. The starting point of the UAV fleet is near the BS. When a UAV u_i is assigned to a target τ or to the BS δ, it is respectfully labelled u_i^τ and u_i^δ. The UAVs can generate "mission data" and send it to the BS at any moment, but the "mission data" has value only if it has been produced within a target area.

B. Mission and chain definition

We consider that a group of UAVs forms a "chain" when a throughput and delay condition is achieved between a UAV positioned in a target area and another UAV positioned near the BS. In most cases, the target areas are not within the one-hop communication range of the BS, forcing the UAV fleet to create a multi-hop relay network. To do so, they must autonomously navigate through an environment cluttered with unknown obstacles, using only their perception and communication capabilities, and cooperate to form the chain. In Fig. 1, the chain transporting the mission data is illustrated by red arrows.

C. Performance criteria

The mission success is evaluated by the three following key performance indicators (KPI). The UAV fleet must reach their targets as fast as possible, and be able to transmit data from the target locations to the BS with a good throughput and a limited delay.

- Deployment time:

$$\psi = \min_{t \in \mathbb{R}^+}(t) : \begin{cases} \forall \tau \in T, \exists u \in \mathcal{U} : \|p(u,t) - p(\tau)\| \leq R_\tau \\ \exists u \in \mathcal{U} : \|p(u,t) - p(\delta)\| \leq R_\delta \end{cases}$$

  where R_τ and R_δ are the accepted radius around the target locations.

Ref.	Year	Title	Architecture	Obstacles	QoS-aware	Multi-targets	Relay number
[1]	2008	Distributed Connectivity Control of Mobile Networks	Centralized	No	No	No	12
[3]	2010	Generating UAV communication networks for monitoring and surveillance	Centralized	Yes	Yes	Yes	26
[4]	2010	Robotic router formation - A bit error rate approach	Centralized	Yes	Yes	No	[4-6]
[11]	2012	Optimizing Cascaded Chains of Unmanned Aircraft Acting as Communication Relays	Distributed	No	Locally	No	2
[6]	2020	Multi-objective drone path planning for search and rescue with quality-of-service requirements	Distributed	No	Yes	No	[4 - 12]
[5]	2020	Mobile Wireless Network Infrastructure on Demand	Centralized	No	Yes	No	[3 - 9]
[12]	2020	A cost-efficient elastic UAV relay network construction method with guaranteed QoS	Distributed	No	No	No	4
[2]	2021	Signal-Based Self-Organization of a Chain of UAVs for Subterranean Exploration	Distributed	Yes	Yes	No	[2 - 5]
[13]	2023	UAV relay network deployment through the area with barriers	Distributed	Yes	No	No	6
Our solution	2025	UAV Chain Network Creation in Complex Environment with Flocking Rules and Routing Data	Distributed	Yes	Yes	Yes	[4 - 20]

TABLE I

AUTONOMOUS RELAY CHAIN CREATION STUDIES

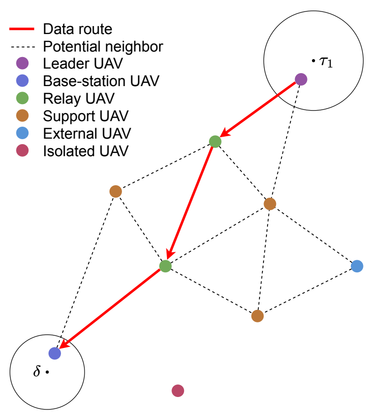

Fig. 1. Role-based flocking model for relay chain creation

- Cumulated throughput of mission flows:

$$\phi = \begin{cases} \sum_{\tau \in T} \phi_{\tau,\delta} & \text{if } \phi_{\tau,\delta} \geq \phi_{min} \text{ for all } \tau \in T, \\ 0 & \text{otherwise.} \end{cases}$$

  where $\phi_{\tau,\delta}$ denotes the achieved throughput between nodes u^τ and u^δ for the mission data-flow, and ϕ_{min} is the minimum acceptable throughput.
- Average delay:

$$D = \begin{cases} \frac{1}{m} \sum_{\tau \in T} D_{\tau,\delta} & \text{if } D_{\tau,\delta} \leq D_{min} \text{ for all } \tau \in T, \\ 0 & \text{otherwise.} \end{cases}$$

  where $D_{\tau,\delta}$ denotes the average end-to-end delay of the mission data-flow between nodes u^τ and u^δ, and D_{min} is the minimal delay that can be accepted.

