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AN APPROACH TO THE UAV PATH PLANNING PROBLEM IN THE INTERNET OF DRONES CONSIDERING UNCERTAINTIES

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ABSTRACT

In recent years, the use of drones has become more common for **different** practical applications, such as goods delivery, area monitoring, image capture and traffic management. For these applications to be possible, it is necessary that the drones use the same airspace, constituting the **Internet** of Drones (IoD). Considering that IoD is a complex network, different challenges and problems involving this architecture still need to be **studied**. One of the challenges in IoD is the Unmanned Aerial Vehicles (UAV) Path Planning (PP) problem so that they arrive at their destinations safely, fulfilling their assigned tasks. In this paper, we deal with the UAV path planning problem offline in the IoD considering uncertainties, which are modeled using fuzzy numbers (PP-IoD fuzzy problem). As a **resolution** method we used the Dijkstra and Ford Moore Bellman algorithms adapted for the case where there are fuzzy parameters. Comparisons with the classical version of Ford-Moore-Bellman algorithm were performed and demonstrate the effectiveness and accuracy of the solutions obtained through fuzzy versions of two classic and well-known algorithms.

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INTRODUCTION

Drones, as Unmanned Aerial Vehicles (UAVs) are known, are used in urban and non-urban environments for different activities, namely transportation, agriculture, environment monitoring, health, communication, entertainment, search and rescue, to name a few. Considering that all services need to compete for the same airspace, the creation and control of a drone network is necessary and relevant. Gharibi et al (1) presented an architecture to control the coordinated access of drones in the airspace called Internet of Drones (IoD). According to the definition, this environment has well-defined airways and a traffic control to manage this network. Considering this scenario, several companies using drones will probably share the same environment and the same airways, for example in the delivery of goods. Currently, there are several studies related to delivery applications with drones. Large and well-known companies, Amazon (2), Google, Ifood (3) are invest- ing in research and possibilities to make their deliveries via drones. In this sense, it is evident the need for well-defined airways so that drones can use them in a safe and controlled way, making it possible to carry out a range of applications that will facilitate the lives of people as well as urban centers, collaborating so that cities become intelligent. Regarding drones, the biggest limitation is their battery capacity (4). Differ- ent factors affect the consumption and performance of a drone's battery, such as vertical and horizontal maneuvers, acceleration and deceleration, change of direction, and environmental factors that are often difficult to measure. In addition, drones have limited memory on their on-board computers, requiring the development of algorithms for path planning that are efficient and do not use a large amount of the drones' memory. The UAV path planning is one of the big challenges in the IoD context, being necessary to plan effective flight paths that allow drones to reach their destinations, avoiding obstacles and minimizing the amount of energy they need to consume, considering that several drones can share the same airspace. This problem in three-dimensional space can be classified with respect to the time domain into offline or online. In the offline case, information about the environment is required a priori to be used in the construction of the path, whereas in the online case, one does not have information about the environment a priori but during the flight, through sensors. To assist in the organization of the airspace, the IoD is composed of airways. The node respon- sible for coordinating the drones is the Zone Service Provider (ZSP). In the IoD, the ZSP is responsible for controlling the airspace (1).

Considering the layered structure for IoD, proposed by Gharibi et al (1), one way to define and organize the airways is to consider that they are parallel to landways, for which there are well-established rules (5, 6). In this case, it is plausible to consider that we have overlapping airways, which can be represented by layered graphs.

UAV Path Planning sob uncertainties: In the literature, there are different algorithms to solve the UAV path planning problem. Qadir et al (7) classified the algorithms for path planning into conventional (Rapidly exploring random tree (RRT), Artificial Potential Field, Voronoi), cell-based ($A^{\square}$, $D^{\square}$, Dijkstra), model-based (Mixed Integer Linear Programming, RRT Series), and learning-based (neural networks, evo- lutionary). In addition, models that consider uncertainties can be solved via probabilistic methods or using numbers and/or fuzzy sets. In this paper, we propose an approach to the PP-IoD fuzzy by consider- ing airways parallel to landways, represented by layered graphs, which can be used to compactly represent the environment in which drones can fly. In addi- tion, we consider uncertainties in the costs of the arcs, modeled using fuzzy numbers. The uncertainties represent factors that are inherent to the UAV path planning problem and are difficult to predict, such as wind, rain, birds flying in the airway, among others. Finally, we use two classical shortest path algorithms, Dijkstra and Ford-Moore-Bellman, adapted for cases where there are uncertainties in the data. In this scenario, the UAV path planning in the IoD focuses on getting the optimal paths for different drones sharing the same airspace. The remainder of this paper is organized as follows. In section II we present the motivation for this study. In section III, the related papers. In section IV we present the preliminary concepts of set theory. Section V presents the solution methodology. Section VI, the results and their analysis and, finally, in section VII the final considerations and directions for future work.

Motivation and Background: The UAV path planning problem is widely studied, some works in the literature (4, 8–12) address this problem in different contexts, factors, techniques and applications; however, there is still much to be studied and explored regarding this problem in IoD context. Considering the path planning problem in an IoD environment, one of the major challenges is to determine where the airways can pass through. Bine et al (5, 13) consider airways to be parallel to landways, this way drones would only fly through permitted public areas. The Figure 2 illustrates airways parallel to landways. This structure can help organize drone traffic and facilitate the construction of laws that regulate it, especially in the context of IoD. The Figure 2 illustrates overlapping airways on existing airways forming new paths. The overlaps airways provid airway expansion by overlapping them it different altitudes (13). Airways are established to be parallel to landways and are free from static obstacles.

