

A 3D Mobility Model for Autonomous Swarms of Collaborative UAVs

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Abstract— Collaboration between several Unmanned Aerial Vehicles (UAVs) can produce high-quality results in numerous missions, including surveillance, search and rescue, tracking or identification. Such a combination of collaborative drones is referred to as a swarm. These several platforms enhance the global system capabilities by supporting some form of resilience and by increasing the number and/or the variety of embedded sensors. Furthermore, several UAVs organized in swarm can be considered as a single entity from an operator point-of-view.

In order to collaborate, the UAVs have to share information. This is a task of prime importance to perform the mission quickly. Nevertheless, the major task is definitely the path planning that has to be achieved for each UAV, especially when they evolve in unknown environments because decisions must be taken dynamically. To deal with this issue, we have implemented a three-dimensional (3D) mobility model for swarms of UAVs using the Artificial Potential Fields (APF) principle and a global path planning method. In our model, UAVs share their own knowledge of the environment in order to allow the platforms too far of obstacles to detect them to improve their trajectory calculation. To provides a significant validation of our mobility model, We have simulated real-world environments and sensors performances, in the network simulator OMNeT++.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are key players today to help perform numerous tasks in both civilian and military applications. Even if drones are more and more technically advanced, a single one is often not sufficient to perform large-scale or complex (in terms of data collection) missions. Indeed, the variety of tasks one would like to achieve increases quicker than the capacity of a single UAV. Then, swarming became quite recently a central field of research [15]. Among the many advantages offered by swarms are: continuous flight, multi-sensor capabilities, sensors reorganization, resilience, information replication and hiding.

To collaborate, and thus offer high-quality performances, the UAVs have to communicate between each other. Then, additionally to various sensors, the platforms are equipped with wireless network components that make it possible to create data links between them to form a Flying Ad hoc Network (FANET) [6].

The issue that we address here is that of moving the elements of a swarm from a given area to another, which is clearly a basic function that needs to be supported should the swarm be usable for any sensible mission.

A large number of UAV swarm studies that address this problem consider it from the perspective of area coverage (including connectivity constraints [17], [14], [19] *etc.*) but most

of them consider obstacle-free environments. We consider the case, which we believe is more representative, of urban-like areas. In this case, the UAVs have to not always fly above building to get high-quality information and consequently, obstacle avoidance is a task of prime importance.

In this paper we present our 3-dimensional mobility model for autonomous swarms of UAVs based on the Artificial Potential Fields (APF) principle and including a global path planning. This model called 3DGAPF+ (3-Dimensional Global APF+) extends one of our previous model, described in [9], which we call APF+.

This work is organized as follows. Section II presents related works on multi-UAVs mobility strategies and path planning using APF. In section III, we describe the APF+ mobility model and the novel extension 3DGAPF+. Section IV focuses on simulations and results, especially compared to other mobility models for UAVs swarms. Finally, conclusion and future works are presented in section V.

II. RELATED WORK

For decades, many path planning methods have been studied in the robotic field. Here, we focus on methods designed for FANETs and also on mobility strategies based on the the APF principle (introduced in [10]).

A. Mobility Strategies for FANETs

Mobile Ad hoc Networks (MANETs), are continuously self-configuring and infrastructure-less networks, composed of mobile devices connected wirelessly [6]. FANETs are a type of MANETs, composed of UAVs. When several UAVs have to collectively fulfill a task, collaboration between the platforms can enhanced the system performance. Indeed, they can fulfill missions in larger areas, quicker, using higher quality information thanks to the possible plurality of the embedded sensors. Therefore, collaborative mobility models are worth studying. Due to the huge quantity of existing path planning methods, only a few examples are given here, the most studied methods and those which are the closest to our work.

Using multiple UAVs can be very efficient for surveillance missions thanks to collaboration between the platforms because, they propose a large number of capabilities (multi-sensors, multi-platforms, multi-modal capabilities). However, the on board communication systems have a limited range. A compromise has thus to be found between two adversary criteria: maximizing area coverage and preserving network connectivity [17]. A method achieving these objectives, based on chaotic dynamics and ant colony optimization (ACO), has been presented by Rosalie *et al.* [17].

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Boskovic and Moshtag [7] proposed a global system including mission planning, using evolutionary algorithms and biologically-inspired swarm, designed for military activities. Their solution is distributed and robust to communication delays and loss. Furthermore, it uses a real-time learning algorithm and provides dynamic mission re-planning.