IV. A SOLUTION BASED ON FLOCKING

A. Flocking model

In flocking, each agent computes its desired velocity by combining forces derived from local interactions with its neighbors. Our work builds on the "Vásárhelyi with Attraction" (VAT) model [14] which is an extension of [9], selected for its robust performance in environments with obstacles and degraded communications. In [14], the desired velocity vector of an agent u_i is computed as follows:

$$\tilde{\mathbf{v}}_i^{\text{VAT}} = \frac{\mathbf{v}_i}{\|\mathbf{v}_i\|} v_{flock} + \mathbf{v}_i^{\text{rep}} + \mathbf{v}_i^{\text{att}} + \mathbf{v}_i^{\text{ali}} + \sum_{o \in \mathcal{O}} \mathbf{v}_{i,o}^{\text{obst}} \quad (1)$$

where $\tilde{\mathbf{v}}_i^{\text{VAT}}$ is the final desired velocity, $\mathbf{v}_i$ is its current velocity, v_{flock} is the preferred speed of the flock, $\mathbf{v}_i^{\text{rep}}$, $\mathbf{v}_i^{\text{att}}$ and $\mathbf{v}_i^{\text{ali}}$ are the sums of the contributions of the neighbors, respectively for the repulsion, attraction and alignment, and $\mathbf{v}_{i,o}^{\text{obst}}$ is the interaction term of the obstacle o. These flocking forces are represented in Fig. 2.

In this model, the attraction and repulsion forces are implemented using simple half-spring functions, which offers a good balance between simplicity and effectiveness [9]. The alignment equation is more complex. To be able to deal with both large velocity differences and limited acceleration, the authors introduce an ideal braking curve to bound the velocity difference between two agents to a value that depends on the distance between the agents. For obstacle avoidance, a virtual agent is positioned at the closest point on an obstacle, with its velocity vector directed normal to the obstacle's surface and pointing outward. The resulting force resembles the alignment force, but it is applied to this virtual agent. For the sake of conciseness, the reader is referred to [14] and [9] for the details of the equations. In our flocking model, the *auto-propulsion* term $\frac{\mathbf{v}_i}{\|\mathbf{v}_i\|} v_{flock}$ is deactivated.

B. Stretching the flocking

Our main proposition is a modified flocking model able to stretch itself without loss of connectivity, creating a chain of relays between two remote positions. Traditional flocking models naturally aggregate agents and align their velocities, which is quite the opposite of a chain formation. On the contrary, our approach aims to linearly expand the group.

To reshape the typically spherical flock, we designate certain agents as leaders that "pull" the formation in a desired

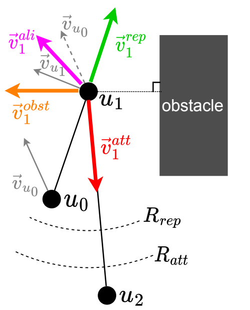

Fig. 2. Flocking forces in the Vásárhelyi with attraction (VAT) model. The red arrow is the attraction force, the green arrow is the repulsion force. The violet arrow is the velocity alignment. The orange arrow is the repulsion force of the obstacle.