Another challenge is the uncertainties, that are present in all real environ- ments, through factors that are difficult to measure, such as wind, rain, birds flying in the airway, among others. Besides climatic factors (such as wind and rain), and obstacles (birds flying, for example), the time or cost of travel can also be considered uncertain since they are usually affected by adverse or even unforeseen conditions. Therefore, considering the aspects listed, in this work

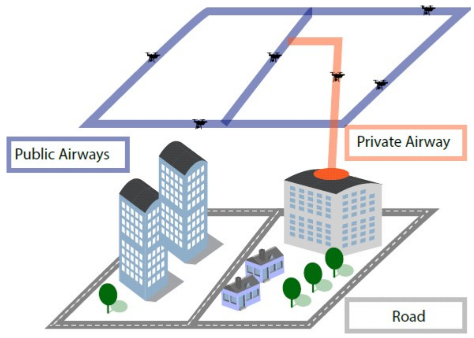

Fig. 1 Parallel Airways and public × private airways illustration (13)

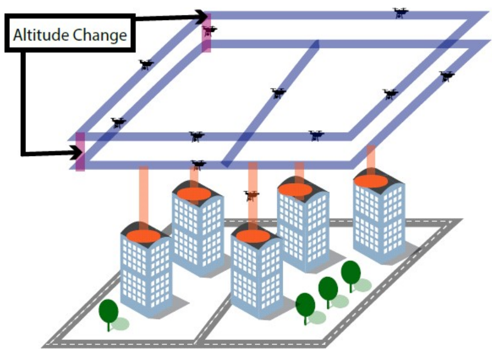

Fig. 2 Overlaps airways illustration (13)

we use two classical and well-known algorithms for the shortest path problem, but in versions adapted for the context of uncertainties considering IoD with airways parallel to the landways.

The contributions of this work comprise:

- Introduce the PP-IoD fuzzy problem;
- Use an airway topological architecture proposed by Bine et al (5, 13) and Svaigen et al (6) that is shown to be efficient for the addressed problem and can be used in different situations involving drones;
- Use the algorithms of Dijkstra (14) and Ford-Moore-Bellman (15) both adapted for the fuzzy case, using different concepts from fuzzy theory: the Dijkstra algorithm adapted finds optimal multipaths and uses the graded mean integration representation method to deal with

fuzzy parameters; whereas the Ford-Moore-Bellman algorithm deals with fuzzy parameters through comparison indices and finds a set of non-dominated solutions.

- Show that graph-based algorithms, adapted for cases where there are uncer- tainties, are useful and provide interesting solutions to current problems, even if they are not new.
- Presents and evaluate the results obtained using both algorithms showing that by considering uncertainties in the arc costs, the solution obtained can be useful and relevant in the context of IoD, where multiple drones share the same airspace.

The Section 3 presents works related to the topics covered in this article.

Related Works: The UAV path planning problem has received extensive attention from researchers from different places in the world. Although existing works address the path planning (PP) under different methodologies, in the context of IoD and considering uncertainties there are still challenges and open research ques- tions that lack studies and propositions. In this section, we first list the works that inspired us and later the related works. Deng et al (2012) (14) propose an adaptation of classical Dijkstra's algo- rithm to deal with uncertain situations. The costs and capabilities of the arcs are modeled using fuzzy numbers and they use the graded mean inte- gration representation of fuzzy numbers to perform the necessary arithmetic operations. At the end of the algorithm, a single shortest path is obtained. Hernandes (15) propose different algorithms considering uncertainties. One of these algorithms is based on the classic Ford-Moore-Bellman algorithm and through possibility indices and order relations of fuzzy set theory, it obtains a set of non-dominated solutions. In this paper, we uses the Dijkstra's fuzzy algorithm proposed by Deng et al (14) and Ford-Moore-Bellman fuzzy algorithm proposed by Hernandes (15). We adapt the same to get multiple paths, since we are considering multiple drones. Regarding IoD, we use the layered architecture proposed by Bine et al (5) and Svaigen et al (6). Bine et al (5) propose a routing protocol for an IoD scenario based on the Geocast protocol and consider an Iod scenario with different airways and different altitudes. Svaigen et al (6) propose a protection mechanism that guarantees privacy and security in IoD scenarios. They consider that the IoD environment is represented by layered graphs, with different overlapping airways and different altitudes. Therefore, the works of Deng et al (14), Hernandes (15), Bine et al (5) and Svaigen et al (6) inspired us and provided ideas to propose this paper. It is noteworthy that although we used the layered structure of IoD proposed by Bine et al (5) and Svaigen et al (6) and small adaptations in the algorithms proposed by Deng et al (14) and Hernandes (15), this work differs from those that inspired us because we are dealing with the UAV path planning fuzzy problem in IoD, which was not addressed in the works listed above.