Li *et al.* recently proposed a Particle Swarm Optimization (PSO) mobility model designed for FANETS[12]. This PSO method takes into account UAVs characteristics, including kinematic and dynamic constraints. Their method generates velocities and waypoints for each UAV, which are adjusted to avoid collision with neighbors.

Li and Chen [11] proposed a global method in order to search a single static target, comprising a collaborative mobility model, information sharing and decision making to continue or terminate the search. There is no obstacle in the Area of Interest (AoI). Information on the presence of the target in each cell of the discretized environment are shared and each UAV builds its own map. They suppose that each UAV is able to cover one cell in a single observation step. At each iteration, each UAV analyzes its own cell, updates its own map, shares it with the other UAVs, update again its own map by merging it with the information received from the other UAVs, eventually decides to stop the search if the target is found, else chooses its next flying direction. For this last step, each UAV has 2 choices: to go in one of the 4 adjacent cells or not to move. The criteria is to go towards the cell with the highest probability of presence.

B. APF-based methods

The original APF method was introduced by Khatib in 1986 [10]. The APFs are composed of two kinds of fields: an attractive one towards a target point and a repulsive one for each obstacle. The robot (drone) moving direction is the negative gradient of the resulting APF.

Numerous studies have been carried out on APF methods, on one hand because they are easy to implement and have low computational cost [20]. On the other hand, because the original method presents some weaknesses, as the local minima when UAV, obstacle and goal are in line, or the the Goal Non Reachable with Obstacle Nearby (GNRON) problem.

A way to avoid local minima has been proposed by Liu and Zhao [13]. Their solution is composed of two steps. First, if there is a superposition in the influence area of several obstacles, they consider them as a single larger obstacle. This step reduces the number of local minima. Second, if a UAV nevertheless enters in such a minima, they create a temporary waypoint allowing the platform (drone) to escape.

Very close to our approach, Sun *et al.* [18] propose a collision avoidance model for cooperative UAVs based on improved artificial potential fields. One can quote their local solution to avoid the jitter problem. Furthermore, their potential fields definition removes local minima, the GNRON problem and the impossibility to go between close obstacles. Their model performs well in 3D and examples are given where all the UAVs go towards the same target

point. Nevertheless, the hypothesis description is not precise enough to appreciate the results relevance.

III. OUR CONTRIBUTION: THE 3DGAPF+ MOBILITY MODEL

In this section we briefly summarize our previous mobility model, described in details in [9], which will be called APF+. Then we will describe 3DGAPF+, an extension of APF+ which includes 3-dimensional environments and trajectories additionally to global path planning. Both mobility models were created for autonomous UAVs making up a swarm and are based on the Artificial Potential Fields principle [10].

A. Common Features of APF+ and 3DGAPF+ Models

In the frame of our simulation, the UAVs evolve in a bounded rectangular area containing obstacles they are not aware of. The environment is meshed by square cells of equal size defined by the user, which are at least as large as a UAV in order to avoid collisions. The flying time is also discretized in steps of one second, empirically. At each iteration, the UAVs probe again the environment thanks to their on board sensor and eventually detect obstacles around them. Then, they calculate their next move in any direction without any kinematic constraint.

B. APF+ Mobility Model

The APF+ mobility model [9] follows the traditional APF method by considering several potential fields with high potentials for the obstacles and low potentials for the target point¹. The field linked to the target point is initialized at the beginning of the mission and those related to the obstacles that have been discovered are updated all along the mission. The UAVs always try to go towards lower potentials. The UAVs evolve in a discrete environment, and can move at each iteration to one of the 8 adjacent cells. The UAVs always choose to go towards the cell with the lowest potential.

This mobility model uses 3 matrices. The first one, noted *pot* stores the APF described above. The second one, noted *avoid*, is re initialized at each iteration and stores temporary APFs linked to neighbors and the anticipation of obstacle avoidance (see definition in [9], section IV-F). To choose their next moves, the UAVs compare the sum of the potentials stored in these two matrices for each adjacent cells. Finally, the third matrix, *obs*, contains the cell status:

- there is no information about the cell;
- it does not contains an obstacle and is safe;
- it does not contains an obstacle but is not safe or has already been revisited;
- it contains an obstacle;
- it is on a path already used by a UAV to reach the target.

This matrix is the only one shared between the platforms.

