

# MÁSTER EN INGENIERÍA DE SISTEMAS Y DE CONTROL



## Intelligent UAV Path Planning for Search and Rescue Operations

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Firmado: Víctor San Juan Díez

Firma del alumno

*A Ángela, por su apoyo en el tiempo y en la distancia, y por todos los días de soledad.*

*A Igor, por la ayuda y la espera.*

## **ABSTRACT**

Searching and Rescue Operations take place in all events and emergency situations where people are involved and their lives are at risk. These operations are carried out with the help of advanced technology, such as Unmanned Aerial Vehicles (UAVs). In this work, several methods to calculate the UAV path planning in these situations are presented.

First, an intelligent characterization of the area of searching is performed in order to estimate a potential Risk/Occupancy degree which will help to the path planning calculation. This estimation is mainly based on Fuzzy Logic. It consists in the consideration of different factors related to the terrain where the search is taking place and where the emergency is occurring as inputs of a Fuzzy Inference System to obtain the potential Risk/Occupancy value.

Then, four methods are applied to calculate the path planning. Three of them are based on Artificial Intelligence techniques, which calculate the location of the waypoints to be followed by the UAVs in order to minimize the distance travelled and the risk the people is exposed to. The first one consists of the calculation of an attraction factor for each point of the area to be explored, so the highest attraction point is then selected to move the UAV to it. The second and third methods are based on the same idea but obtaining the attraction factor by means of fuzzy logic. The fourth one is based on a PSO algorithm, which minimizes distance and risk. Then, all these methods are adapted to the possibility of having more than one UAV searching at the same time, and the swarm formation is discussed.

Finally, these solutions for path planning, including different number of UAVs, are introduced in two different real simulation scenarios, so the performance of each path planning method can be analysed and compared with the other methods.

## **KEYWORDS**

Unmanned Aerial Vehicles (UAV), Search and Rescue (SAR), path planning, PSO, ANFIS, fuzzy logic.

## RESUMEN

Las operaciones de Búsqueda y Rescate se llevan a cabo en todo tipo emergencias donde hay personas involucradas con su vida en riesgo. Estas operaciones se realizan con tecnología avanzada, como son los UAV. En este trabajo se presentan varios métodos para calcular la planificación de la trayectoria de UAVs en estas situaciones.

Primero, se realiza una caracterización inteligente del área que es alcance de la búsqueda con el fin de estimar un valor potencial de riesgo/ocupación, el cual ayudará en el cálculo de la planificación de la trayectoria. Esta estimación está basada en lógica difusa, y consiste en la introducción de diferentes factores relacionados con el terreno donde se está llevando a cabo la búsqueda y la emergencia que está ocurriendo en un sistema de inferencia difuso, para obtener el valor de riesgo/ocupación potencial.

Después se presentan cuatro métodos para calcular la planificación de la trayectoria, tres de ellos basados en técnicas de Inteligencia Artificial, los cuales calculan la posición de los puntos de la trayectoria que debe ser seguida por el UAV para minimizar la distancia recorrida y el riesgo al que las personas están expuestas. El primero consiste en el cálculo de un factor de atracción para cada punto del área a ser explorada, siendo el punto seleccionado el de más alto valor de atracción. El segundo y tercer métodos están basados en la misma idea, pero obteniendo el valor de atracción mediante lógica difusa. El cuarto está basado en una optimización mediante PSO, la cual minimiza la distancia y el riesgo. A continuación, todos estos métodos son adaptados a la posibilidad de tener más de un UAV buscando al mismo tiempo, y se discute también la formación a adquirir en el vuelo.

Finalmente, estas soluciones para planificar la trayectoria, incluyendo varias posibilidades para el número de UAVs, son introducidas en diferentes simulaciones, por lo que el rendimiento de cada método de planificación puede ser analizado y comparado con el resto.

## PALABRAS CLAVE

Vehículo aéreo no tripulado (UAV), Búsqueda y Rescate, planificación de trayectoria, PSO, ANFIS, lógica difusa.

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## LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial Neural Network
FIS	Fuzzy Inference System
GA	Genetic Algorithm
MF	Membership Function
PSO	Particle Swarm Optimization
SAR	Search and Rescue
UAV	Unmanned Aerial Vehicle

## 1 Introduction

Unfortunately, every year we see in the news some cases of natural disasters, like fires or earthquakes which affect cities, towns and natural environments. Besides, we also see human tragedies, as maritime accidents, or people who get lost in hazardous places.

All these situations, and many others, have one important aspect in common. They suppose a danger and a direct risk for the life of many people involved in these situations in one way or another.

The most critical aspect in these cases, even before starting to mitigate the risk (i.e. fight the fire), is the Search and Rescue (SAR) of potential survivors. The SAR process is carried out by specialized teams that even risk their own lives to save others.

Fortunately, these SAR teams are, in most of the cases, well equipped with advanced technology, which nowadays includes Unmanned Aerial Vehicles (UAVs) to improve people searching and also to prevent rescue team lives from going through risky places with no real evidences of finding survivors.

### 1.1 Motivation

UAVs have had a big development during the last ten years. UAVs are used in many different applications such as defence, surveillance, or package delivery, among others.

Lot of these applications use automatically controlled UAVs, which are able to flight over a pre-planned trajectory, or even to decide real-time trajectories in some cases. But the reality is that most of the commercial applications still use an off-board pilot to control the UAV. This control may be complete, controlling all the movements, or in other cases the pre-planned trajectory can be designed by someone and then loaded in the UAV, which goes to the specified places controlling its own movements and avoiding obstacles.

In SAR operations, UAVs are equipped with on-board cameras and are usually fully operated by an off-board pilot, who manoeuvres the UAV and moves it to the desired places, which are chosen under his experience or intuition.

The final motivation of this work is to find people at risk in SAR operations as fast as possible using UAVs, with a fully automatic operation. So, the UAV will decide where to go and when, and to find people in danger by visual means with an on-board camera. Moreover, it will include the possibility to have more than one UAV searching together.

To reach these goals, decision making and analysis methods are evaluated and adapted to this case of study. These methods are based on classical techniques, as well as on Artificial intelligence and optimization algorithms.

### 1.2 Objectives

The main objective of this project is to develop methodologies that can help to find a person in a specific area as fast as possible, minimizing the risk or hazard the person is exposed to.

The hypothesis we work with is the following. To minimize the hazard, when analysing a specific surface, there are some places where the risk is higher than in others, e. g., if we have a forest fire, it would be more critical to find a person near the fire than further.

Therefore, to find a person as fast as possible, we must optimize the search. To do that, those areas in which there are more probability for a person to get lost or injured are first analysed. This will have a great influence on the trajectory planning, which has also to be optimal.

Assuming all mentioned, the objectives are established as follows:

1. Develop a method to analyse the surface to be explored and estimate the degree of potential hazard and the probability of a person to be at that spot.
2. Develop a path planner to find people as fast as possible using the data obtained from the objective number one.
3. Study how the number of UAVs in swarm formation affects the speed and effectiveness of people searching.

The following tasks are not included in the scope of this work: UAV on-board control and obstacle avoidance, UAV path following and image processing. In fact, we are not working with a model of the dynamics of the UAV. The path planning is calculated as a trajectory along some discrete points, corresponding to different cells. The UAV moves from one cell to another (the adjacent one) with a constant speed. The number of cells visited gives the length of the trajectory and therefore the time spent.

### 1.3 Outline

This work is outlined in several sections which are the following:

- **State of the art**, where basic aspects of UAV, SAR and AI are presented, as well as a review of works and publications related to this work (Chapter 2).
- **Development and Analysis**. In these chapters the different solutions developed are described. First, the solution for map and area data estimation and characterization is presented (Chapter 3), where a method based on fuzzy logic is used. The path planning solutions are described in Chapter 4. There are four different proposals based on: attraction factors, fuzzy logic, ANFIS and Particle Swarm Optimization. These methods are developed and applied to simulation scenarios. Finally, UAV swarm formation is presented and analysed.
- **Simulations**. Two simulation cases are presented, the first one in a forest fire and the second one in a fisher boat sink framework. Thirty cases of missing people are created for each framework, after characterizing the area and calculating the path planning. The time employed in finding the people is compared for the different methods and configurations (Chapter 5).
- Finally, the **conclusions** and **future work** are presented.

## 2 State of the art

In this section, several basic concepts are briefly described in relation to Unmanned Aerial Vehicles, Search and Rescue operations, and Artificial intelligence, as well as cases where these three concepts interact between them.

### 2.1 Unmanned aerial vehicles

An Unmanned Aerial Vehicle (UAV) is a powered pilotless aircraft, which is controlled remotely or autonomously [8].

UAVs design has been developed from the early 20<sup>th</sup> century till the date. First designs of aerial vehicles without any pilot or crew are dated during the World War I. Like many other technologies, the development of this kind of vehicles, especially at the beginning, was made almost exclusively for defence, and a big part of the investigations about topics related with UAVs are still focused on this sector. However, in the last fifteen years, civil applications have had an exponential growth, making possible to find many different uses for UAVs.

Nowadays, thanks to electronics advances, which allow more sophisticated and smaller devices every time, all kinds of UAV applications can be found. A list with examples of these numerous applications is presented below:

- Security
  - Security and Control
  - Aerial Reconnaissance
  - Aerial Policeman and Crowd Monitoring
  - Aerial Traffic and Security Watch
  - Surveillance of public events
  
- Monitoring
  - Civil engineering sites
  - Waterways and shipping
  - Oil and gas pipeline
  - Power line /cable inspection
  - Wind turbine inspection
  - Radiation monitoring
  - Forestry
  - Fishery Protection
  - Pollution Control and Air Sampling
  - Crop Performance
  - Litter on beaches and in parks
  
- Disaster Management
  - Disaster effects management
  - Rescue and clear up effort supervision
  - Disaster damage estimation
  
- Crop Management
  - Countryside and Agriculture

- Agricultural Activities
- Crop Dusting
  
- Communications
  - Telecommunications
  - Telecom relay and signal coverage survey
  
- Survey
  - Oil and Gas Exploration and Production
  - Mineral exploration
  - Geophysical surveys
  
- Audio visual
  - Aerial video
  - Aerial photography
  
- Cargo
  - Product delivery

## 2.2 Search and Rescue

Search and Rescue (SAR) operations must be carried out by the competent authorities in case of emergency that involves people in danger. The nature of these emergencies can be very different; therefore, the hazards will vary depending on the kind of emergency and the SAR operation has also to be adapted to each situation. Some common emergency situations are, for instance: people lost in uninhabitable places, natural disasters like fires, aircraft or vessel accidents, etc.

In all those cases, a SAR must be performed in order to search for survivors and to rescue them. There are normally five sequential events in the development of a searching plan [13]:

1. Estimating all the possible information, determining the location of the emergency and its environmental features, day time, etc.
2. Determining the size of the searching area, considering errors in position estimation, navigation errors, possible people movements, etc.
3. Selecting searching patterns, considering the size of the area, type of terrain and capabilities of searching units.
4. Determining the desired area coverage, considering factors affecting the probability of detection, track spacing and number of sweeps.
5. Developing an optimum and feasible searching plan, considering the number of search units available and other limiting factors and circumstances.