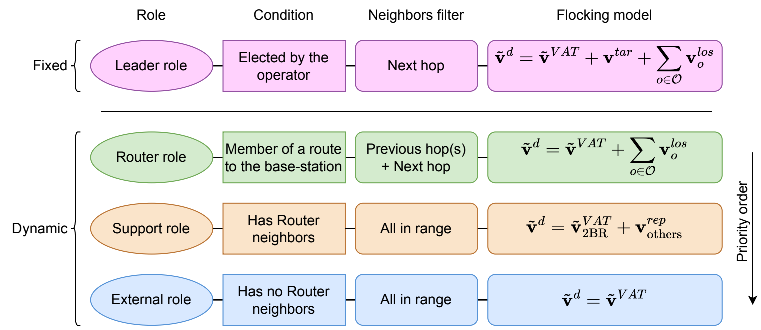

Fig. 3. Flocking roles with role selection feature, associated neighbor filter and modified flocking model. For the Support role, $\tilde{\mathbf{v}}_{2\mathrm{BR}}^{\mathrm{VAT}}$ means that the complete VAT model is activated for the two closest Router neighbors, and $\mathbf{v}_{\mathrm{others}}^{\mathrm{rep}}$ means that repulsion is activated with all other neighbors.

direction. With another UAV fixed at the BS, the group naturally stretches. However, tuning the target force exerted by the leaders is challenging, as it depends on factors such as neighborhood size and inter-agent interactions. Inappropriate tuning may cause leader disconnections or lead to deadlocks, where the attraction toward the target is neutralized by the cohesive forces from neighboring agents.

We observe that when a leader is connected to only one neighbor, it gains increased freedom to move toward its target, provided that the target force is properly tuned. More broadly, selectively "breaking" certain flocking links — by filtering neighborhoods — can facilitate effective stretching.

Importantly, not all links are equally expendable. The communication route defined by the routing algorithm must be maintained and reinforced, as it is critical for data transmission and overall QoS. By incorporating network information into the flocking model, our approach achieves two key objectives:

- Enhance the mobility of leaders by selectively breaking non-critical flocking links, allowing them to navigate toward their targets.
- Improve QoS by incorporating UAVs in the chain, to reinforce the links that actually transmit important data.

C. Modified flocking model based on roles

Our modified flocking model is based on dynamic agent roles. Each UAV determines its role using only its own state and information shared by its neighbors. Fig. 1 and Fig. 3 illustrate the different roles, the role selection process, the filtering of flocking neighbors, and the associated modifications to the flocking model.

The proposed flocking model works as follows: each role corresponds to a slightly modified version of the flocking model presented in Eq. 1. Specifically, the neighbors considered for the flocking computations are filtered, and some forces are activated / deactivated. When a UAV self-assigns a role, it follows the associated flocking model. The roles are designed so that Leaders move toward their designated target areas, with attraction and alignment forces ensuring that nearby UAVs follow their motion. A stream of data is continuously sent between each leader and the BS, allowing the non-leader UAVs to know if they should take the role of Router. The flocking model of the Router role releases some cohesive constraints letting the chains expand. The roles and associated flocking model modifications are presented in details hereafter.

1) Leader role: The most important role is probably the Leaders. Before the start of the mission, the operator arbitrarily associates a UAV u_i to a target τ, creating the leader u_i^τ. Leaders have a supplementary attractive force $\mathbf{v}_i^{\mathrm{tar}}$ toward their target area:

$$\mathbf{v}_i^{\mathrm{tar}} = \begin{cases} v_{\mathrm{max}}^{\mathrm{tar}} * \dfrac{\mathbf{r}_{\tau i}}{\|\mathbf{r}_{\tau i}\|} & \text{if } R_\tau \leq \|\mathbf{r}_{\tau i}\|, \\ \dfrac{v_{\mathrm{max}}^{\mathrm{tar}}}{R_\tau} * \dfrac{\mathbf{r}_{\tau i}}{\|\mathbf{r}_{\tau i}\|} & \text{otherwise.} \end{cases} \tag{2}$$

where $v_{\mathrm{max}}^{\mathrm{tar}} \in \mathbb{R}$ is a flocking parameter controlling the force of attraction toward the target and $\mathbf{r}_{\tau i} = p(\tau) - p(u_i^\tau)$ is the vector between the Leader UAV u_i^τ and its associated target τ. Leader UAVs continuously transmit mission data to keep an active route toward the BS. Leaders only consider one neighbor for flocking: the next hop toward the BS as computed by the routing algorithm. They can be seen as being the "first router" of their chain. The Leader role could also be dynamically assigned, based on distributed task-assignment methods, but this is a field of research in itself, and we did not focus on this problem.