In this model, we introduced an innovative method allowing to anticipate obstacle avoidance and preventing the local minima problem.

¹Contrary to the definition given in [9], we use the Euclidian norm to calculate the APF related to the target because it reduces the number of adjacent cells compared to the uniform norm.

C. 3DGAPF+ Mobility Model

In this extension of APF+, we kept the same potential definitions and a UAV will still go towards lower potentials. The two main enhancements are the following: 1) the UAVs can evolve in 3D and 2) they calculate a global path towards the target with as few waypoints as possible.

1) *3D*: In order to move in 3D, the environment is meshed as cuboids and the matrices supporting the potentials thus also have 3 dimensions, as each element of a matrix represents a cell of the discretized environment. Potentials definitions are an extension in 3D of those defined in APF+. The user can choose independently the horizontal and vertical cells sizes (but cuboids bases are square).

2) *Global Path*: When movements are limited to surrounding cells, only 8 directions can be taken in 2D and 26 in 3D. In order to shorten the paths, it is necessary to authorize more directions. In this model, the UAVs compute one or several waypoints at each iteration. The calculation method depends on the locations of the UAVs and on the characteristics of the obstacles (width, height, shape...). The resulting waypoints are not necessarily in adjacent cells and the UAVs are allowed to move in any direction. Their speed is limited to a given value noted s_{max} . We suppose that the distance traveled by a UAV in one iteration at maximal speed is smaller than the embedded obstacle sensor range. The principle of our model is as follows: one move is decided at each iteration. This move depends only on the first waypoint of the computed path. If it is close enough to be reached in one iteration, the UAV reaches it, else it goes towards it. Consequently, to get paths as short as possible, the waypoints should be as far as possible of the UAV.

Nevertheless, when a UAV is close to an obstacle, it is not always possible to find safe waypoints far away from this drone. For this reason, we have to consider 3 cases depending on the UAV environment, in order to optimize the path:

- 1) No obstacle detected in the direction of the target
- 2) Obstacle detected in the direction of the target
- 3) UAV in a U-shape obstacle (dead-end)

When a UAV changes of mode, the path is reinitialized and recalculated. Fig.1 illustrates the path calculation depending on the UAV environment in 2D for more readability, but the process is identical in 3D.

In the first mode, the UAV goes at maximal speed towards the target (see Fig. 1(a), 1(f), 1(g) and 1(h)). While a UAV is in this situation, it uses the shortest path to join the target. The path is then composed of one single waypoint: the cell closest to the target in the UAV sensor range.

In the second mode, the UAV cannot go directly towards the target because of obstacles or neighbors. Then the APF+ algorithm is ran iteratively using the UAV current knowledge of the environment to add waypoints to the path until the target is reached (see Fig. 1(b), 1(c) and 1(d)).

Finally, as a UAV sensor range is limited, a drone can first consider that two obstacles are around it, and later discover that it is actually surrounded by a single building (or several buildings too close to allow a passage between them). In

this case, the UAV is in a dead-end: it will retrace its steps until the exit of the dead-end and significantly increase the potential (in the pot matrix) of the cells inside this obstacle in order to avoid them next time. In this mode, the path is composed of the cells already crossed by the UAV, from the most recent to the oldest, inside the dead-end.

As noticed before, only the first waypoint is used to make the move decision at each iteration, independently of its distance from the UAV. Then, in order to have flights as short as possible, as few waypoints as possible should be considered, and they should be as far as possible from the UAV. We thus created a function to delete useless waypoints. Let's note WP_i the i^{th} waypoint in the path. If the cells between WP_0 and WP_2 are safe, then the UAV deletes WP_1 . It follows this procedure iteratively while it can delete WP_1 and while WP_0 is within its sensor range. Such deletion of waypoints has been performed on Fig. 1(b), 1(c) and 1(d) and makes it possible to reduce the necessary number of iteration to reach the target.

IV. SIMULATIONS AND RESULTS

A. Embedded Equipments

Each UAV carries equipment to ensure communication with its neighbors and obstacles detection.