### 2.2.1 UAVs in SAR operations

Nowadays UAVs are often used in SAR operations. The most common method of operation of these UAVs is to pilot them remotely by a SAR team member.

The UAV is moved by its pilot to the desired areas in order to collect the relevant information to help the team in the SAR operation. The payload of the UAV may be of different nature: cameras

to record video or to take pictures, and to get an overview of what is happening, or even gas analysers to detect smokes composition.



Figure 2.1 Fireman using a SAR UAV. Source: microdrones

It is clear that the main advantage of the UAVs is to have an overview from the sky, but since they do not carry any person, they could get into hazardous areas like high temperatures zones, radioactive or inaccessible zones.

Some UAVs applications in hazardous or difficult environments for SAR are:

- Tracking landslides and earthquakes or tsunamis areas
- Tracking and contamination measuring in nuclear accident areas
- Fire scene inspections and tracking forest fires
- Tracking ship collisions and sinks
- Tracking volcanic eruptions affected areas
- Sea SAR

## 2.3 Artificial intelligence

It is not easy to synthesize a definition of Artificial Intelligence (AI) which englobes very different methods, applications and areas. Therefore, many AI definitions can be found in the literature depending on the goals, area, etc. In this work, the definition stated in [12] has been selected: *“AI as a science is to make machines do things that would require intelligence if done by humans”*.

### 2.3.1 AI techniques

There are four basic techniques used in AI applications that belong to the so called Soft Computing discipline:

#### Expert Systems

Expert systems have a knowledge base and an inference system. The knowledge base is a bunch of rules with “if...then” structure, which have been established by a human expert. The inference system decides which rule must be fired at each moment, and a conclusion is drawn.

#### Fuzzy logic

Fuzzy Inference Systems or Fuzzy Logic is a set of rules with the “if...then” structures, as well as expert systems, but with the difference that fuzzy systems are adapted to work with inaccurate or uncertain information. This fact makes possible to work with words more than with numbers as human reasoning does.

### **Artificial Neural Networks (ANN)**

A neural network can be defined as a computational model based on the human brain structure. It consists in a parallel and distributed process structure, having each unit different inputs and outputs, each one with a weight associated. The main difference of ANN with the two previous techniques is that ANN has learning capabilities.

### **Genetic Algorithms (GA)**

GAs are an optimization method based on Darwin’s theory of evolution. GAs are formed by a population of individuals among whom the best fitted can be reproduced, so during the generations individuals get better. GA, together with ANN, are the main approaches of machine learning.

## **2.4 Autonomous UAVs and path planning**

Autonomous robots and vehicles have been used to carry out missions in hazardous environments, such as operations in nuclear power plants, exploration of Mars, and surveillance of enemy forces in the battle field [11]. Autonomous UAVs are a particular case of these autonomous robots.

Before we listed some UAVs applications where the drones needed to be remotely controlled by an off-board pilot. However, in recent years, research is mainly focused on autonomous UAVs, which can fly without any remote control.

The autonomous UAVs flight is based on a pre-planned path, or even it is calculated online. The level of autonomy achieved by the UAVs depends on the methodology used to control the vehicle and to generate its routes [2]. Therefore, autonomous UAVs must have an auto path-planning calculation functionality to be really autonomous.

Among path planning research works, it must be differentiated those which focus on how the UAV follows the trajectory, and those which calculates the trajectory itself.

For the first case, geometrical methods such as spline interpolation are used in order to get smooth curves through a number of points [1]. Some the path following algorithms often used for UAVs are presented in [16], including a comparison between them in order to help in the selection of one or another.

For the second case, which is closer to the work presented in this report, most of the works are focused on the optimization of the path between two points, which will be followed by the UAV. Most of these methods are based on waypoints calculation, in which the location of these points is optimized, very often by GA [3, 4, 5, 6, 10, 12] and also other methods like estimation of distribution algorithms [17] or A\*[15]. Generally, in these cases, the UAV needs to move in a known environment, and the optimal path is obtained avoiding problems like radar zones, buildings, battery run out, distance, etc.

Other studies present on board path planning calculation [14], or even something more sophisticated, as in [8], where path planning is defined using a Monte Carlo searching of the best path using on-line detected parameters.



## 3 Risk / Occupancy map

For the SAR operations procedure, we need to take the following actions:

1. To estimate all the possible data and information
2. To determine the searching area and the desired area coverage level
3. To select the searching patterns
4. To establish an optimum searching plan

The first two items will be covered by the generation of a surface of the desired area, with some properties. Depending on the available data, different zones will be defined which will help to determine an optimum plan of searching.

The second two items will be developed by the path planning strategy and the UAV formation (next chapter).

In this section, the area characterization is described and applied to the problems defined in this work.

### 3.1 Area characterization

The area characterization involves the analysis of a determined surface where the search will take place and the quantification of some characteristics in order to estimate the potential risk and people occupancy of the area.

The input is a map of the area to be covered during the search. This map is divided into a grid of cells, being each of these cells assigned a value of potential Risk/Occupancy. Once this value is calculated for each cell of the map, the path planning module will take this information as input to calculate the waypoints that the UAV will follow.

To make a grid partition, first the size of the cell is considered. It is assumed that the UAV will be able to track the whole cell when located at the geometrical centre of it. That is, the size of the cells will not be bigger than the area covered by the on board camera of the UAV.

Nevertheless, the area covered by the on board camera is difficult to be estimated since it depends on two main factors: the altitude of the UAV and the opening angle of the camera lens. At the same time, the altitude of the UAV in case of visual tracking will be limited for the camera characteristics, because if the altitude is too high, it is possible that the camera will not be able to focus correctly, and the tracking cannot be done. Taking that into consideration, it has been established a limit of 100 by 100 meters for the cells size in order to ensure, in a realistic way, enough resolution to visual tracking.

Once having the size dimension of a cell, the number of cells is calculated straightforward.

#### 3.1.1 Potential Risk/Occupancy estimation

The potential Risk/Occupancy aims to give a value of the possibility of each cell to be occupied by people and, in that case, the potential hazard for the life of that person.

To calculate this value some information from different sources is necessary. To obtain the potential occupancy we need to know, for example, if the area is often visited by people. The potential risk can be affected by emergencies, such as fires, or by a dangerous terrain such as mountains or deserts. Regarding to that, the input information has been divided into two groups: inputs related to the terrain and inputs related to the emergency event (Tables 3-1 and 3-2). As it is possible to see, some of them can be described by linguistic terms, which will allow us to apply fuzzy logic to better deal with it.

Table 3-1. Terrain factors

TERRAIN FACTORS	
Factor	Description
<b>Staying</b>	<p>Staying factor describes whether the area is often visited by people or not. It gets high values for areas often visited and lower values on the contrary. Higher values increase potential occupancy. For a marine environment, since the staying definition does not apply, it can be used to select those areas where the sea currents converge, so the probability to find people is higher.</p> <p>This data can be obtained from an analysis of the area and from historical data that can tell us which areas are more often occupied.</p>
<b>Risk</b>	<p>Risk factor quantifies the hazards and risks inherent to the area, affected by animals, weather conditions, terrain access, etc. Higher values increase potential risk.</p> <p>This data can be obtained from an analysis of the area and also from surveys made by experts in the zone (SAR teams, rangers, etc.).</p>
<b>Transit</b>	<p>Transit factor expresses whether the area is usually transited by people, if there is a road or a promenade, where people can be easily found by other people while travelling through these areas. The potential occupancy of these areas is increased but the risk decreases.</p>

Table 3-2. Emergency factors

EMERGENCY FACTORS	
Factor	Description
<b>Emergency</b>	<p>Emergency factor represents how the area is affected by an emergency. High values represent highly affected and low values the opposite. High values increase potential risk.</p>
<b>SAR team position</b>	<p>SAR team position represents the location of the SAR team, e.g., in the case of a fire, when firefighters are in the emergency area, this area is already covered. The risk is cancelled.</p>
<b>Injuries</b>	<p>Injuries factor describes the possibility of people being injured. High values increase potential risk.</p>

Once the different inputs are defined, the goal is to obtain a unique value to characterize the potential Risk/Occupancy of each cell of the map.

The factors considered come from very different sources. Thus, it is very difficult to find a relationship between the staying factor and the disorientation one, or even more with the SAR team position. Because of this reason, analytical methods have not been taken into account to obtain the potential Risk/Occupancy value.

Instead of classical methods, AI techniques are applied. Before making a decision on which technique is more appropriate, the AI techniques named before have been briefly examined. A Fuzzy Inference System (FIS) handles the problem very well because input information is uncertain and vague. Therefore, two FIS are generated to obtain a Risk/Occupancy map of the area of interest, one based on the terrain factors and another on emergency characteristics.

### 3.1.2 Terrain Fuzzy Inference System

There are two variables related to the terrain. These are the Staying and the Risk factors, which can get values in the range [0,1], quantifying the related data, so we will use these variables as fuzzy inputs. Figure 3.1 shows the membership functions of the input and output variables. They are defined by three fuzzy sets with triangular and trapezoidal membership functions.

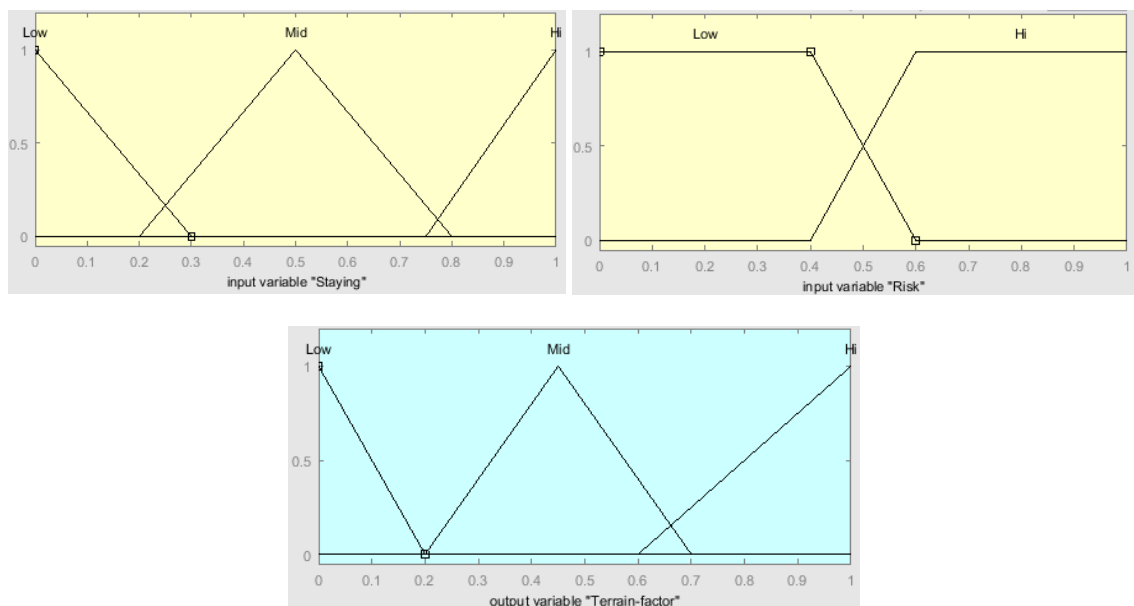


Figure 3.1 Terrain fuzzy sets

The fuzzy rules of the system are shown in Table 3-3. They are obtained by applying expert knowledge. Besides, we have considered different cases to weight them:

1. The area is affected by the transit factor, i.e., there is road or similar going through it. In this case, we multiply the result obtain from the FIS by 0.2 for main roads and 0.5 for secondary roads and promenades. The risk decreases as it is very likely that people do not get lost there.
2. The area is defined as a SAR team position, that means that they rescue team is already there. The result is cancelled.