UAV Path Planning sob uncertainties: Below, we briefly list works that address UAV path planning in different ways and that can be considered works related to this paper. Bine et al (2022) (16) proposes a heuristic method for coverage path planning in the IoD environment (CPP-IoD). They presents a mathematicalmodels for the CPP-IoD and uses nearest neighbor heuristic for to get the paths of all drones, later they use refinement heuristics to improve the obtained solutions. Liu et al (2022) (17) deal with surveillance problem with multiple drones. A multi-UAV cooperative path optimization (MCPO) model is proposed. They proposed a strategy to avoid obstacles or inaccessibleregions using fuzzy constraints. Ntakolia et al (2022) (18) propose a novel Genetic Algorithm with Fuzzy Logic Inference System to solve the UAV multi-objective path planning prob- lem. They presents a formulation for the multi-objective problem considering the minimization of the traveled distance, smoothness of the path, and the maximization of energy efficiency. Wang (2022) (19) propose a method based in the fuzzy control to solve the collision avoidance problem in the path planning of mobile robots. Wan et al (2022) (20) propose a method to the 3D UAV path planning problem based on improved multi-objective swarm intelligence algorithm. The trajectory planning mission is transformed a multi-objective optimization task with multiple constraints, and the objective function is minimize the total fight path length and size of terrain threat. Ahmed et al (2021) (12) address the UAV path planning problem in the con- text of IoD, proposing an energy efficient strategy to avoid static and dynamic obstacles. An energy model for UAV path planning problem is presented, and considers the impact of motion (hovering, vertical and horizontal flight). The paths are represented using Bezier curves. Ergezer and Leblebicioğlu (2021) (21) propose an algorithm for the online path planning with multiple UAVs. The objective is collect information from desired regions and avoid forbidden regions in a fixed time window. The environment considered is two-dimensional. Chen et al (2020) (22) deal with the dynamic UAV path planning problem in 2D and 3D environments. A fuzzy logic inference system was proposed to avoid obstacles in a dynamic environment. To obtain the dynamic paths, the authors proposed Fuzzy-Kinodynamic Rapidly Exploring Random Tree. Golabi et al (2020)(23) present a mathematical formulation for the multi- objective UAV path planning problem in three-dimensional static environment. The objective function is composed of path length, energy consumption, and maximum cumulative path risk. To solve the problem, they uses sev- eral evolutionary multi-objective optimization algorithms and obtains a set of non-dominated paths. Song et al (2020) (24) proposes a dynamic path planning strategy based on fuzzy logic and improved ant colony optimization (ACO). They integrated the improved ACO with the fuzzy logic, constituting the fuzzy logic ant colony optimization (FLACO) to find the optimal path for UAVs.

UAV Path Planning sob uncertainties: The work by Liu et al (2019) (25) addresses the dynamic UAV path planning problem in a three-dimensional environment through an improvement in the evolutionary optimization algorithm. The drone flight environment considered in this paper is complex and there is little information about it. Adhikari et al (2017) (26) propose the fuzzy differential evolution method for 3D path planning for drones. The problem is modeled through bi-objective (fuel and threat cost) unrestricted optimization. They use a fuzzy controller to find the values of the differential evolution parameters during the optimization process. Although works in the literature have achieved great advances regarding UAV path planning problem, there is still much to be done in the context of IoD. Moreover, the UAV path planning problem in three-dimensional space has been studied by different authors, but they consider only one drone, or they consider multiple drones but do not consider IoD. Uncertainties are usually modeled using fuzzy set theory or probabilistic methods and represent factors that are difficult to predict and are usually incorporated into classical methods, such as shortest path algorithms, genetic algorithms, among others. Based on related works and existing gaps regarding UAV path planning in IoD, this work aims to solve the UAV path planning problem in IoD consider- ing uncertainties, since in this architecture several drones can share the same airspace. The optimal paths are obtained offline, leaving the ZSP to transmit their information to each of the drones.
The Section 4 presents the succinct form used in the concepts of fuzzy set theory in this work.

Preliminaries: In this section, some basic concepts are briefly introduced. For more details, see the references (14, 27–29). The fundamental idea of the fuzzy set is the pertinence gradual, that is, relaxing this requirement by admitting values between 0 and 1 to quantify the degree to which each element of the universe is associated with a class. The closer the value closer the value is to 1, the more compatible the element is with the properties that distinguish the class.
A fuzzy set A is described by a function that maps the elements of a universe X into the unitary interval (0, 1):

$$\mu_A : X \rightarrow (0, 1).$$

A fuzzy set can be seen as a set of ordered pairs ordered pairs $\{x, \mu_A(x)\}$, where x is an element of X and $\mu_A(x)$ denotes the degree of membership of x in A.
8

- **Fuzzy Numbers**

A triangular fuzzy number, illustrated in the Figure 3, denoted by $\tilde{a} = (m, \alpha, \beta)$, is described by the following membership function:

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, & x \leq m-\alpha \\ \frac{x-(m-\alpha)}{\alpha}, & m-\alpha < x < m \\ 1, & x = m \\ \frac{(m+\beta)-x}{\beta}, & m < x < m+\beta \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where m is the modal value (element of the universe with degree of pertinence degree equal to 1), α is the left spread and β is the right spread (α, β, and$\neq 0$). The values $m - \alpha$ and $m + \beta$ are the limiting, lower and upper limits, respectively. Thus, a triangular fuzzy number can also be denoted by $\tilde{a} = (m - \alpha, m, m + \beta)$.

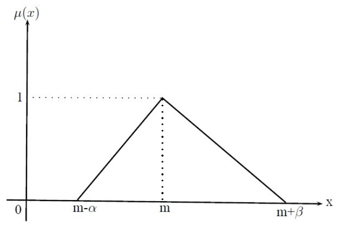

Fig. 3 Triangular fuzzy number

A trapezoidal fuzzy number or a fuzzy interval, illustrated in the Figure 4, denoted by $\tilde{a} = (m_1, m_2, \alpha, \beta)$ is described by the following membership function:

$$\mu_{\tilde{a}}(x) = \begin{cases} \frac{x-(m_1-\alpha)}{\alpha}, & m_1-\alpha < x < m_1 \\ 1, & m_1 \leq x \leq m_2 \\ \frac{(m_2+\beta)-x}{\beta}, & m_2 < x < m_2+\beta \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

0, otherwise. (2)

where m_1 is the lower extreme of the modal value, m_2 the upper extreme of the modal value the upper end of the modal value, α the left spread and β the right spread, (α, β, and$\neq 0$). The values $m_1 - \alpha$ and $m_2 + \beta$ are the lower and upper limits, respectively. Thus, a trapezoidal fuzzy number can also be denoted by $a = (m_1 - \alpha;\ m_1;\ m_2;\ m_2 + \beta)$.

Arithmetic operations with fuzzy numbers: There are different ways to perform operations with fuzzy numbers and in this paper we will use the ones described below. For more information, see the references (14, 27).