1) *Obstacle Detection*: The recent drone "DJI Mavic Air" seems to have the most advanced collision avoidance system of the small drones market [4], [16], [8]. To fulfill this complex task, this UAV is equipped with several sensors [2], [8] including forward, backward and downward dual vision sensors. The best characteristics are those of the forward stereo vision system, in particular a detection range up to 24 meters and fields of view of 50° in horizontal and 38° in vertical [2]. In our context, the UAVs evolve in an unknown environment and may have to go in any direction, while a Mavic Air using its sense and avoid system follows a given direction. Then, we chose to simulate an obstacle detection sensor of 24-meter-range, representing 2 stereo cameras (one on the top and one on the bottom) each mounted on a gimbal supporting rotations. The UAVs then know their environment in a sphere centered on themselves, as shown on Fig. 2.

2) *Communication Module*: In our model, the swarm is collaborative because its UAVs share information on the environment. Along with the APF+ model, the UAVs carry XBee communication modules, which are particularly adapted for multi-rotors application because they are small require little energy, have light weight and are easily customizable [1].

B. Experimental Setup

In order to simulate realistic communications characteristics, we chose the highly customizable network simulator OMNeT++ [5]. The main parameters used are the same as in our previous paper [9] where they were given in appendix. The sensor simulations are not as precise as the communication ones: we only suppose that UAVs have information on the presence of obstacles within their sensors ranges. For all the simulations, we make the following assumptions:

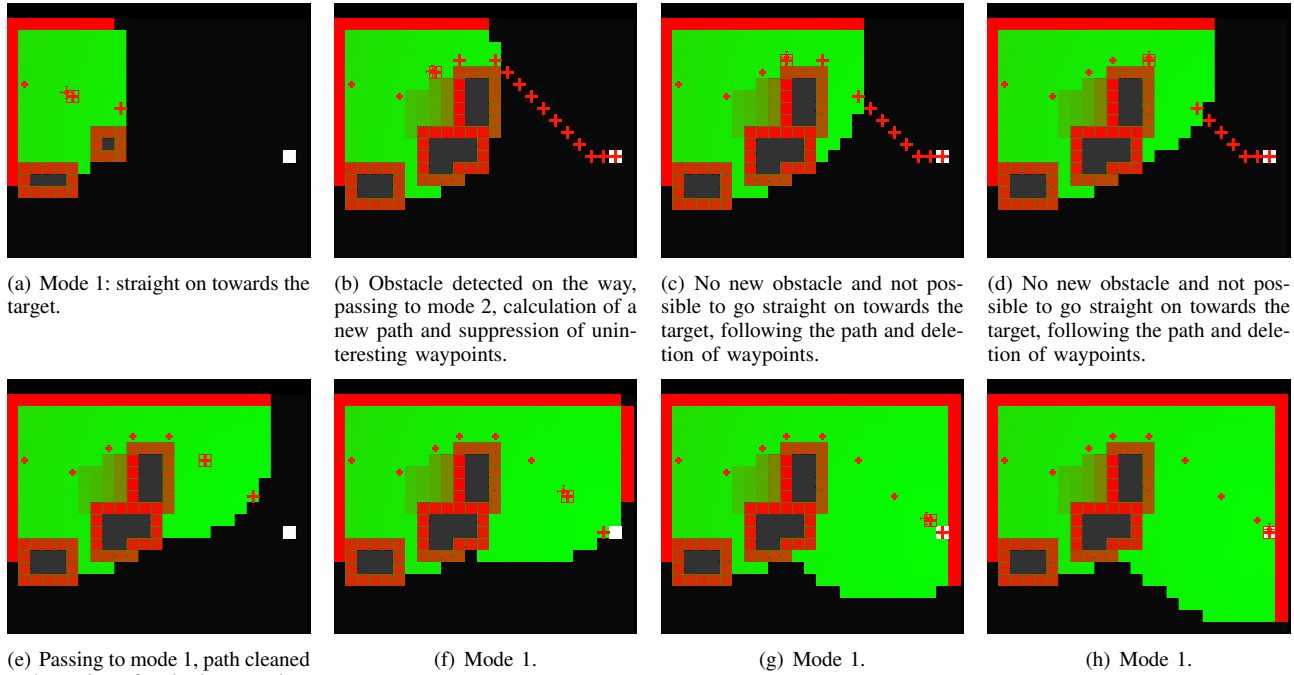


Fig. 1: Moves of a UAV in an unknown environment iteration by iteration. Small crosses represent the cells where the UAV has been, and the large one represent the waypoints. The target cell is the white one, cells in black are unknown, the colored one have been discovered. The color of each known cell corresponds to its potential (green: low potential, red: high, dark blue: highest corresponding to obstacles).