3. If the area is affected by other factors that have not been considered, a weight can be manually introduced by the user or the expert.
4. Otherwise the rules are applied with weight equal to one.

Table 3-3 Terrain FIS rules

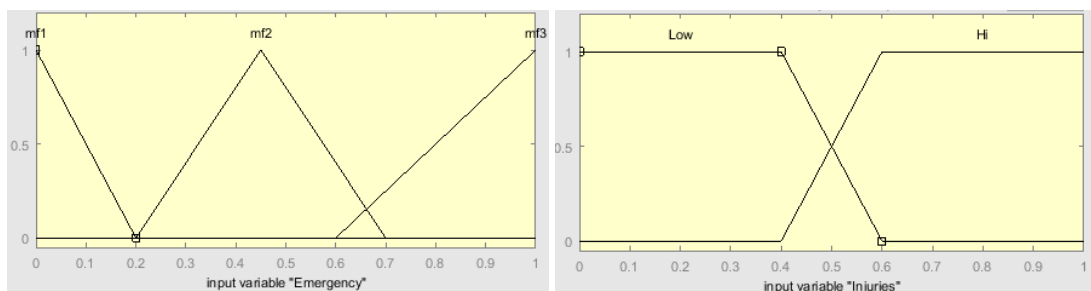
Rule	Staying	Risk	Output
1	high	high	high
2	High	low	high
3	medium	high	high
4	medium	low	medium
5	low	high	medium
6	low	low	low

### 3.1.3 Emergency Fuzzy Inference System

The same procedure has been applied for the emergency FIS. The two fuzzy inputs, emergency and injuries, are defined by three fuzzy sets with triangular membership functions, and injuries have two trapezoidal ones. Rules and membership functions are shown in Table 3-4 and Figure 3.2

Table 3-4 Emergency FIS rules

Rule	Staying	Risk	Output
1	high	high	high
2	High	low	high
3	medium	high	high
4	medium	low	medium
5	low	high	medium
6	low	low	low



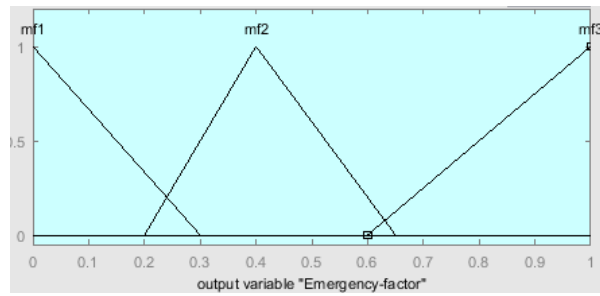


Figure 3.2 Emergency FIS membership functions

In this case, the FIS output is again weighted by one, except for the SAR team position like in the terrain factor.

### 3.2 Potential Risk/Occupancy map

We know apply the result of these fuzzy systems to each cell, to generate the map.

First, the cells with the same characteristics are grouped and a tag is assigned to them. For example, if there is a forest in the map, all the cells that represent it, that will have the same staying, risk and transit factor, are considered a group. The same value of the terrain factors will be assigned to all the cells of the group. This way we calculate it once for many cells.

We have generated an artificial map to test the proposed method, with several areas with different characteristics. In Figures 3.3 and 3.4 we can see the tags assigned to all the cells for terrain and emergency contributions.

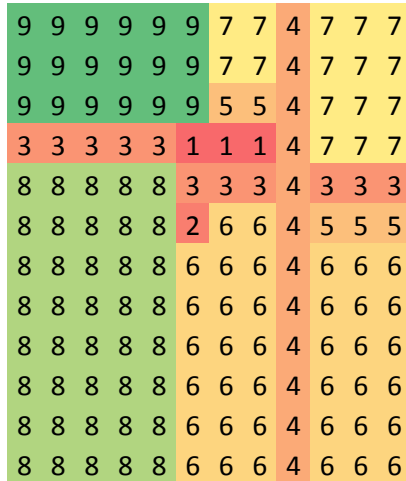


Figure 3.3 Terrain contribution tags

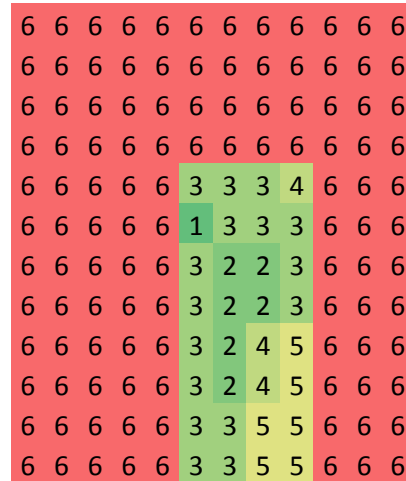


Figure 3.4 Emergency contribution tags

The values generated for this test have been obtained as shown in Tables 3-5 and 3-6.

Table 3-5 Terrain contribution tags

Tag	Description	Manual	Staying	Risk
1	Other	0.50	0.00	0.00
2	SAR team	0.00	0.00	0.00
3	Road level 1	0.20	0.50	0.10
4	Road level 2	0.50	0.30	0.10
5	Mountains	1.00	0.70	0.90
6	Plain	1.00	0.80	0.20
7	Forest type 1	0.80	0.60	0.40
8	Forest type 2	1.00	0.30	0.80
9	Desert	1.00	0.30	0.50

Table 3-6 Emergency contribution tags

Tag	Description	Manual	Emergency	injuries
1	SAR team	0.00	0.00	0.00
2	Emergency	1.00	0.90	0.00
3	Next to emergency	1.00	0.60	0.00
4	Em + injuries	1.00	0.90	0.50
5	Next em + injuries	1.00	0.60	0.30
6	Not affected	0.00	0.00	0.00

With this data as inputs of the FIS, the terrain and emergency map is obtained. Figures 3.5 and 3.6 shows the contributions. The colors represent the values obtained in the calculation, from dark blue (value 0) to yellow (value 1).

In both maps we can see the different areas determined by each tag as explained before. For example, in the terrain contribution (Figure 3.5), the two blue lines are clearly identified as the roads with low contribution values, and the yellow areas correspond to the forest and the plain, those ones with higher staying and risk values.

In the emergency contribution map (Figure 3.6), we can see a yellow area representing the emergency surrounded by a green one corresponding to less affected zones.

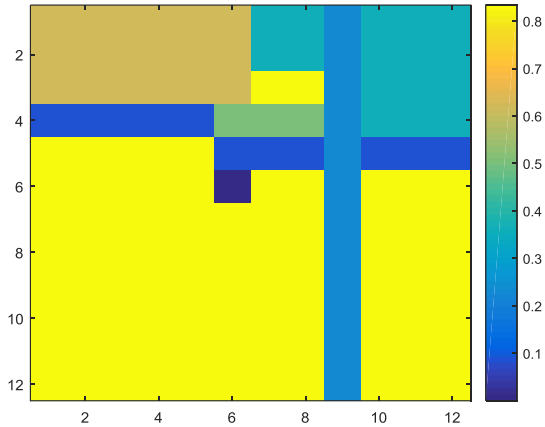


Figure 3.5 Terarin contribution

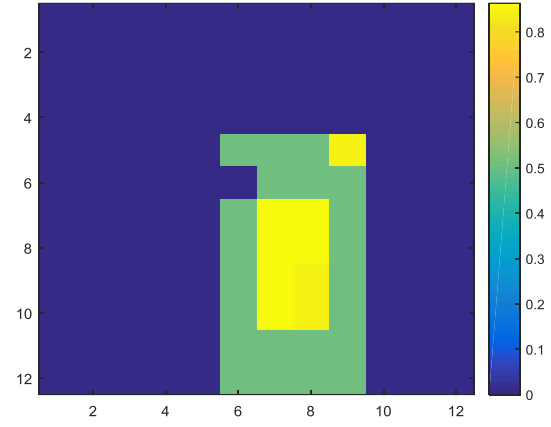


Figure 3.6 Emergency contribution

The final step is to combine these two values into one, in order to have a unique map that will be the input for the path planning step. This value is calculated with the following relation:

$$P = 0.5 \cdot P_{TERRAIN} + 0.4 \cdot P_{EMERGENCY} + 0.1 \cdot P_{HISTORICAL} \quad (1)$$

Where we have also introduced a historical contribution, which quantifies the possibility of an event to happen again in the same place. It will be 1 in the positive case and 0 otherwise. In the data used for testing, we have introduced a historical incident at points (8,10) and (9,10). An example of the Potential Risk/Occupancy map is shown in Figure 3.7.

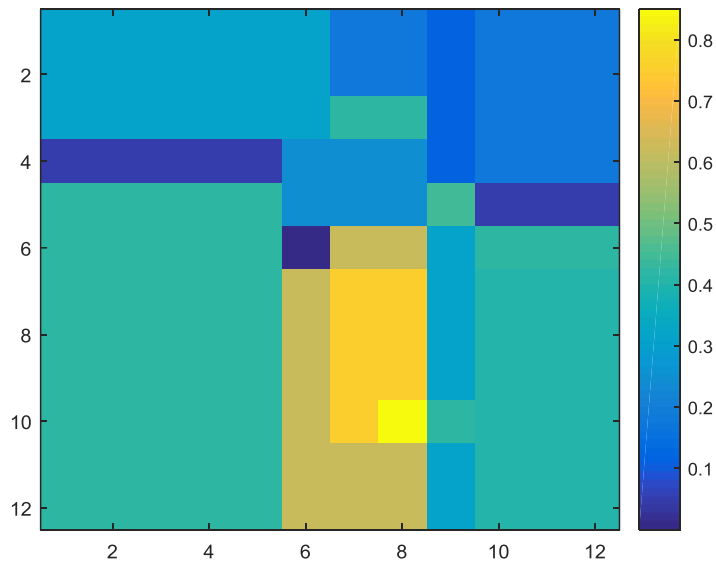


Figure 3.7 Potential Risk/Occupancy map

We can see in the map the combination of the two different effects seen in the individual contribution, having then a distribution which combines the factors due to the emergency and the terrain itself.



## 4 Path planning

The aim of this chapter is to propose a series of possible solutions to calculate the path planning and improve them to get better results. Another goal is to use AI techniques studied to this problem.

The objective of the path planning is to define the waypoints the UAV must follow, in order to find as soon as possible the people involved in a SAR operation and to minimize the risk for their lives.

The goal when searching for people is to explore the whole area minimizing the travelled distance. Moreover, we want to minimize the risk too, not only the time, so we need to go first to those areas which imply more risk or hazard.

Although the aims seem clear in their approach, the difficulty is that both problems can not be solved at the same time. If we minimize the distance, we do not necessarily cover the areas with a high risk associated first, and the opposite, if we first go to the riskiest areas, in a very high percentage of the cases we are not minimizing the distance.