UAV Path Planning sob uncertainties

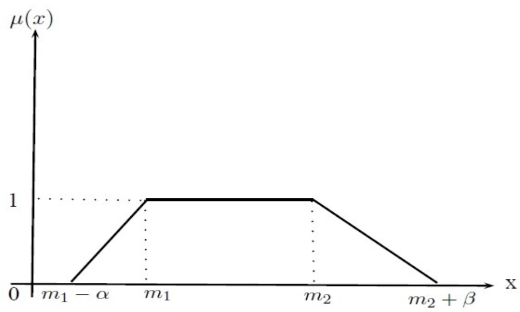

Fig. 4 Trapezoidal *fuzzy* number

Let $\tilde{a} = (m_1, \alpha_1, \beta_1)$ and $\tilde{b} = (m_2, \alpha_2, \beta_2)$ two triangular fuzzy numbers and k □ R. The operations are defined:

- Sum:

$\tilde{a} + \tilde{b} = (m_1 + m_2, \alpha_1 + \alpha_2, \beta_1 + \beta_2)$

- Multiplication by scalar:

$k\tilde{a} = (km_1, k\alpha_1, k\beta_1)$, se $k \geq 0$

- Subtraction:

$k\tilde{a} = (km_1, -k\alpha_1, -k\beta_1)$, se $k < 0$

$\tilde{a} - \tilde{b} = \tilde{a} + (-\tilde{b}) = (m_1 - m_2, \alpha_1 + \beta_2, \beta_1 + \alpha_2)$

The algebraic operations of trapezoidal fuzzy numbers occur in a similar manner. Another way to perform operations with fuzzy numbers is through the graded mean integration representation method, which can be used to obtain a single minimum fuzzy path (14). Given a triangular fuzzy number $\tilde{a} = (m_1, \alpha_1, \beta_1)$, and defining $a_1 = m_1 - \alpha_1$, $a_2 = m_1$ and $a_3 = m_1 + \beta_1$ the graded mean integration representation integration method of triangular fuzzy number $\tilde{a}$ is defined as (14):

$$P(\tilde{a}) = \frac{1}{6}(a_1 + 4 \times a_2 + a_3)$$

Now, let $\tilde{a} = (m_1, \alpha_1, \beta_1)$ and $\tilde{b} = (m_2, \alpha_2, \beta_2)$ where $a_1 = m_1 - \alpha_1$, $a_2 = m_1$, $a_3 = m_1 + \beta_1$ and $b_1 = m_2 - \alpha_2$, $b_2 = m_2$ and $b_3 = m_2 + \beta_2$, we have that addition is defined as (14):

$$P(\tilde{a} \oplus \tilde{b}) = P(\tilde{a}) + P(\tilde{b}) = \frac{1}{6}(a_1 + 4 \times a_2 + a_3) + \frac{1}{6}(b_1 + 4 \times b_2 + b_3)$$

The multiplication is defined as:

$$P(\tilde{a} \otimes \tilde{b}) = P(\tilde{a}) \times P(\tilde{b}) = \frac{1}{6}(a_1 + 4 \times a_2 + a_3) \times \frac{1}{6}(b_1 + 4 \times b_2 + b_3)$$

UAV Path Planning sob uncertainties

Given a trapezoidal fuzzy number, $\tilde{a} = (m_1, m_2, \alpha, \beta)$, we define $a_1 = m_1 - \alpha$, $a_2 = m_1$, $a_3 = m_2$, $a_4 = m_2 + \beta$. The graded mean integration representation integration method of trapezoidal fuzzy number is defined as (14):

$$P(\tilde{a}) = \frac{1}{6}(a_1 + 2 \times a_2 + 2 \times a_3 + a_4)$$

Similar to that of triangular numbers, addition via the graded mean inte- gration representation integration method of two trapezoidal fuzzy numbers is defined by (14):

$$P(\tilde{a} \oplus \tilde{b}) = P(\tilde{a}) + P(\tilde{b}) = \frac{1}{6}(a_1+2\times a_2+2\times a_3+a_4) + \frac{1}{6}(b_1+2\times b_2+2\times b_3+b_4)$$

And the multiplication by:

$$P(\tilde{a} \otimes \tilde{b}) = P(\tilde{a}) \times P(\tilde{b}) = \frac{1}{6}(a_1+2\times a_2+2\times a_3+a_4) \times \frac{1}{6}(b_1+2\times b_2+2\times b_3+b_4)$$

Comparison between fuzzy numbers: There are different ways to compare *fuzzy* numbers, for example, dominance, possibility index, etc. In this paper, we uses the possiblity index of Okada and Soper (30) as follows.

Let $\tilde{a} = (m_1, \alpha_1, \beta_1)$ and $\tilde{b} = (m_2, \alpha_2, \beta_2)$ two triangular *fuzzy* numbers, then $\tilde{a} \prec \tilde{b}$ ($\tilde{a}$ dominates $\tilde{b}$) if and only if

$m_1 \leq m_2$, $(m_1 - \alpha_1) \leq (m_2 - \alpha_2)$, $(m_1 + \beta_1) \leq (m_2 + \beta_2)$ e $\tilde{a} \neq \tilde{b}$.

Through the definition above, Okada and Soper (30) introduced the concept of path dominance for the optimal path problem fuzzy. With the theory of possibility it is attributed to each solution a degree of possibility of being the optimal solution. It is necessary to find all solutions and compare them to obtain the degree of possibility of each one (31).

Let $G = (N, A)$ be a graph with cost $\tilde{c} = \tilde{c}_{ij}$ associated to its arcs. Let two subgraphs T^1 and T^2 be, $T^1 \neq T^2$. The degree of possibility that T^1 has cost smaller than T^2 is given by (31):

$$\tilde{w} = Poss\left(\sum_{(i,j)\in T^1} \tilde{c}_{ij} \leq \sum_{(i,j)\in T^2} \tilde{c}_{ij}\right) = \sup_{u \leq v} \min\{\mu_{T^1}(u), \mu_{T^2}(v)\}$$

where:

Poss: possibility measure;

- $\mu_T 1\ (u)$ and $\mu_T 2\ (v)$ are the cost membership functions of the subgraphs $T^1$and T^2, respectively;
- sup min : the supreme value of the minimum (intersection), that is, the largest degree of pertinence that can be obtained from the set resulting from the intersection of the $\mu_T 1\ (u)$ and $\mu_T 2\ (v)$ membership functions.