2) Router role: Router UAVs form the communication chains between Leaders and the BS. A Router self-elects when its routing module takes the decision to forward a mission packet. Routers reduce their flocking neighborhood to the upstream and downstream UAVs: the sender of the forwarded mission packet and the next hop toward the BS, as computed by the routing algorithm. When multiple target areas are considered, a Router can have more than one "upstream" neighbor, but it has only one "downstream" neighbor (as long as multi-path routing is not considered). Router UAVs activate all the flocking forces with its flocking neighbors, and add a new force $\mathbf{v}_{i,o}^{\mathrm{los}}$, that prevents the link with their neighbors to be suddenly blocked by an obstacle (see Subsec. IV-D).

3) Support role: The UAVs that do not actively route mission data are called Supports. They provide secondary routes in case a router UAV fails, and explore the space around the established chain for a path with a better QoS. Their modified flocking model is the following: they activate the attraction and the alignment forces only with their two closest Router neighbor (this has the effect of drawing Support UAVs between a pair of Router UAVs), but keep the repulsion force with all of their neighbors for collision avoidance. Support UAVs can know the role of their neighbors because each UAV broadcasts its role periodically (see Subsec. V-A).

4) External role: If a UAV has zero Router neighbor, it is considered as External UAVs. This role appears when UAVs are far from the communication chains, or when there is no route between a Leader and the BS. In this case all the UAVs have the External role (there is no Router). The External role does not change the flocking model.

D. Avoiding communication failures due to Obstacles

Obstacles can block the line of sight (LOS) between UAVs, causing disconnections in multi-hop networks. In point-to-point communication, an obstacle between two Routers can result in a broken link from the Leader to the BS, forcing the routing algorithm to detect the failure and recompute a route — a process that can take several seconds and adversely affect the end-to-end packet delivery ratio.

To mitigate these issues, we introduce a new flocking interaction term, $\mathbf{v}_i^{\text{los}}$, activated only between two Router UAVs, which helps maintain LOS. UAVs can detect nearby obstacles using sensors (e.g., LIDAR) and identify neighbor UAVs via relative sensing. Based on this information, each Router UAV u_i computes a "LOS conservation force" using the following procedure, illustrated in Fig. 4:

For each Router neighbor u_j and for each obstacle o_k, u_i first computes the boundaries of an inflated version of the obstacle, o_k^* (*e.g.,* via an homothetic transformation). If the straight line $L = (p(u_i), p(u_j))$ intersects o_k^*, the UAV determines the nearest parallel line L' that does not intersect the inflated obstacle. The translation vector $\vec{d}$ between L and L' then indicates the direction of the adjustment needed to restore or preserve LOS. The resulting LOS conservation force applied to u_i for its link with u_j intersecting the inflated obstacle o_k^* has a direction $\vec{d}$ and a magnitude proportional to the size of the intersection.

$$\mathbf{v}_{i,j,o}^{\text{los}} = p^{\text{los}} \| [p(u_i), p(u_j)] \cap o_k^* \| \vec{d} \tag{3}$$

where p^{los} is a coefficient.

This innovative force proved efficient to solve LOS obstruction in simple environment, such as obstacles relatively large compared to the inter-agent distance (see Fig. 5). It is fully distributed and does not break the principles of flocking. However, its behavior in complex environments should be studied, for example environments with small and numerous obstacles.

The final flocking equation applied to all the UAVs of the fleet is then:

$$\tilde{\mathbf{v}}_i^d = \tilde{\mathbf{v}}_i^{\text{VAT}} + \mathbf{v}_i^{\text{tar}} + \sum_{o \in \mathcal{O}} \mathbf{v}_{i,o}^{\text{los}} \tag{4}$$

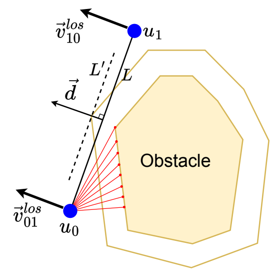

Fig. 4. LOS conservation force. The red lines illustrate a LIDAR sensor.