Despite these issues, we have estimated the potential Risk/Occupancy value as shown in the previous section, which quantifies the risk associated to a spot, but it also quantifies the possible occupancy. So, if we should go first to the areas which a high potential Risk/Occupancy, we will minimize the distance somehow. Anyway, the best solution for the whole problem is based on a good balance between the two aims.

In this section, different solutions to this problem will be analysed. The first assumption to be taken into account is the one made for the grid partition, that is, that the on board camera is able to track the whole cell area from its centre, so the waypoints will be related to the centre of the cells. Then the order of cells the UAV must follow is then calculated.

In order to analyse the quality of the solution, several simulations are performed over a predetermined map of potential Risk/Occupancy values. The results are quantified by two factors:

- Distance (d): the total distance travelled by the UAV.
- Weight (w): The factor called weight is calculated as:

$$w = \sum_i^n \sum_j^m order(i, j) \cdot P(i, j) \quad (2)$$

where *order* is the matrix containing the number of each cell, and *P* is the potential Risk/Occupancy matrix.

As said before, all solutions are simulated in the same scenario. The dimension of the matrix that represents this scenario is 25x25 cells. An example of the values of potential Risk/Occupancy are shown in Figure 4.1.

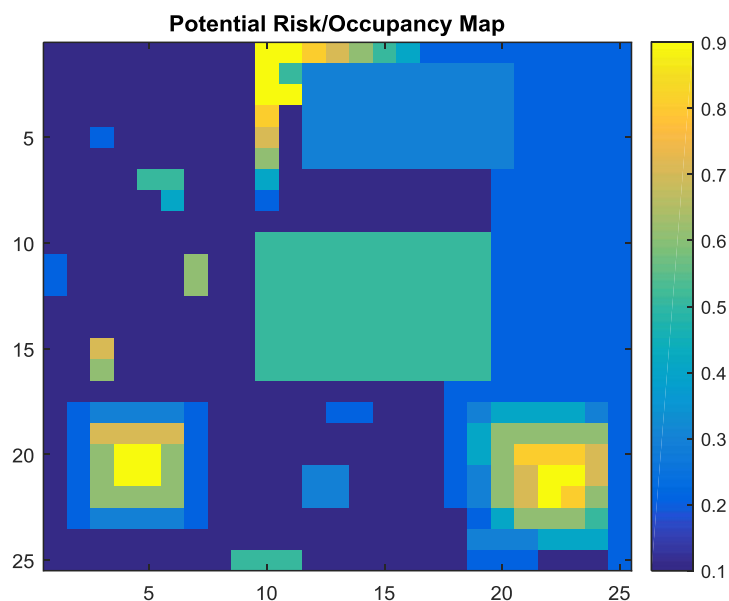


Figure 4.1 Potential Risk/Occupancy map

#### 4.1 Attraction approach

The first proposal is based on potential fields theory. In general, potential fields are used when the final point is known, so a vector is calculated and its direction and magnitude depends on the distance to the final point and the obstacles or forbidden zones affecting the trajectory.

In our case, the final point is unknown. Then, an attraction value is calculated so that the cell with the highest attraction value is the next waypoint. This attraction value depends directly on the potential Risk/Occupancy of each cell and the distance to the current position.

The attraction formula proposed is shown in Equation 2.  $A(i, j)$  represents the  $ij^{\text{th}}$  cell of the attraction matrix  $A$  and  $P(i, j)$  the potential Risk/Occupancy associated to the cell. *Covered* matrix contains the historical information about if the cell has been already tracked, i.e. *Covered* is a matrix, the same dimension as  $P$  and  $A$ , with value 1 for non-tracked cells and 0 for tracked ones. So if a cell has been already visited, its attraction value is 0. The denominator is the Euclidean distance from the  $ij^{\text{th}}$  cell to the current position one.

$$A(i, j) = \frac{P(i, j) \cdot \text{Covered}(i, j)}{\sqrt{(x_{ij} - x)^2 + (y_{ij} - y)^2}} \quad (3)$$

With this relation, we try to go to the points with high  $P$  values but near the current position, so further points with high  $P$  values have less attraction than nearer points. Therefore, the trajectory is consistent and the UAV can track low and high  $P$  cells minimizing the distance, but always being more attracted by high  $P$  cells. If the distance was not taken into account, only  $P$  values would decide the waypoints, so the trajectory could have jumps from one waypoint to another and it would not be smooth.

A simulation is performed to show this approach. The value of the distance is 680.84 units, while the weight is 44125. Since it's difficult to interpret these numeric data, some graphics have been generated.

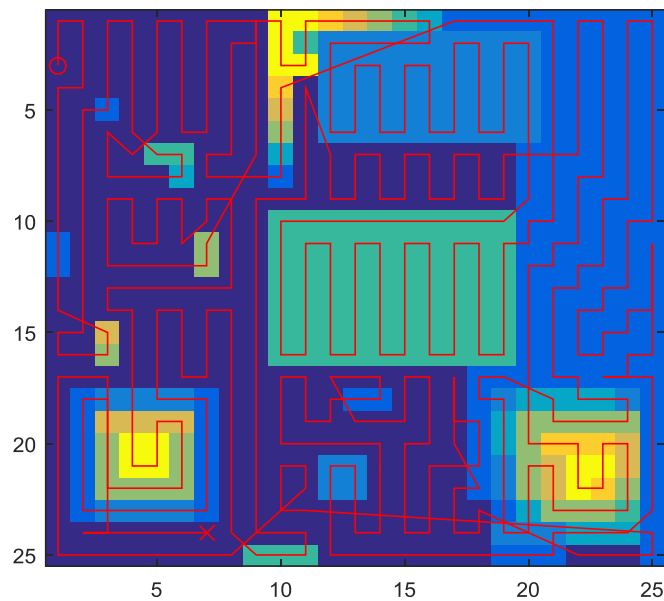
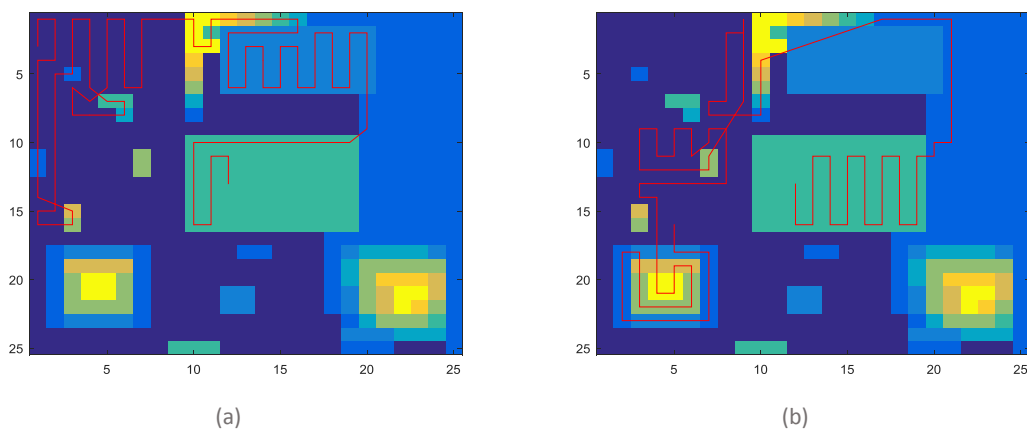


Figure 4.2 Attraction solution path planning 1

Figure 4.2 shows the complete trajectory of the UAV. The trajectory is consistent, having a good continuity and covers all the surface. The starting point is marked with an O and the finishing one with an X.

To get a better view of the UAV flight, the next sequence of figures shows the trajectory divided in chronological steps, so we can see the order the cells are tracked (Figure 4.3).



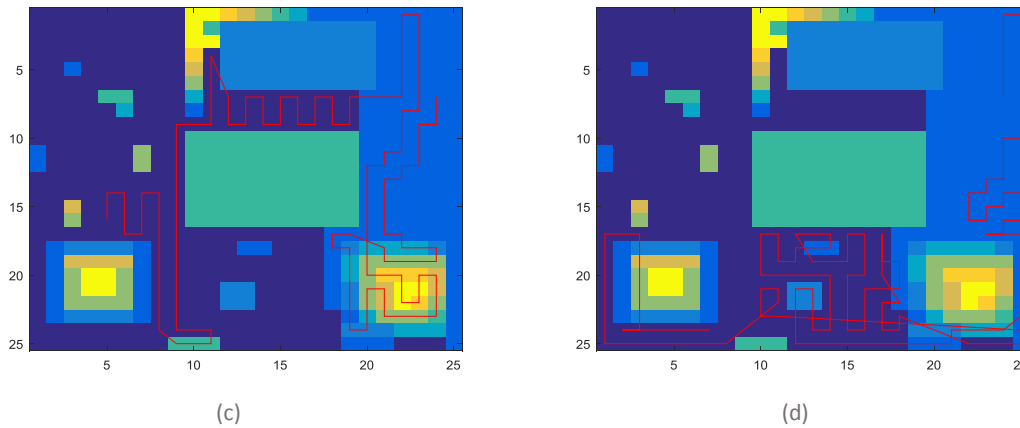


Figure 4.3 Attraction solution path planning 1, divided in four steps

As shown in the figures, the trajectory starts properly (a), going to the cells with higher  $P$  (yellow) (b). When the UAV arrives near a yellow cell, it goes directly to it, and then, covers all these nearer low  $P$  cells. Then it goes to the other yellow zone at the bottom-right position (c), and finally goes to (d), but covering all the surface (Figure 4.3)

In this approach, the attraction by the distance is bigger than by the potential Risk/Occupancy value, so the trajectory tries to first minimize the distance and then the potential Risk/Occupancy.

While minimizing the distance is interesting, minimize the weight is even more important because, due to the occupancy, the searching time is also minimized. Therefore, some modifications are applied in order to have a more balanced relation between those factors.

$$A(i, j) = \frac{P(i, j) \cdot Covered(i, j)}{EXP \left[ \sqrt{(x_{ij} - x)^2 + (y_{ij} - y)^2} \right]} \quad (4)$$

The change is that the exponential of the distance is used for. The exponential function has been chosen because of its asymptotics, so the very close cells will take advantage of the distance, but in a short period, all the cells will be similarly affected, in opposition to the linear relation, where further cells had less chance than nearer ones.

Besides the change in the attraction formula, two more improvements are made in order to get a better solution.

The first one is about the trajectory continuity. During the UAV trajectory, in some cases, there were jumps between consecutive cells, or even cells in the same horizontal or vertical line. Regarding that, a sequence of conditional structures is implemented so, if two consecutive waypoints are located in the same vertical or horizontal line, all cells between the two points become automatically waypoints. This way these cells are considered already tracked and the UAV will not have to go backwards to them.

The second improvement is about the waypoint selection. The cell with the maximum attraction is chosen as waypoint, but sometimes more than one cell has the maximum value. In fact, in the

simulation of Figure 4.2, the selection arbitrary, choosing the first maximum found, so it depended on the starting point.