The degree of possibility that T is the optimal solution is given by:

$$D_T = \min_{T^k \in \tau} \left\{ Poss \left(\sum_{(i,j) \in T} \tilde{c_{ij}} \leq \sum_{(i,j) \in T^k} \tilde{c_{ij}} \right) \right\}$$

This makes the problem difficult to solve because, besides having to enu- merating all the solutions, comparing them makes the problem *NP* - complete.

METHODOLOGY

In this section, we present the considerations on the PP-IoD fuzzy problem, with parallel airways to landways, considering uncertainties. As already men- tioned, the topological architecture of the airways used in this work is based on the models of airways parallel to land ways according to the works of Bine et al (5, 13, 16) and Svaigen et al (6). The Figure 2 and the Figure 2 exemplifies the considered airway architecture. This airway architecture allows the creation of overlapping airways, as shown in Figure 2. In this architecture, drones can change altitude using spe- cific airways to avoid collisions with other drones during flight, for example. Figure 2 classifies the routes into public and private as there are areas where drone flight is prohibited, such as airports and government buildings. This airway format helps protect private airways, so it can be used in different applications and scenarios. Still regarding the architecture of the airways, according to Bine et al (13), it is important to consider priority airways for deliveries related to health, life saving and search missions. It is worth noting that when considering this airway architecture and the UAV path planning problem, there are no obstacles as the ground routes are free of them (here we are not considering difficult to predict situations in this scenario). The airways are represented through graphs, where each layer (airway) is a graph and there are links between them through connecting arcs. Table 1 presents the characteristics that differentiate the UAV path plan- ning in IoD fuzzy from traditional PP. As in the work by Bine et al (16), in this paper the airways are parallel to landways and are free from static obstacles.

The three main differences between PP-IoD fuzzy and traditional PP are described as follows.

First, in traditional PP, the goal is finding a collision-free path concerning a given origin-destination pair, while in PP-IoD, the goal is to finding a collision-free path in each airway considered.

Table 1 PP-IoD fuzzy characteristics.

Feature Description

Uncertainties Winds and temporary obstructions can occur in the airways, such as the pres- ence of animals (e.g., birds) are modeled through fuzzy set theory. Airways-parallel to Terrestrial Roads Determine where airways can pass. Helps to share and coordinate the drone access to the airspace. Shared airspace Multiples UAVs can share the same airspace for different applications.

- Second, in traditional PP, drones can fly in any direction and any altitude, while in PP-IoD, drones must follow the airways altitudes and directions.
- Third, in PP-IoD fuzzy, we consider uncertanties in the costs of the arcs that are modeled through the theory of fuzzy sets, which allows, in some cases, to obtain more than one optimal path from a given origin to a given destination, while in the traditional PP the costs are classical numbers and a single shortest path is obtained, regardless of the method used.

Scenario definition for the UAV path planning: In this work, the IoD is composed of a set of drones *D*, a single ZSP that coordinates the drones, a layered graph *G* representing the airways and their connections.

- Airways: similar to a real urban road scenario. A graph $G = (N, E)$, where *N* represents the set of airway points(nodes) and *E* is the set of air arcs such that $\forall e \in E,\ e = (n_1, n_2, altitude),\ n_1, n_2 \in N$.
- Drones: each drone $d \in D$ has an origin and a destination on the route. Thus, it is assumed that there is one airway for takeoff and one for points chosen for the beginning and the end of the route.
- ZSP: responsible for coordinating the set of drones *D* and send the infor- mation of the path to be followed by each drone, since it is offline in this case.

The different airways considered are represented by the graph *G* and their altitude, so if we have *n* overlapping airways, we have that each one is rep- resented by $(G_1, h_1), (G_2, h_2), (G_3, h_3), \cdots, (G_n, h_n)$, where $h_1, h_2, h_3, \cdots, h_n$ are the altitudes. In the scenario considered, the takeoff and landing airways were not spec- ified. It is assumed that there is one airway for takeoff and one airway for landing at the points chosen for the start and end of the route.

In the next sections, we present the Dijkstra and Ford-Moore-Bellman algo- rithms adapted for the case where there are uncertainties in the costs the arcs of the graph.

Dijkstra's algorithm for the optimal path problem with uncertainty: The adaptation of the Dijkstra algorithm used in this work is authored by Deng et al (14), which generalizes it to obtain shortest fuzzy paths based on the graded mean integration representation method. It is worth noting that this algorithm finds the shortest fuzzy path between an origin and a destination, and to obtain the paths for each of the drones considered in the IoD context, we adapt it to find multiple paths, considering that the drones have different origins and destinations.

Algorithm 1 Dijkstra Fuzzy.

- for each vertex v in Graph:
  - $dist(v) = \infty$;
  - previous(v) = undefined;
- end for;
- $dist(source) = 0$;
- Q : the set of all nodes in Graph;
- While Q is not empty:
- u : vertex in Q with smallest $dist()$;
  - if $dist(u) = \infty$:
  - break
  - end if;
- remove u from Q;
  - for each neighbor v of u:
  - $alt = dist(u) + dist(u, v)$ (here, the graded mean integration representation of addition operation of fuzzy numbers ir used).
    * if $alt < dist(v)$
    * $dist(v) = alt$;
    * $previous(v) = u$;
    * decrease key v in Q;
    * end if;
  - end for;
- end while
- return $dist()$;
- end Dijkstra.