- At the beginning of the mission, all the UAVs are within the AoI, they know how many they are in the swarm, they know the AoI limits.
- The only moving obstacles within the AoI are the UAVs composing the swarm.
- Calculation power and battery are sufficient.
- Each UAV knows with sufficient precision its own location and its target point location (inside the AoI).
- Each UAV is equipped with an XBee communication module and with sensors allowing obstacle detection in a range of 24 meters.
- UAVs maximum speed is $10\text{m}\cdot\text{s}^{-1}$ and they are not submitted to kinematics constraints.

Xbee data rate is up to $250\text{ kbits}\cdot\text{s}^{-1}$ and is a half-duplex system. Then, if we want the UAVs to communicate every

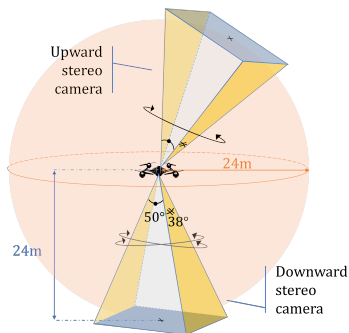


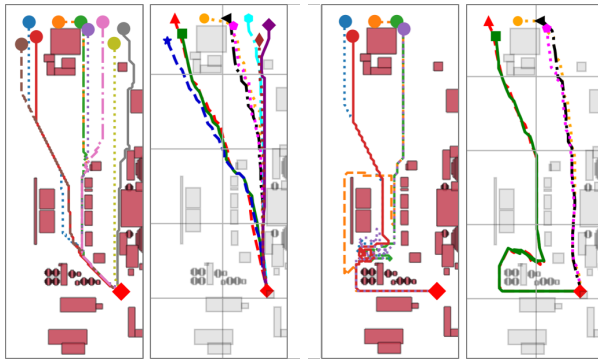
Fig. 2: Embedded sensors allowing obstacle detection.

two seconds, the maximal possible volume of the exchanged matrix is 500kbit. One matrix is exchanged between the platform, containing as many elements as cells in the discretized environment, and each element contains an integer coded on 8bits. Furthermore, the whole AoI is 500m-large, 500m-long, and UAVs can eventually fly between 4m (to avoid people and the vehicles) and 24m (camera range) of altitude. So a meshing constituted of cubes with edge lengths of 4m is adapted. Each UAV has a unique ID. Every 2 seconds, one UAV sends its vision of the environment, by increasing ID.

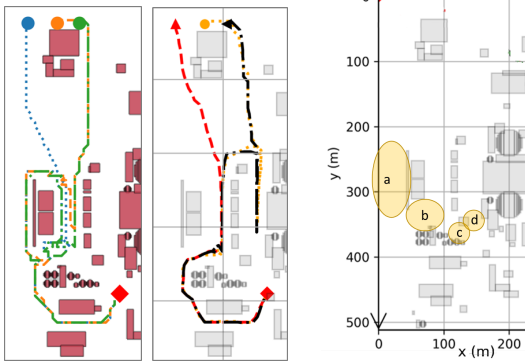
C. Comparison with APF+

The first step to evaluate our model was to compare the trajectories computed with 3DGAPF+ to those computed with APF+, in a real environment: the Blayais power station, of which we reproduced the buildings from the French land register [3]. Fig. 3 shows some examples of simulations performed in 2 dimensions. The trajectories followed by the UAVs with 3DGAPF+ model are smoother and shorter than with APF+. There were no collision either.

More precisely, the UAVs paths computed considering a cell width of 2 meters are clearly shorter than those considering larger cells (see Fig. 4). Indeed, the discretization is thin enough to allow the passage between close obstacles, especially in areas c and d (defined on Fig. 3(d)). With a cell width of 4 meters, it is not possible to cross area c anymore. In this case, the median traveled distance is significantly shorter with 3DGAPF+ than with APF+. The substantial difference with APF+ is due to two factors. First, when several UAVs are in area b, they needed a large



(a) 9-UAV swarm, horizontal discretization of 2m. (b) 3-UAV swarm, horizontal discretization of 4m.