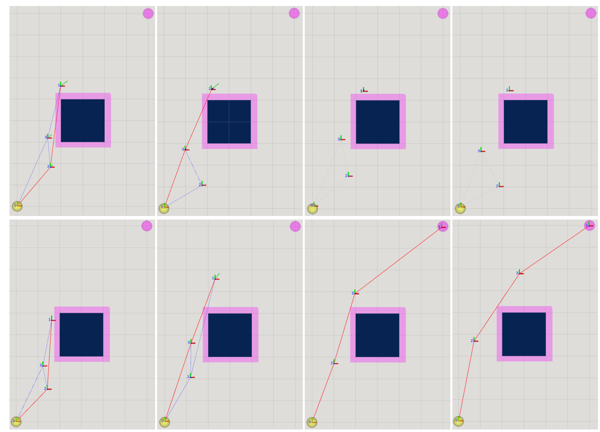

Fig. 5. Effect of an obstacle between the target area and the base-station, with (bottom) and without (top) the LOS conservation force. The pink area represents the inflated obstacle.

where $\tilde{\mathbf{v}}_i^{\text{VAT}}$ is the same as in [14] and Eq. 1 without the *auto-propulsion term*. Remember that all the components of Eq. 4 are sums of the contributions of the *flocking neighbors* of the UAV u_i, depending on its role, and that some of the components are activated only for a specific role, or between two roles (for example, a Support UAV activates $\mathbf{v}_i^{\text{att}}$ only with its two closest Router neighbors).

Finally, the desired velocity is bounded to a maximum velocity v_{max}:

$$\mathbf{v}_i^d = \frac{\tilde{\mathbf{v}}_i^d}{\|\tilde{\mathbf{v}}_i^d\|} \min\{\|\tilde{\mathbf{v}}_i^d\|, v_{\text{max}}\} \tag{5}$$

V. Evaluation and results analysis

To evaluate our flocking algorithm, we use DANCERS, a joint robotics and network co-simulator [15]. UAV dynamics are modeled using the realistic multi-rotor framework by the MRS Group at the Czech Technical University [16], while network communications are simulated via ns-3. We evaluate our approach in two scenarios of varying complexity.

A. Simulated packet exchange for neighborhood definition

Traditional flocking studies often define an agent's neighborhood using simple interaction ranges, such as disk-shaped areas [9], [17] or communication models with varying degrees of realism [18], [19]. However, these approaches typically overlook environmental effects (such as obstacle-induced shadowing) and complex networking effects (such as wireless channel congestion).

In our work, we define each agent's neighborhood through realistic packet exchange within a simulated wireless network. Each UAV runs a "heartbeat" application that periodically (with period T_h) broadcasts a 64-byte UDP/IP packet containing the robot's ID, position, velocity, and current flocking role. These heartbeat messages are locally broadcast and not forwarded, ensuring that only UAVs within the sender's communication range receive them.

An agent considers another UAV as a *potential neighbor* if it has received its heartbeat message within the past Δ_h seconds (*e.g.,* $\Delta_h = 2s$). Potential neighbors are maintained in a list ordered by reception power or estimated distance.

B. Simulation settings

Our simulations use Wi-Fi communication under the 802.11n standard operating at 2.4 GHz, with MCS[1] 7, a 20 MHz bandwidth, and 800 ns guard interval, yielding a theoretical data rate of 65 Mbps. We employ the `NistErrorRateModel` for error modeling alongside the `3GPP V2V Urban` propagation model.

Routing plays a central role in our flocking model. In fact, having a QoS-aware routing algorithm is critical for successful relay chain formation using our relay chain algorithm. If the routing algorithm solely relies on hop count, Leaders may form long, low-quality links with the BS, leading to disconnections. Unfortunately, QoS-aware MANET routing protocols are not yet implemented in ns-3. To evaluate our algorithm nonetheless, we implement a routing algorithm based on inter-UAV distance, close in principles to OLSRv2.