Ford-Moore-Bellman algorithm for the optimal path problem with uncertainty: The algorithm proposed by Hernandes (15) is based on the classical Ford- Moore-Bellman algorithm (33). The proposed algorithm is iterative, having as a stopping the number of iterations or the non-changing costs of all paths found in the previous iteration with respect to the current iteration. In this algorithm, for the construction of the solution set, the concept of path dominance of Okada and Soper (30), then each path receives a label so that it is at the end of the algorithm, since the Okada and Soper relation can present, between two nodes, more than one non-dominated path between two nodes.

Algorithm 2 Ford-Moore-Bellman Fuzzy.

Notations used in the algorithm

N: set of nodes;

it: iteration counter;

$(m+\beta)^i$ upper bound on the cost of node i;

$\tilde{l}_{ji}$: cost of arc (j,i);

$\tilde{c}^{it}_{(i,k)}$: cost of the path between nodes 1 and i, with label k at iteration it;

na: number of arcs

r: number of nodes;

$M = \sum_{i=1}^{na} |$, large value that replaces ∞ of the classical Ford-Moore-Bellman algorithm;

Γ_i^{-1}: set of predecessor nodes of node i.

Algorithm

Step 1: Initialization

- $\tilde{c}^{0}_{(1,1)} = (0,0,0)$
- $\tilde{c}^{0}_{(j,1)} = (M+1, M, M+2) \;\; j = 2,3,\ldots,r$
- $it \leftarrow 1$.

Step 2: Path determination and dominance check

- $\tilde{c}^{it}_{(1,1)} = (0,0,0)$
- $\forall j \in \Gamma_i^{-1} \;\; i = 2,3,\ldots,r$, faça:
- $\tilde{c}^{it}_{(i,k_1)} = \tilde{c}^{it-1}_{(j,k_2)} \oplus \tilde{l}_{ji}$
- Checking the dominance between the labels of node i, using the order relation of Okada and Soper:
  - If $\tilde{c}^{it}_{(i,m)} \succ \tilde{c}^{it}_{(i,n)}$ then delete the m-th label.
  - If $\tilde{c}^{it}_{(i,m)} \prec \tilde{c}^{it}_{(i,n)}$ then delete the nth label.

Step 3: Stopping criteria

- If $(\tilde{c}^{it}_{(i,k_1)} = \tilde{c}^{it-1}_{(i,k_1)} \;\; \forall i \in N)$ or $it = r$ do:
  - If $it = r$ or $\tilde{c}^{it}_{(i,k_1)} = \tilde{c}^{it-1}_{(i,k_1)}$ go to step 5;
  - Otherwise go to step 4.
- Otherwise: $it \leftarrow it + 1$, go to step 2.

Step 4: Path composition

- Find all non-dominated paths between nodes 1 and i.

:cost of the path between nodes 1 and *i*,with label *k* at iteration *it*;

UAV Path Planning sob uncertainties

Experimental Results and Analysis: In this section we present the results obtained from the implementation of the Dijkstra and Ford-Moore-Belman algorithms considering uncertainties in the arc costs, described previously. Both algorithms were implemented in Matlab R2020b software on a Lenovo, Core I7 notebook. The costs on the arcs were modeled using triangular fuzzy numbers. The data for the computational tests was obtained from the RioBuses dataset. RioBuses dataset had its data col- lected from the public transport system in Rio de Janeiro, Brazil. The dataset used was collected on October 1, 2014 in the simulations presented in Section. 6.1 and Section 6.2. The area used is part of the neighborhood of Ipanema beach, Rio de Janeiro, Brazil, as illustred in Figure 6.1. The data contained in RioBuses are real-time position data reported by buses, updated every minute, from the city of Rio de Janeiro, Brazil. The file is CSV, containing the date, time(24h format), bus ID, bus line, latitude, lon- gitude and speed of more than 12.000 buses (https://crawdad.org/coppe-ufrj/ RioBuses/20180319/RioBuses/index.html). In order to obtain input data for the algorithms used in this work, latitudes and longitudes were transformed into distances, and later they were fuzzified into fuzzy triangular numbers. Right and left spreads were chosen at random.

Simulation 1: The first computational simulation performed was solved using the graph presented in Figure 6.1.

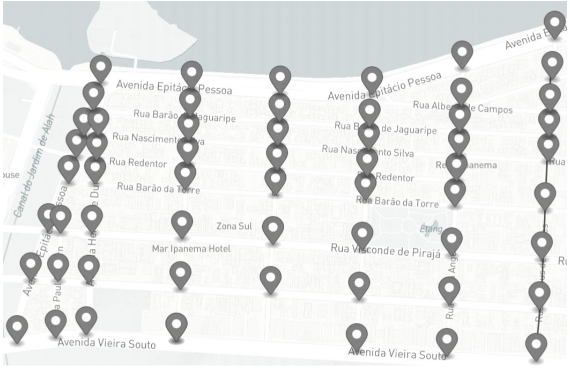

Fig. 5 Ipanema neighborhood, Rio de Janeiro, Brazil

A graph of the main roads was generated to create the simulation of routes and airways, illustrated in Figure 6.1. We consider an airway parallel to the landway (this data is for the bus network). In this case, we consider one airway and 10 drones. The nodes of
16

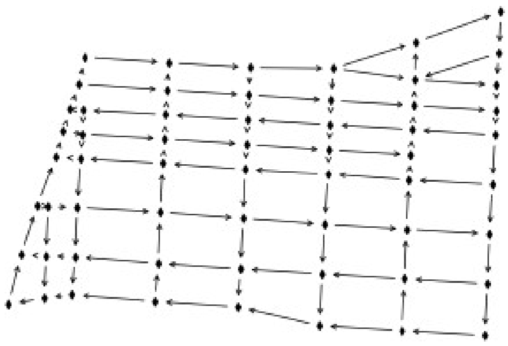

Fig. 6 Graph of Ipanema (13)

the graph representing the region illustrated in the Figure 6.1 were arbitrar- ily enumerated in order to obtain the paths for each drone in the computer simulations. The graph representing the chosen region has 59 nodes and 96 arcs. The origins and destinations of each drone were randomly chosen and are shown in Table 2.