Now, the first waypoint is chosen as the cell that, having the maximum attraction, is surrounded by cells with higher P values than the other candidates, i.e. is located in areas with more P density. A matrix with this density is generated, according to the formula (5).

$$Pg(i, j) = \sum_{n=i-2}^{i+2} \sum_{m=j-2}^{j+2} \frac{P(m, n)}{\sqrt{(x_{ij} - x_{nm})^2 + (y_{ij} - y_{nm})^2}}, \text{ except for } n = i \text{ \& } m = j \quad (5)$$

With this approach, after finding the maximum values of attraction of matrix A, a search for the maximum Pg values is carried out. The cell with higher density among the maximum attractions cells is selected as next waypoint.

With these modifications, a simulation is run. In this case, the distance is 735.66, and the weight 36084. Although the distance is a little higher, the weight is much lower. Therefore, this second solution is better. Figure 4.4 shows the final trajectory followed by the UAV, and Figure 4.5 shows de order the cells of the surface have been covered.

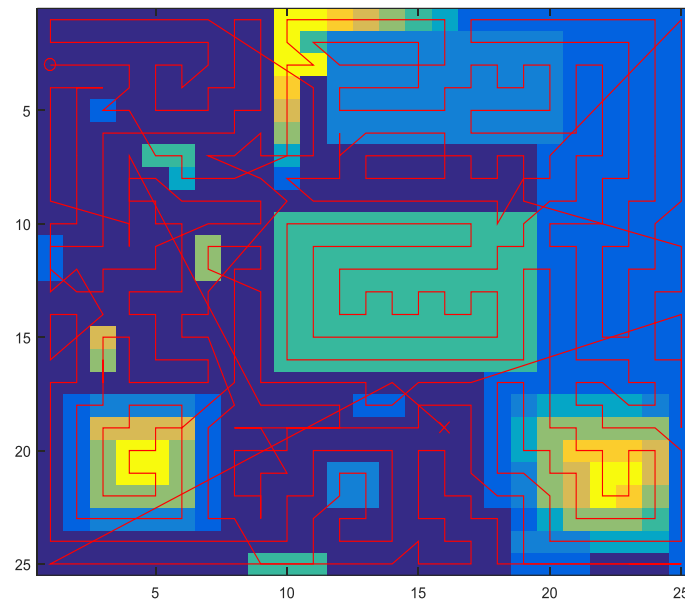


Figure 4.4 Attraction solution path planning

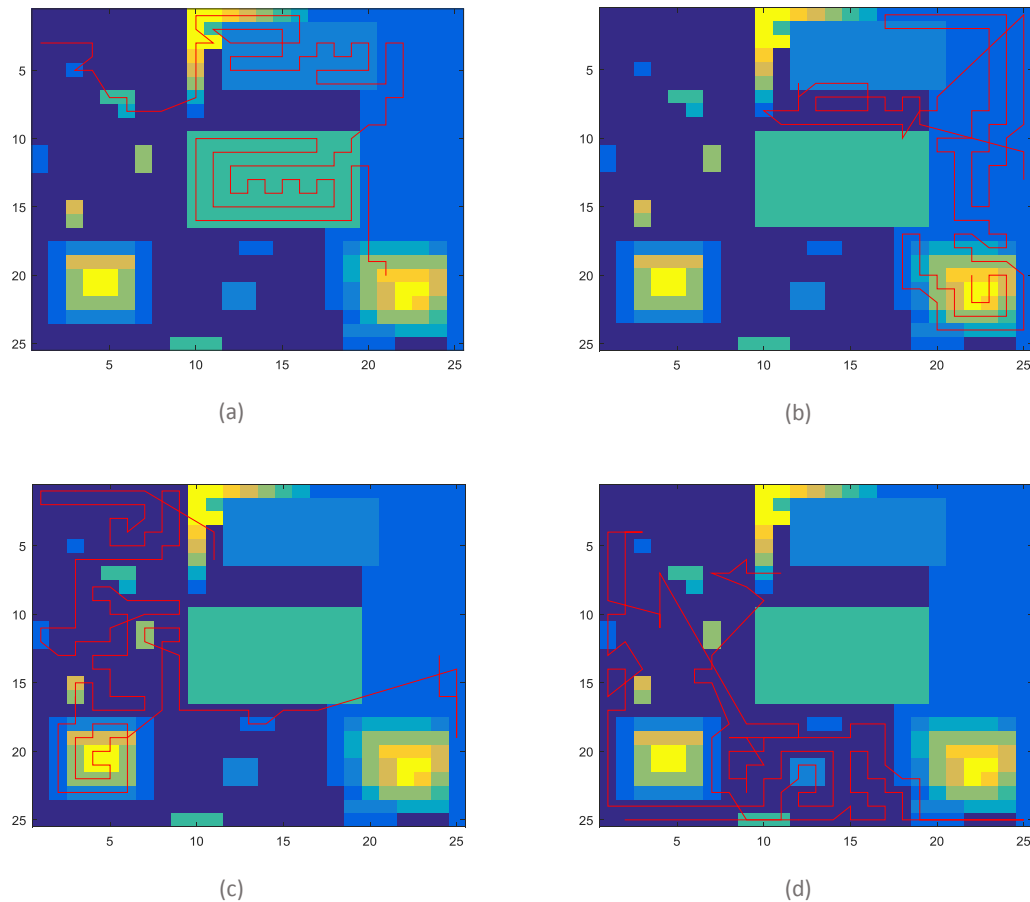


Figure 4.5. Attraction solution path planning, divided in four steps

In the sequence of images we can see how the UAV goes straightforward to the yellow areas, and does not waste time exploring low P areas unlike the first simulation. However, the UAV is still going to one of the main yellow zones after several steps.

## 4.2 Fuzzy logic approach

In order to try to improve the attraction approach, a different solution using Fuzzy logic is implemented.

We separate the contribution of the potential Risk/Occupancy and the distance creating a Fuzzy Inference System (FIS) with two inputs and one output. That is, we generate a nonlinear relation between P and d, resulting in a better solution.

Firstly, a Mandami-type FIS with two inputs (P and d) and one output (A) is created. The FIS is implemented with the Fuzzy Logic Toolbox of Matlab. It has three 3 fuzzy sets for each input (high, medium and low) and two for the output. The nine rules included in the FIS are:

Table 4-1. Fuzzy Logic solution FIS rules

Rule	P	D	A
1	high	high	high
2	medium	high	low
3	low	high	low
4	high	medium	high
5	medium	medium	low
6	low	medium	low
7	high	low	high
8	medium	low	high
9	low	low	high

The membership functions are trapezoidal ones, and are adjusted based on the desired trajectory to be followed by the UAV, taking into account the values of the attraction solution (Figure 4.6).

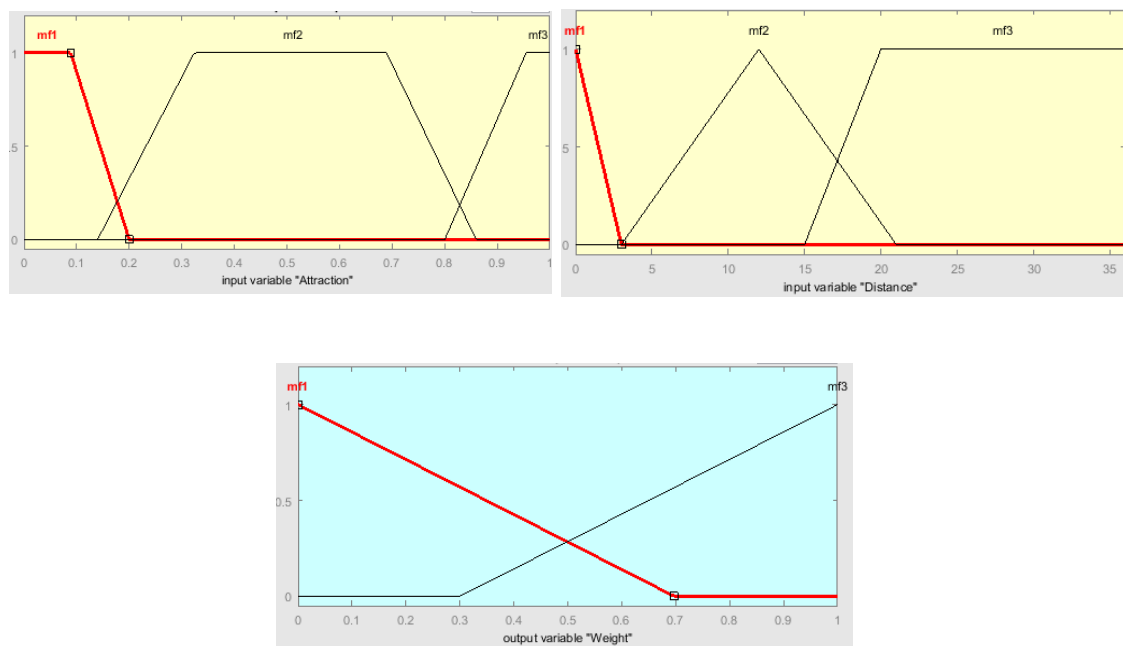


Figure 4.6 Fuzzy Logic solution 1 membership functions

A simulation has been performed using the FIS created to the same map where we applied the. It has the same characteristics than the previous one for attraction solution. The results of the simulations are a distance of 811.8 and a weight of 43199 (Figure 4.7).

The results are worse than with the previous approach. When analysing the evolution of the trajectory, we found that the problem was that the UAV prefers to go to an adjacent cell with a lower P value more than going to further cells with high P values. In fact, the yellow cells are first

surrounded by the UAV but not tracked until later, jumping from another further zone. These effects must be avoided in order to improve the result.

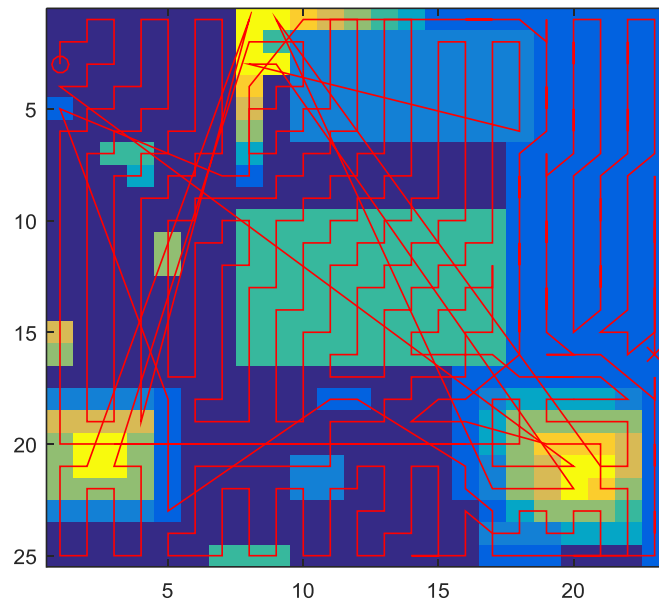
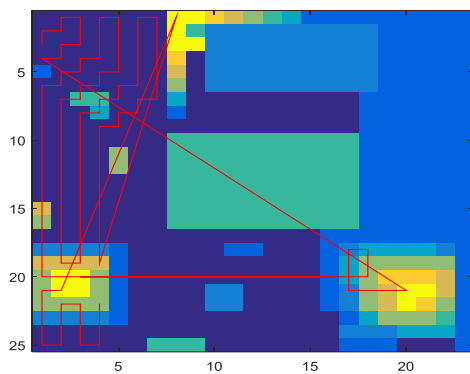
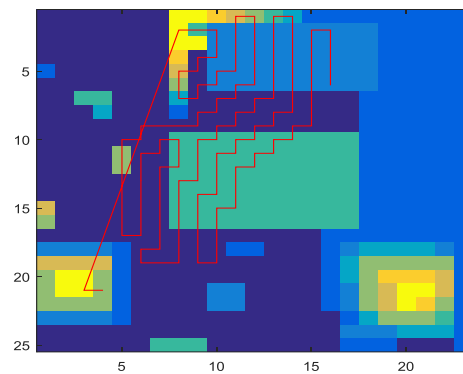