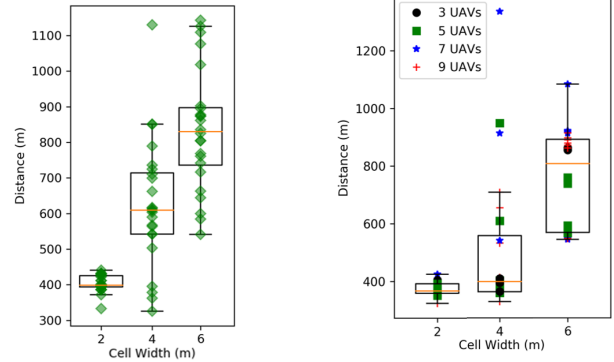


(c) 3-UAV swarm, horizontal discretization of 6m. (d) Areas legend.

Fig. 3: Trajectories followed by autonomous swarms of UAVs. On the the left, calculations made with APF+, on the right, calculation made with 3DGAPF+

number of moves to escape this complex area while avoiding collisions with the neighbors, because at each iteration the move decision is taken independently from the previous and next one. Second, when many drones were close to area c, some escaped this passage and preferred area d to avoid collisions. These two solutions increase the traveled distance. 3DGAPF+ solves both problems and most of the UAVs easily escape from area c. Finally, a cell width of 6 meters forbids the passage to area d in addition to area c. As a result, the traveled distance with both models are substantially longer. Nevertheless, with 3DGAPF+ more than 25% of the UAVs travel was shorter than 600m, which is the shortest possible path in this configuration (distance traveled by the red UAV Fig. 3(c)). The UAVs whose path measured approximately 800 meters had a trajectory close to the orange and black drones shown on Fig. 3(c). For all these platforms, the path cannot be shorter because of their limited vision of the environment. Finally, one can notice that the longest traveled distance with cell width of 6 meters are followed by UAVs in the largest swarms. This is due to the collision avoidance system between the platforms which reduces the optimization of the path, by decreasing the deletion of waypoints.

These simulations show that the smaller the cells, the shorter the path. Nevertheless, UAVs wingspan is approx-



(a) Results for APF+ mobility model. The 72 UAVs reached the target.

(b) Results for 3DGAPF+ mobility model. 3 UAVs out of 72 did not reach the target.

Fig. 4: Superposition for a given cell width (2, 4 and 6m) of the distances traveled until the goal by each individual UAV in swarms of 3, 5, 7 and 9 vehicles in the 2-dimensional environment represented Fig. 3.

imately 50cm so it would not be useful to use thinner discretization. Furthermore, the mobility model is based on three matrices representing the environment (see section III) which contain as many elements as cells. Then, the smaller the cells the larger the matrices. Because one of these three matrices is exchanged between the platforms and as the XBee data rate is limited, a very thin discretization would not allow collaboration between the platforms.

To conclude, our mobility model performs well in a complex environment in 2 dimensions, especially with a thin discretization.

Nevertheless, 3DGAPF+ has a weakness: in 2 simulations out of 12, some UAVs remained in local minima. Indeed, they alternated with the mode 1 and a path calculation. Fig. 5 shows such a simulation, were the dark blue UAV never reaches the target point.

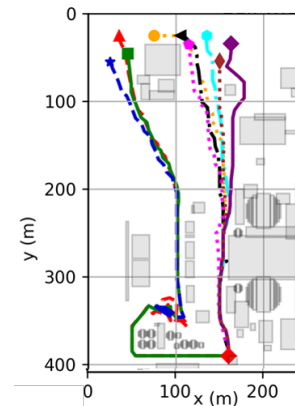


Fig. 5: Trajectories followed by 9 autonomous UAVs evolving in swarm in 2 dimensions, with a discretization of 4m.

D. Comparison with Sun *et al.*'s Model

As explained in section II-B, Sun *et al.* study [18] is close to ours. Then, we reproduced one of their testing environment to compare the trajectories calculated by their and our model (see Fig. 6 of their paper [18]). Their experimental setup is not clearly given, but from their figure we suppose that the environment was 110m long and 70m high, and we arbitrary chose a width of 15m. In order to allow the UAVs to pass these thin passages, we chose a vertical discretization of 1m. Fig. 6 shows a sectional view of a 6-UAV swarm trajectory in this environment and Fig. 7 shows a 3D view of such a configuration.

There were not any collision, between UAVs or with an obstacle. As for Sun *et al.* results, the UAVs use different ways to reach the target point. One can note that the trajectories are smooth except for some UAVs which shift from their shortest trajectories to avoid collisions with others, especially when close to obstacles. Furthermore, the distance traveled in one iteration is much larger in obstacle-free environment than in thin passages, because only few waypoints can be deleted there. To conclude, our model performs well in this 3-dimensional complex environment, and can take advantage of obstacle-free areas to increase the speed of the UAVs.