Table 2 Origins and destinations for each UAV

Origin node	Destination node
1	59
2	38
6	51
8	55
9	30
16	50
19	49
40	2
47	7
56	18

We consider the directed network (with only one direction), from the algo- rithms fuzzy Dijkstra and fuzzy Ford-Moore-Bellman, the optimal paths were obtained. It is worth noting that the Dijkstra algorithm proposed by (14) uses the graded mean integration representation method, and therefore, finds a sin- gle path between the origin and destination, while the Ford-Moore-Bellman algorithm considers the fuzzy form in the costs of the arcs during the entire resolution process and finds non-dominated solutions (here we can have more than one optimal path between a given origin-destination pair). Table 3 presents the optimal paths obtained by Dijkstra's algorithm adapted for the fuzzy case.

Table 3 Paths obtained by Dijkstra's Fuzzy algorithm.

Path	Path Cost
1 → 2 → 3 →4→6→13→59	1.372, 8m
2→3→4→6→13→59→28→37→44→43→38	4.682, 5m
6→13→59→28→37→44→51	1.775, 7m
8→11→24→26→39→42→53→54→55	3.923, 6m
9→10→25→58→40→39→38→37→44→51→50→49→48→34→33→32→19→20→21→30	4.157, 8m
16 →4→6→13→59→28→37→44→51→50	3.250, 9m
19→20→21→30→35→46→49	1.716, 9m
40→39→38→37→44→51→50→49→48→34→33→32→19→18→1→2	2.147, 1m
47→33→32→19→18→1→2→3→4→6→7	2.202m
56→57→51→50→49→48→34→33→32→19→18	1.198, 6m

Table 4 shows the non-dominated paths obtained from the Ford-Moore- Bellman algorithm adapted for the fuzzy case. In order to compare the results obtained by both algorithms in the fuzzy version, we use the classic Ford-Moore-Bellman algorithm to obtain the short- est paths for the same origin-destination pairs that we use in the Dijkstra Fuzzy and Ford-Moore-Bellman Fuzzy algorithms. It is worth mentioning that in the classic versions, the Dijkstra and Ford-Moore-Bellman algorithms obtain the same shortest paths, what differs is the iterative process of each one. The Table 5 presents the shortest paths for each origin-destination pair of each drone.

Some relevant considerations from the paths obtained by both algorithms in the Simulation 1 are described below.

- Analyzing the origin-destination pair (9, 30), we have that the Ford-Moore- Bellman algorithm finds 3 non-dominated paths for it, which can be important when dealing with real situations and applications, because we can consider 3 drones in this origin-destination pair (obviously, we are con- sidering that collisions are avoided through sensors of the drones themselves or through helical movements (34)).
- Still regarding the origin-destination pair (9, 30), practical applications such as delivery via drones, can benefit from this type of solution, choosing the one that best fits the context considered.
- The use of two algorithms that address uncertainty differently is important for comparisons between the solutions obtained, as well as to provide more solution options to the decision maker when dealing with situations where a single path must be chosen, for example.
- The use of fuzzy numbers makes it possible to model uncertainties that are difficult to predict, such as travel time from origin to destination, since it can be affected by conditions difficult to predict.
- Comparing the results obtained by the Dijkstra and Ford-Moore-Bellman algorithms in the fuzzy versions with the classic Ford-Moore-Bellman algo- rithm, regarding the path costs, the paths obtained by the Dijsktra Fuzzy algorithm for each origin-destination pair of each drone is the closest to classic shortest paths. On the other hand, the results obtained by the Ford-Moore-Bellman Fuzzy algorithm present, in some cases, a set of non- dominated solutions, making it possible to choose between any of them, depending on the context and application in which the drones are inserted.

Table 4. Paths obtained by the Ford-Moore-Bellman Fuzzy algorithm.

Path	Path Cost
1 → 2→ 3→ 4→ 5→ 6→ 13→ 59	(1.372, 8, 35, 49)
2 → 3 → 4→ 5→ 6→ 13→ 59→ 28→ 37→ 44→ 43→ 38	(4.679, 2, 55, 77)
2 → 3 → 4→ 5→ 6→ 13→ 59→ 28→ 37→ 44→ 43→ 42 → 38	(4.679, 2, 60, 84)
6 → 13 → 59 →28 →37 →44 →51	(1.773, 7, 30, 42)
8 → 11 → 24 → 26 → 39 → 42 → 53 → 54 → 55	(3.920, 9, 40, 56)
9 → 10 → 25 → 58 → 40 → 39 → 38 → 37 → 44 → 51 → 50 → 49 → 48→ 34 → 31 → 20 → 21 → 30	(4.159, 85, 119)
9 → 10 → 25 → 58 → 40 → 39 → 38 → 37 → 44 → 51 → 50 → 49 → 48→ 34 → 33 → 32 →19 →20→ 21→ 30	(4.151, 4, 95, 133)
9 → 10 → 25 → 58 → 40 → 39 → 38 → 37 → 44 → 51 → 50 → 49 → 48→ 34 → 33 → 32 →31 →20→ 21→ 30	(4.156, 1, 95, 133)
16 → 4 → 5 → 6 → 13 → 59 → 28 → 37 → 44 → 51 → 50	(3.247, 9, 50, 70)
19 → 20 → 21 → 30 → 35 → 46 → 49	(1.904, 4, 25, 35)
40 → 39 → 38 → 37 → 44 → 51 → 50→ 49 →48 →34→ 33→32→19→18→1→2	(2.142, 1, 75, 105)
47 → 33 → 32 → 19 → 18 → 1 → 2→ 3 →4 →5→ 6→7	(2.198, 6, 55, 77)
56 → 57 → 51 → 50 → 49 → 48 → 34→ 33 →32 →19→ 18	(1.195, 2, 50, 70)

Table 5. Paths obtained by classical Ford-Moore-Bellman algorithm.