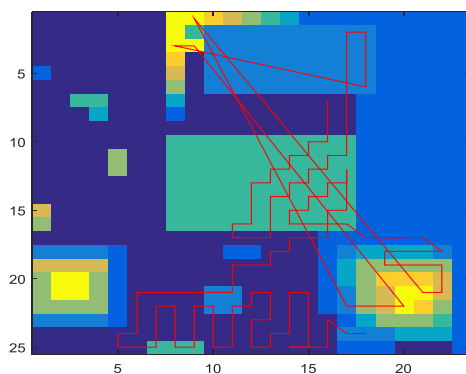
Figure 4.7. Fuzzy logic solution path planning 1



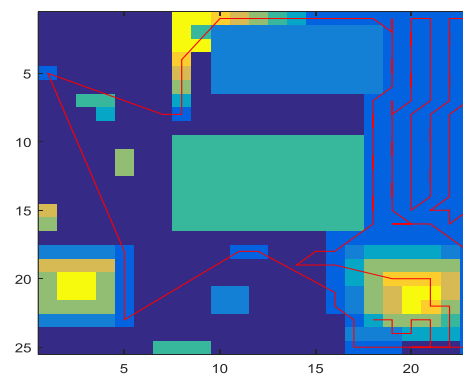
(a)



(b)



(c)



(d)

Figure 4.8 Fuzzy Logic path planning 1, divided in four steps

Generally, FIS are adjusted by an expert who knows the behaviour of the system. In this case, there is not an expert but, since the aim is to minimize distance and risk, an optimization method can be used to adjust the membership functions. Therefore, an evolutionary FIS is implemented, which consists of the same FIS proposed but adjusted with algorithms.

The main problem is now the definition of the GA fitness function, which has as variables the membership functions of the FIS.

The membership functions are trapezoidal type, so we have 32 variables. The configuration of the GA is as follows:

**Fitness Function.** This function is a combination of the distance and the weight, both to be minimized. A normalization has been done according the following relation.

$$f = \left[ 1 - \frac{\sum_{i=1}^{\max(i)} \sum_{j=1}^{\max(j)} P(i,j)}{w} \right] + \left[ 1 - \frac{\max(i) \cdot \max(j)}{d} \right] \quad (6)$$

Thus, P and D have been normalized to [0,1].

The trapezoidal membership functions are defined by 4 points:  $x_1, x_2, x_3$  and  $x_4$ . The value of these variables must be correlative, i.e.  $x_1$  must be smaller than  $x_2$ ,  $x_2$  than  $x_3$  and so on. These restrictions are defined by the linear constraints  $Ax < b$ , being  $b = 0.001$  in our case.

**GA parameters.** They are the following:

Table 4-2. GA parameters

Parameter	Value
<b>Generations</b>	300
<b>Population</b>	200
<b>Stall Generations limit</b>	100
<b>Average relative change limit (TolFun)</b>	$10^{-10}$
<b>Crossover fraction</b>	0.8
<b>Mutation distribution</b>	Gaussian, Scale and Shrink equal to 1

Initially, the process was very slow, about 8 hours to show the first generation. Indeed, with the resources available, it takes about 110 seconds to evaluate the fitness function, which means 22000 seconds per generation, i.e., 6.1 hours to evaluate the function for one generation. Multiplying by 300 generations, it would take 76.3 days to only evaluate the fitness function. This makes the problem unaffordable for this work.

In order to reduce the computational time, we consider a smaller P map, and once the membership functions have been adjusted, it is scaled to a bigger one to see how it fits. Therefore, the GA is executed with the same configuration described but for a 5x5 P matrix (Figure 4.9). The trajectory is also shown, and it is as expected.

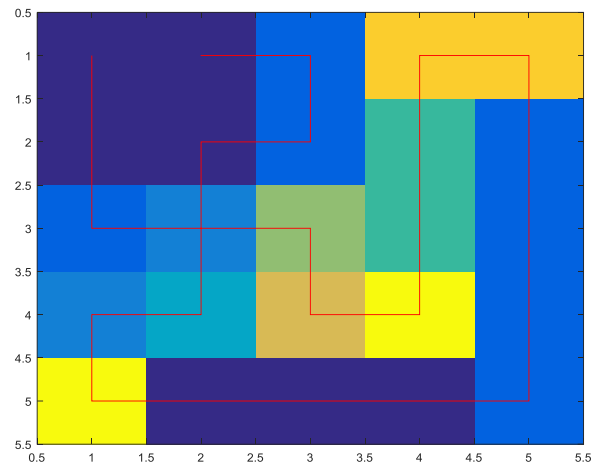


Figure 4.9. GA adjusted FIS path planning

Figure 4.10 shows the membership functions of the variable and the output surface after the GA adjustment. In the surface (Figure 4.11) we see high values for short distances and also for high P values in long distances.

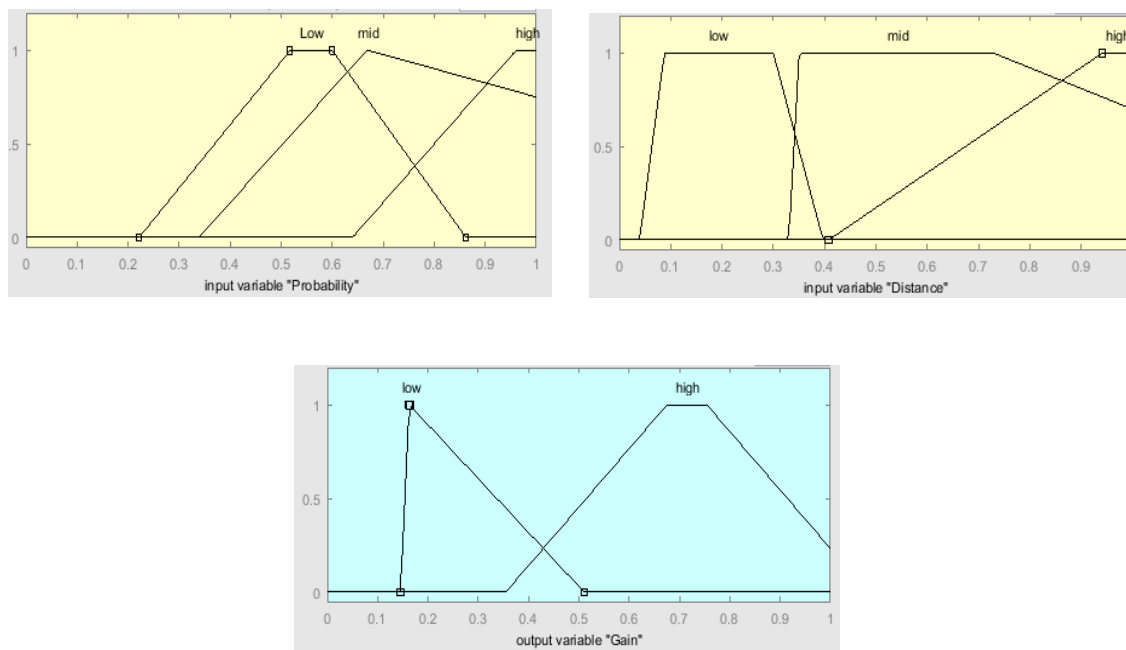


Figure 4.10. Output membership functions

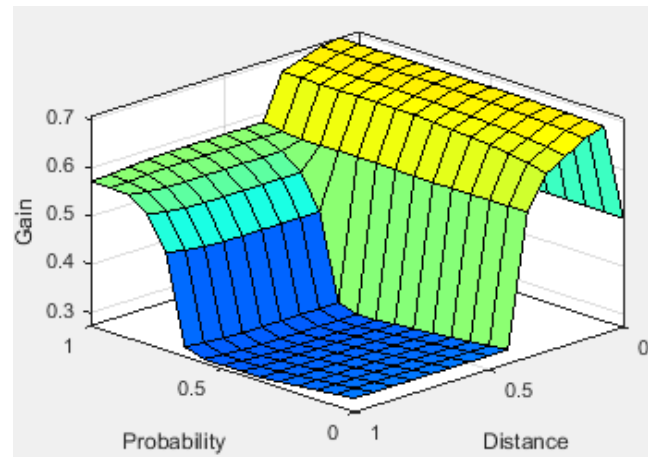


Figure 4.11. FIS surface

A test is now carried out with the 25x25 P map, using the membership functions calculated for the 5x5 map. The results are  $d=1762$  and  $w=32802$ . Although the distance is longer than in the attraction solution, weight is lower, so we can say this solution can also meet the objective, but having more inclination to minimize Risk/Occupancy than distance (Figure 4.12). However, the small angles created in most of the connections between two consecutive waypoints makes the trajectory unaffordable for a UAV.