E. Swarm in Complex 3-Dimensional Environment

Finally, we tested our mobility model in 3D in the Blayais power station. Fig. 8 shows the trajectories of a 4-UAV swarm in this complex environment. One can note that in this test, the UAVs have different goals. Indeed, as the collaborative process is based on the obstacle location sharing, the mobility model can be used as-it-is with individual departures position and/or targets.

Furthermore, the UAVs performs horizontal or vertical obstacle avoidance, depending on the building height and on their neighbors location. In this test also, there were no collision.

V. CONCLUSIONS AND FUTURE WORK

This paper presents a 3D mobility model for swarms of collaborative UAVs based on APF method. In this paper we introduced 3DGAPF+ mobility model for swarms of collaborative UAVs, an extension of APF+ mobility model, to which we added a global path planning method and the third dimension. The method is validated using OMNeT++ with swarms of 3 to 9 UAVs in several environments containing 3D obstacles. Simulations are used for comparisons with a mobility model of Sun *et al.* [18] and for comparison with our previous work [9] in a real environment. Communication between the platforms precisely simulate XBee module, and simulations of embedded sensors allowing obstacle detection are also performed. In future work, we will target even more realistic simulations. In particular we will work on a kinetic model of multi rotors and sensors. Then, we will work on complete missions with complex scenarios.

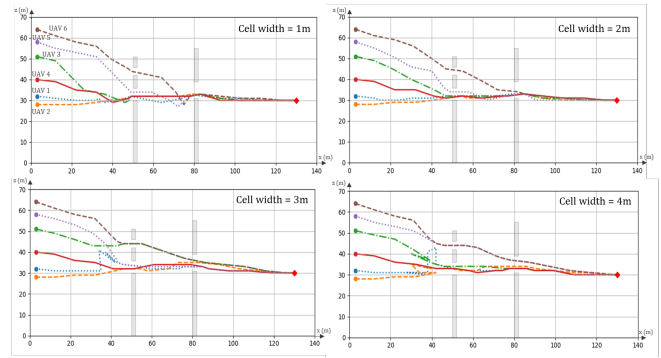


Fig. 6: Projections in a vertical plan of the trajectories of a 6-UAV swarm, with a vertical discretization of 1m and horizontal discretization of 1, 2, 3 and 4m, towards a common target point represented by a red square.

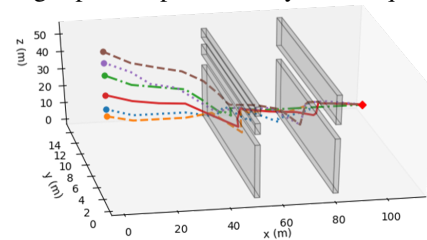
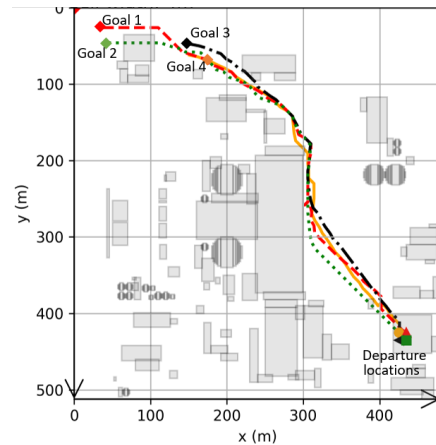
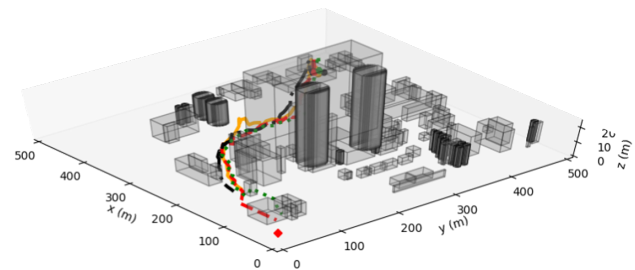


Fig. 7: 3-dimensional perspective of the simulation with 6 UAVs and horizontal and vertical discretization of 1m.



(a) Upper view of the trajectories.



(b) 3D view of the trajectories.

Fig. 8: Trajectories of a 4-UAV swarm in 3D with an horizontal discretization of 4m and a vertical one of 4m between 4 and 24m of altitude.

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