Path	Path Cost
1 → 2 → 3 →4→6→13→59	1.370, 8
2→3→4→6→13→59→28→37→44→43→38	4.679, 2
6→13→59→28→37→44→51	1.773, 7
8→11→24→26→39→42→53→54→55	3.920, 9
9→10→25→58→40→39→38→37→44→51→50→49→48→34→33→32→19→20→21→30	4.151, 4
16 →4→6→13→59→28→37→44→51→50	3.247, 9
19→20→21→30→35→46→49	1.714, 9
40→39→38→37→44→51→50→49→48→34→33→32→19→18→1→2	2.142, 1
47→33→32→19→18→1→2→3→4→6→7	2.198, 6
56→57→51→50→49→48→34→33→32→19→18	1.195, 2

Simulation 2: In this case, we consider 2 airways, one with 100 meters of altitude and the other with 250 meters of altitude and 15 drones, being 10 drones on airway 1 and 5 drones on airway 2. The origins and destination for drone 1 to 10 are the same as in Table 2 and for the other drones they follow in Table 6.

Table 6 Origins and destinations for each UAV in the airway 2.

Origin node	Destination node
65	119
75	115
80	105
82	111
115	97

The Table 7 presents the optimal paths obtained by Dijkstra's Fuzzy algorithm.

Table 7 Paths obtained by Dijkstra's fuzzy algorithm.

Path	Path Cost
65 → 66→ 73→ 119	952, 6857
75→81→82→119→88→97→104→103→102→113→114→115	4.032, 8
80→81→90→95→106→105	1.485
82→119→88→97→104→111	1.702, 3
115→116→117→112→103→98→97	1.546, 2

The Table 8 shows the non-dominated paths obtained from the Ford- Moore-Bellman Fuzzy algorithm for the drones in airway 2. In this case, for the origin-destination pair 115-97, the adapted Ford Moore Belman algorithm obtained two optimal paths, called non-dominated. For origin-destination pairs where there is more than one optimal path, in a real context, for example delivery of goods, both paths can be used by different

Table 8 Paths obtained by the Ford-Moore-Bellman Fuzzy algorithm .

Path	Path Cost
65 → 66→ 73→ 119	(951, 6857, 15, 21)
75→81→82→119→88→97→104→103→102→113→114→115	(4.029, 2, 55, 77)
80→81→90→95→106→105	(1.483, 3, 55, 77)
82→119→88→97→104→111	(1.700, 7, 25, 35)
115→116→117→112→103→98→97	(1.544, 2, 30, 42)
115→116→117→112→103→102→98→97	(1.544, 2, 35, 49)

drones, but not at the same time, since most arcs are the same. An alternative is to schedule the drones to travel on these paths at different times so that there is no collision, given that in this work we approach the UAV path planning 3D offline. It is worth mentioning that our approach considers that drones have different origins and destinations, so the suggestion described above applies in cases where more than one drone with the same origin-destination pair is considered. The Table 9 presents the shortest paths obtained by classical Ford-Moore- Bellman algorithm.

Table 9 Paths obtained by classical Ford-Moore-Bellman algorithm.

Path	Path Cost
65 → 66→ 73→ 119	951, 6857
75→81→82→119→88→97→104→103→102→113→114→115	4.029, 2
80→81→90→95→106→105	1.483, 3
82→119→88→97→104→111	1.700, 7
115→116→117→112→103→98→97	1.544, 2

Comparing the path costs obtained by the Dijkstra and Ford-Moore- Bellman Fuzzy algorithms with the classic Ford-Moore-Bellman algorithm, in this simulation the results obtained by the Ford-Moore-Bellman Fuzzy algo- rithm, (considering the modal value), is the closest to the results of the classic case. However, the results obtained by the Dijkstra Fuzzy algorithm are very close to the classic one, this shows the efficiency of both algorithms in the fuzzy form.

Final Considerations: This paper addresses the UAV path planning problem in IoD considering uncertainties in the costs of arcs, with airways parallel to landdways. Two clas- sical and widely used algorithms for the shortest path problem were used with adaptations for the case where there are uncertainties, such as the cost in the

The main focus of this work was to show that fuzzy theory models uncer- tain or imprecise information efficiently and that classical algorithms can be adapted in different ways, obtaining interesting solutions, especially from the point of view of practical applications, such as drone delivery, since in general we find a set of non-dominated solutions (optimal paths, in this case) and not just one solution in the case of the Ford-Moore-Bellman Fuzzy algorithm. The Dijkstra and Ford-Moore-Bellman algorithms have been used since their propositions and different variations for both are found in the literature, not least, the use of fuzzy theory makes it possible to consider uncertainties, which are inherent to the problem studied in this article. In this way, the combination of classic and well-established algorithms in the literature with the fuzzy theory, allows us to obtain promising and interesting solutions that can be used, for example, in the long-awaited drone delivery. Considering a scenario where delivery and others applications by UAVs are possible, airspace will be different from the current one, and UAV path planning problem will be indispensable. Therefore, this work contributes to the state of art introducing the PP-IoD fuzzy problem. As future work, it could be interesting to focus in consider how to avoid collisions between drones as well as minimize the amount of energy used to travel a given path in an IoD fuzzy environment; Use temporal graphs to prevent different drones from sharing the same arcs in cases where there is more than one path to the same origin-destination pair; Use mixed integer linear programming models to build a multi-objective optimization model for PP-IoD fuzzy and solve it using some solver.

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