The physics of the UAVs is computed using the realistic multi-rotor model developed by the MRS Group at Czech Technical University [16]. It uses an ODE solver for UAV dynamics and a multi-rotor controller that supports various levels of control (*e.g.,* position, velocity, attitude + thrust). To keep simulations computationally lightweight, we do not use a full physics engine. Instead, UAVs are modeled as 50 cm spheres to detect collisions.

Obstacles are represented as axis-aligned bounding boxes, a constraint of the ns-3 buildings module. These obstacles are randomly generated based on a given area, obstacle count, and the mean and standard deviation of their radii.

In all scenarios presented, the UAV fleet takes off from a location near the base station.

C. Scenario 1: Single target relay chain

The first scenario involves a single target area and a group of 6 UAVs that uses Wi-Fi to communicate. The primary objectives are to demonstrate that our algorithm can:

1) adapt the number of routers depending on the distance between the target and the BS,
2) evenly distribute the routers along a straight line between the target and the BS,
3) avoid collisions among UAVs and with obstacles.

Note that it is proven in [2] that under the hypothesis of the two ray propagation model, equally distributing the routers along a straight line is the optimal router placement.

[1]Modulation and Coding Scheme

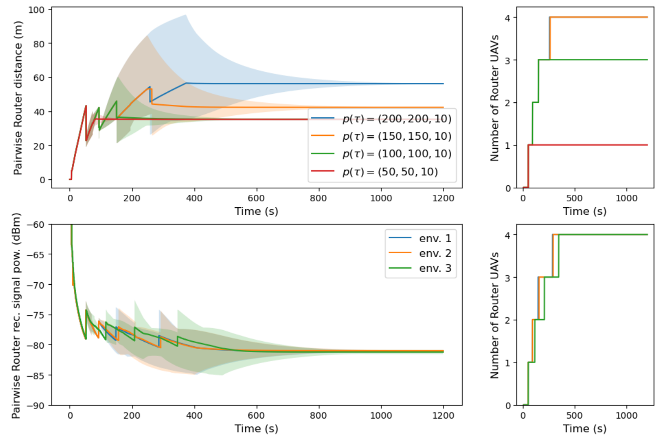

Fig. 6. On top left, Router link length in an obstacle-free environment. On bottom left, received signal power in cluttered environments. On the right, the evolution of the number of Router UAVs.

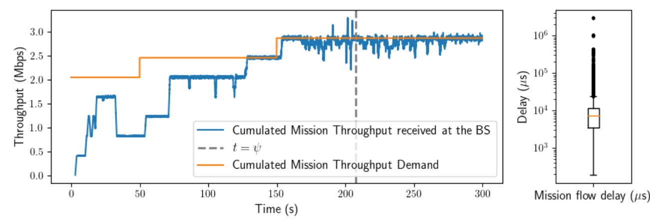

Fig. 7. On the left, cumulated throughput request and received at the BS (ϕ) where each Leader generates 0.4 Mbps of mission data. On the right, end-to-end delay of the mission flow.

We record both the inter-router distances and the received signal power between pairs of Router UAVs (the chain links). The first key finding is that these metrics converge over time. This convergence is depicted in Fig. 6 as time series with min-max bands. In the top-left panel, link lengths in an obstacle-free environment are shown for various target positions (the BS is fixed at $p(\delta) = (0, 0, 10)$). Once the Leader UAV reaches the target area ($\psi = 93$ seconds for $p(\tau) = (200, 200, 10)$), the average link length stabilizes. In the bottom-left panel, the target is fixed at $p(\tau) = (200, 200, 10)$ for three different obstacles environments. The received signal power between pairs of Router UAVs similarly converges.

Additionally, the algorithm dynamically adjusts the number of relays: by directly leveraging the routing algorithm's results to elect chain members, the number of Router UAVs automatically adapts as long as sufficient Support UAVs are available. As illustrated in the top-right panel of Fig. 6, a target at $p(\tau) = (50, 50, 10)$ requires only a single Router (resulting in a two-hop chain). Importantly, no collisions were recorded in any of the scenarios.