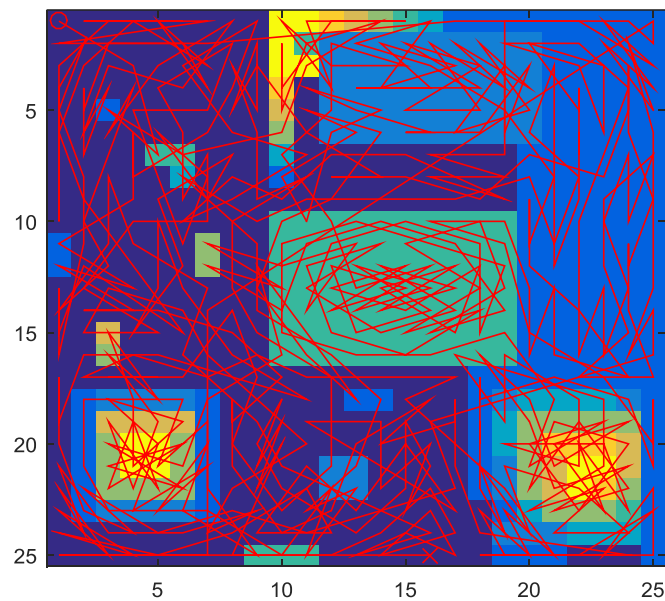


Figure 4.12. Fuzzy Logic solution path planning

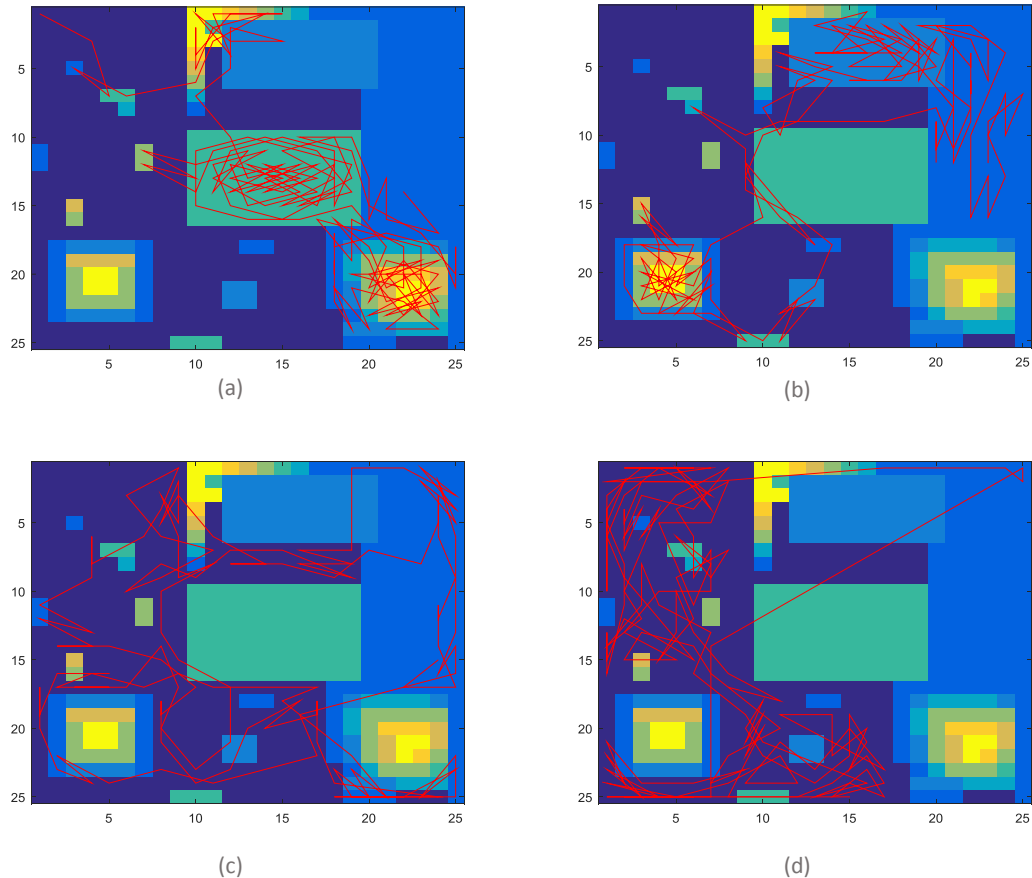


Figure 4.13. Fuzzy logic solution path planning, divided in four steps

The good point of this approach is the fast convergence to the high P value cells, visiting later the lower P cells. This means that, even covering all the cells in a longer time, since the weight is lower and it also quantifies the occupancy, the probability of finding people in a short time is higher.

### 4.3 ANFIS approach

Another attraction based solution is implemented, this time using an Adaptive-Network-based Fuzzy Inference System (ANFIS) [7]. The basis is the same as the Fuzzy logic previous solution, but in this case, the FIS is changed by an ANFIS system.

However, in this case a modification is introduced, which consists of three inputs instead of two; the density (5) used for the maximum selection is added as another input. With this modification, the system is able to give higher attraction values to higher density areas, unlike only use this data for the maximum selection.

Table 4-3. ANFIS fuzzy sets

input	MFs	Range
<b>P</b>	3	[0,1]
<b>Pg</b>	3	[0.5,5]
<b>d</b>	3	[0,1]

But ANFIS requires samples for training. Hence, we have generated synthetic data manually, as shown in Table 4-4.

Table 4-4. ANFIS training data sample

	1	15	23	26	33	46	60	63	67	68
<b>P</b>	0.9	0.9	0.7	0.7	0.5	0.5	0.25	0.25	0.1	0.1
<b>Pg</b>	5	0.5	3	1.5	5	0.5	1.5	0.5	5	5
<b>d</b>	1	0.23	0.23	0.5	1	0.5	0.06	0.23	0.23	0.06
<b>A</b>	0.25	0.7	0.3	0.1	0.1	0.1	0.48	0.03	0.01	0.5

Three Gaussian bell membership function are selected for each input, and a sample of 80 points is created to train the system. The training is performed during 50 epochs. Figure 4.14 shows the results of the training test.

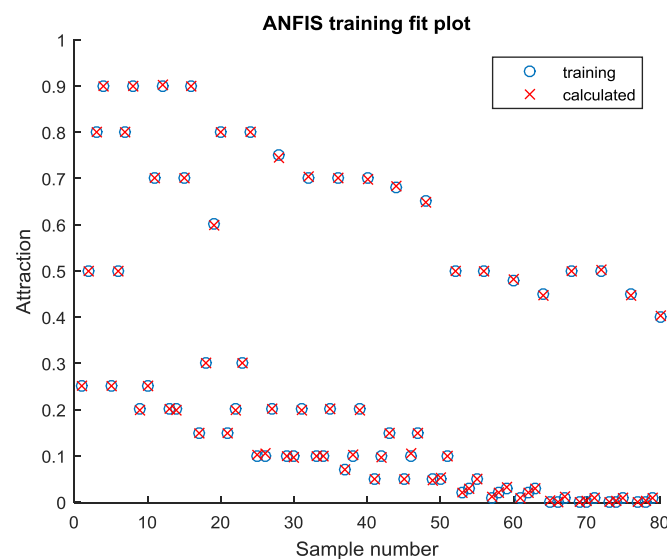


Figure 4.14. ANFIS solution training fit

Figure 4.15 shows the membership functions that have been created and Figures 4.16 to 4.18 the control surfaces.

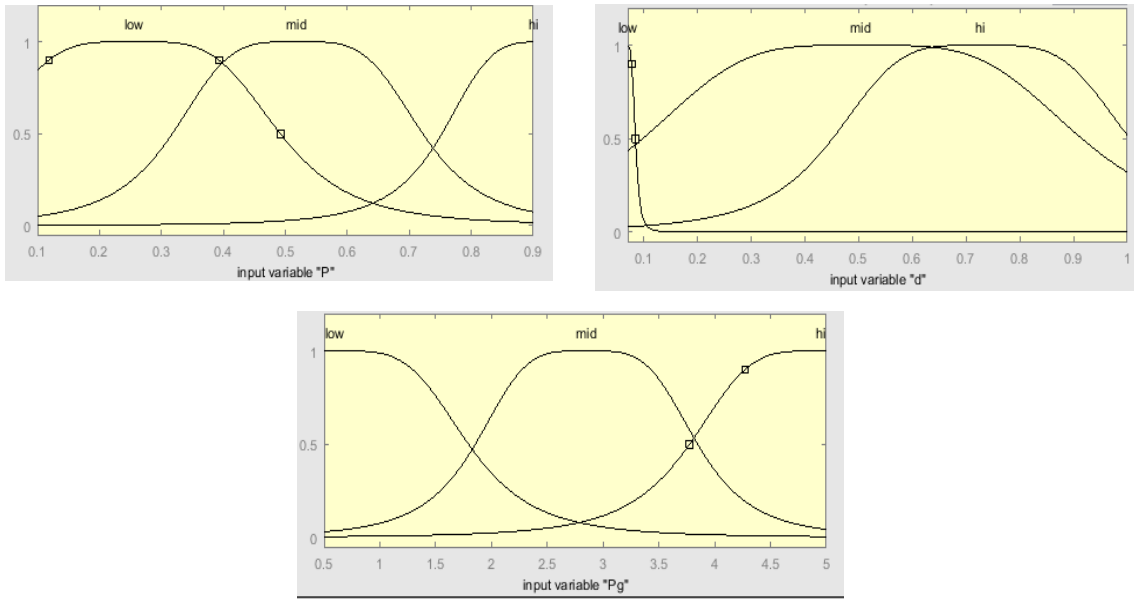


Figure 4.15. ANFIS d membership functions

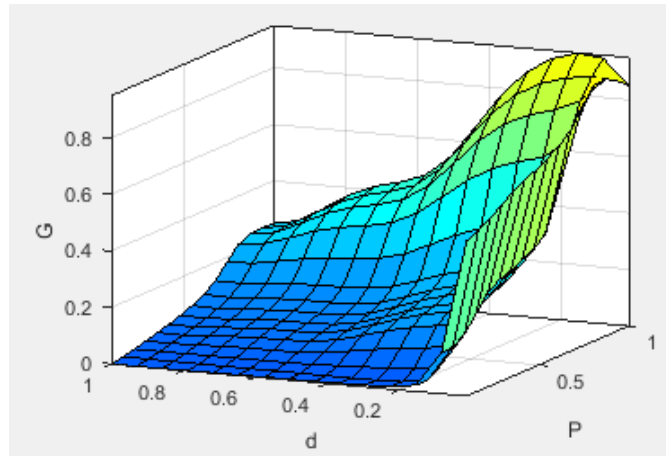


Figure 4.16. ANFIS P-d surface

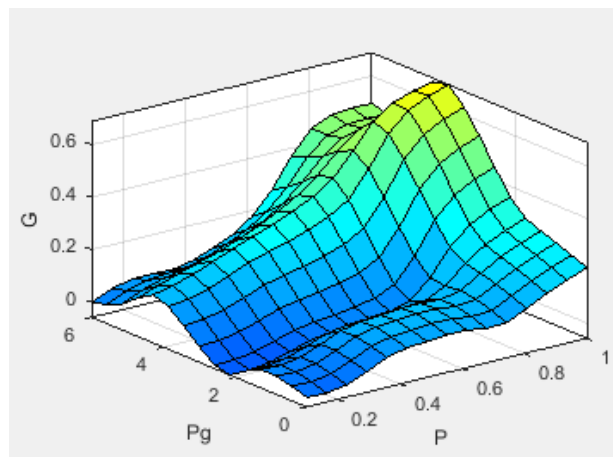


Figure 4.17. ANFIS P-Pg surface

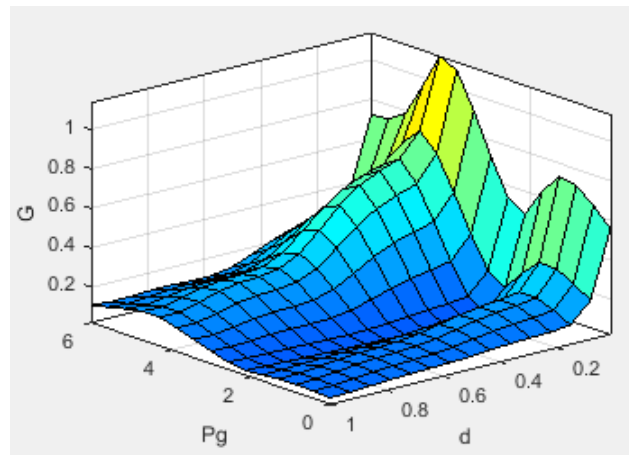


Figure 4.18. ANFIS Pg-d surface

Once the ANFIS has been generated, the simulation is run. The results obtained are  $d=1455$  and  $w=33445$ . In this case, compared with the fuzzy logic solution, the weight is higher but distance is shorter, so it is difficult to quantify which is better. However, what is really interesting of this approach is how the UAV go over the highest P cells first, finishing the searching in low P cells (Figures 4.19 and 4.20).