D. Scenario 2: Relay tree with dynamic targets

In this scenario, the UAV fleet is challenged with a dynamic environment featuring multiple target areas and the appearance of new targets during the experiment. The primary goal is to demonstrate the scalability and flexibility of our approach.

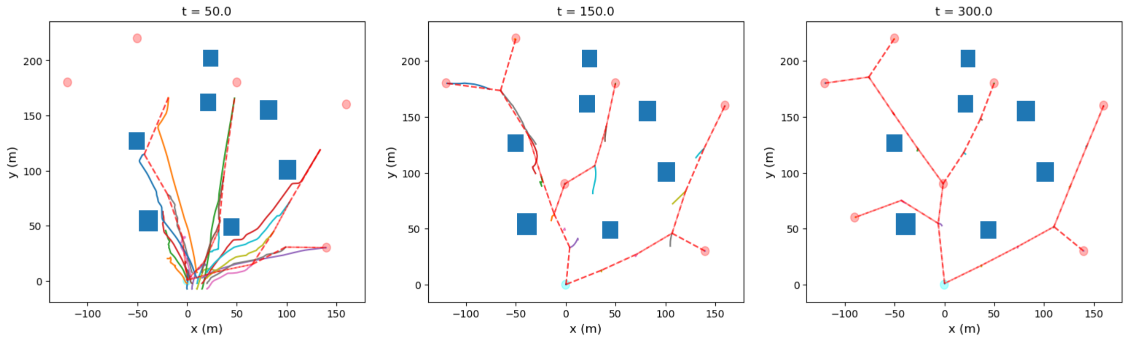

Fig. 8. Trajectories of a fleet of 20 UAVs forming a relay tree with multiple targets. New targets appear at t=50s and t=150s. The data chains are represented in red dashed lines. The "tail" trajectories of the UAVs are represented over 50s.

Initially, 20 UAVs are deployed to establish communication chains with 5 target areas. At t=50s and t=150s, two additional target areas emerge, prompting the fleet to reorganize. Fig. 8 illustrates the environment, UAV trajectories, and the corresponding Router links.

Qualitative results indicate that our flocking model effectively disperses agents to form a relay tree, ensuring that each Leader reaches its assigned target while maintaining continuous communication with the BS. The first of the initial five targets is reached at t=34s, the sixth target at t=69s (19s after emerging), and the final target of the initial set at t=121s. The seventh target is reached at t=ψ=208s. Quantitatively, once all targets are reached, the cumulative throughput stabilizes at $\phi = 2.63$ Mbps, representing 94% of the total mission flow generated by the Leaders (see Fig. 7). The average packet delay is low, averaging $D = 9.2$ms, with occasional spikes up to 3 s during abrupt route changes.

Overall, this scenario demonstrates that our solution can effectively manage large fleets of autonomous UAVs in obstacle-rich unknown environments and dynamically adapt to the introduction of new target areas, all while maintaining robust QoS in terms of throughput and delay.

VI. Conclusion and Future Work

This paper introduced a novel UAV-based relay network formation strategy that leverages an enhanced flocking model integrating dynamic role assignment, routing-aware neighbor selection, and a novel LOS conservation force. Our approach enables the formation of robust relay chains that maintain connectivity, evenly distribute agents along the communication path, and prevent collisions. Simulation results across scenarios of various complexity demonstrate the method's effectiveness in achieving stable throughput and low delay, even in challenging environments.

Future work will address several key directions. We plan to analyze and manage network congestion to further enhance Quality of Service, and to adapt the model for multi-path routing protocols, thereby improving resilience and load balancing. Improving the behavior of the Support role to promote spatial diversity would be beneficial. Extending the approach to heterogeneous fleets and including random UAV failures in simulation would increase operational flexibility. Finally, real-world experiments should be pursued to validate our findings and tackle practical deployment challenges.

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