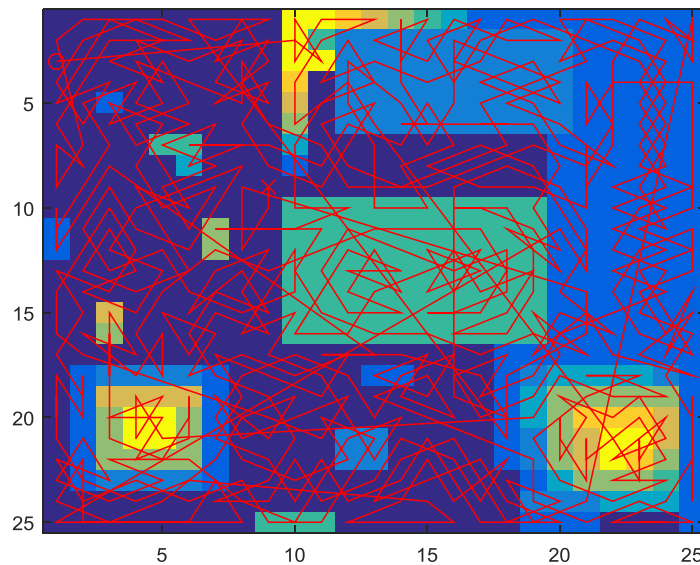


Figure 4.19. ANFIS path planning

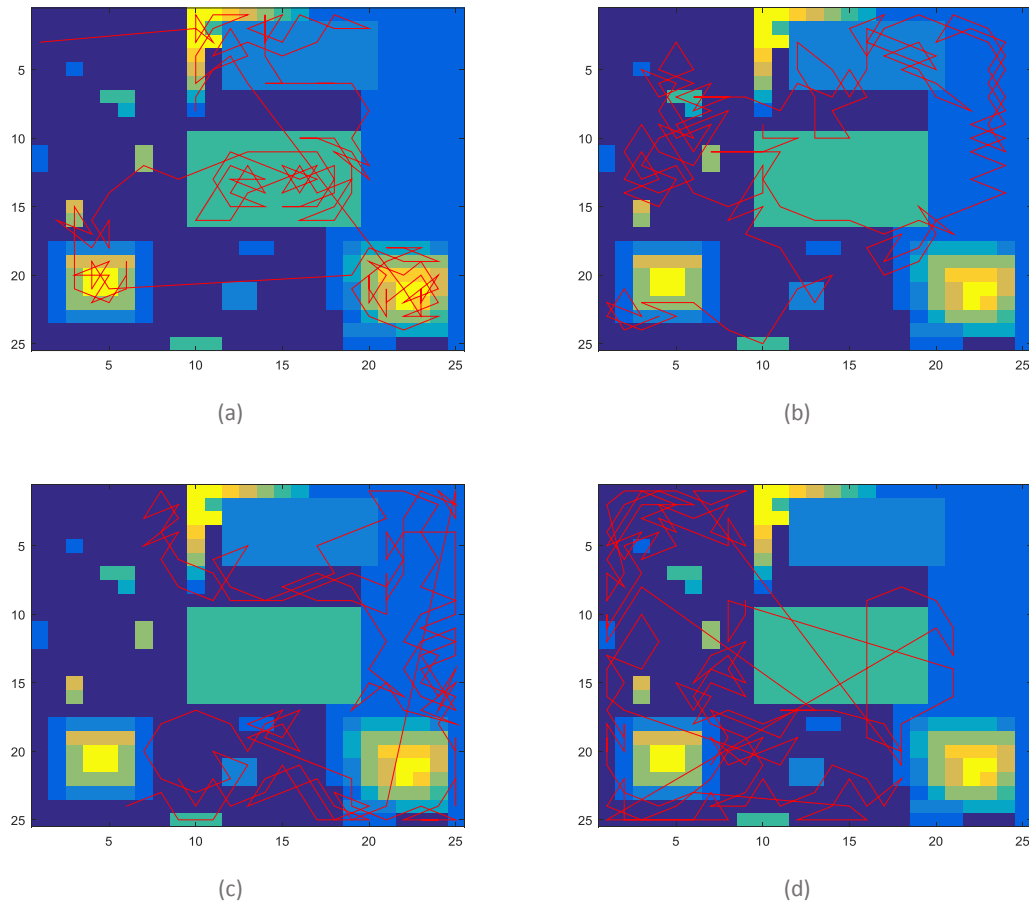


Figure 4.20. ANFIS path planning, divided in ten steps

#### 4.4 Using Particle Swarm Optimization (PSO)

Despite the previous solutions seem to meet the goal, the solutions can be improved. Thus, a PSO based solution is now proposed.

The GA was used to obtain the order of the cells that must be visited. GA worked well in very small maps but, when scaled to the 25x25 map, many problems raised. Searching for a solution for this problem, the decision was to use a PSO algorithm.

On the other hand, in all the previous solutions, the waypoint calculation was very static, being all the cells tracked from its central point. Despite the assumptions made at the beginning, with this PSO solution we try to find a continuous method.

In this case the approach is totally different. We start from the same P map, but it is divided into 10, in order to obtain a bigger discretization. Each smaller cell has the same P value than the bigger cell that contains it. Once the map is divided, the waypoints are searched with the aid of a PSO algorithm, which needs a fitness function to obtain the value to be minimized. The configuration is:

## Fitness function

The variables of the fitness function are the coordinates of the waypoints. The calculation is structured in bunches of 10 waypoints, so each calculation will have 20 variables: 10 “x” coordinates and 10 “y” coordinates. Then, the distance, the weight and the number of tracked cells are calculated. It is clear that the distance has to be minimized, and the tracked cells needs to be maximized, what implies that the UAV is travelling over the maximum number of new cells, since the tracked ones will not be taken into account more than once.

To obtain the tracked cells, a straight path will be traced between two consecutive waypoints, and all the cells inside a square of 10x10 along the trajectory will be considered as tracked, which means that the UAV is continually taking images with the same area used in previous solutions. This is the first relevant modification.

Another important modification is the maximization of the weight. In the other cases, a minimization of the weight was interesting because it meant that the UAV went first to the areas with high P cells. However, with this approach it is more interesting to maximize the weight, because, as said, the calculation is made in bunches of ten waypoints. So, if weight is maximized for the first ten points, that means that the weight in the second ten points will be lower. That is, the UAV is going over the high P cells first.

The relation between these factors is shown in equation 7.

$$f = \frac{1}{\left(\sum_{i=1}^{\max(i)} \sum_{j=1}^{\max(j)} covered(i,j)\right)^{0.1}} + \frac{1}{w^{0.1}} + \left[1 - \frac{1}{d}\right] \quad (7)$$

Table 4-5. PSO configuration parameters

Parameter	Value
Creation distribution	Uniform
Maximum iterations	4000
Stall Iterations limit	20
Average relative change limit (TolFun)	10 <sup>-6</sup>
Swarm size	100
Inertia range	[0.1,1.1]

Once the setup is finished, the process is executed. The numeric results (d and w) are not calculated because they are not relevant respect to the other solution, since the nature of the approach is totally different. However, the graphics of the results helps to carry out the analysis (Figure 4.21).

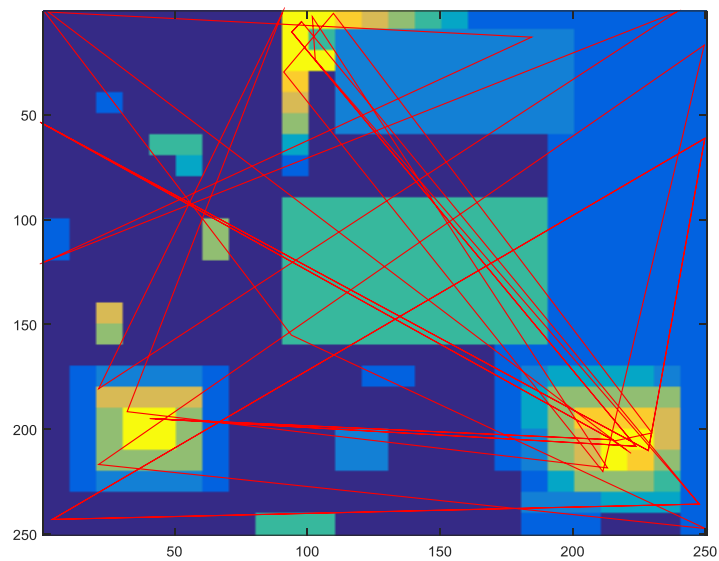


Figure 4.21. PSO solution path planning

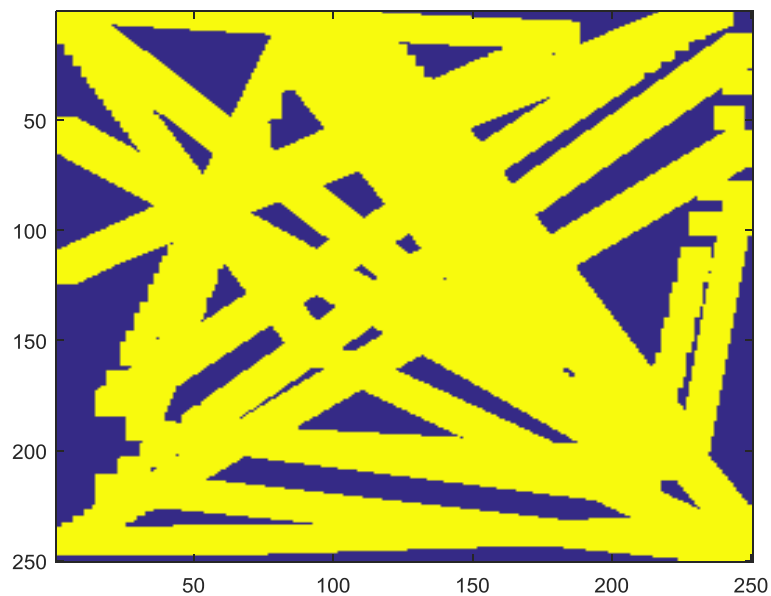


Figure 4.22. PSO solution area coverage

In Figure 4.21, we can see that the trajectory has many straight lines covering all possible space, specially between high P areas. In Figure 4.22 it is possible to observe how the UAV covers most of the map, which makes possible to find the objectives. More iterations could be performed in order to cover the 100% of the map. However, we can also see that the UAV goes and returns repeatedly to the same points, what tells us that this is not an optimum solution.

#### 4.5 Using several UAVs

In SAR operations, some times more than one UAVs are used. Swarm systems utilize simple local behaviours to collectively solve complex problems, where the capability of the group is greater

than the sum of its parts [9]. Therefore, two different swarm formations of UAVs are studied here: free and distributed. The different UAVs have different starting positions and they track all the desired area.

#### 4.5.1 Free swarm formation

The free swarm formation consists of the calculation of the waypoints for two or more UAVs at the same time in parallel, so each UAV has independent path assigned along the coverage area. When calculating new waypoints, the information of the tracked cells by other UAVs is available, so the UAVs do not visit any already tracked cell.

A method to calculate the paths for several UAVs is developed for the Attraction, Fuzzy Logic and ANFIS approaches. The solution is the same as the one presented for one UAV with the difference that in each iteration the number of waypoints calculated is the same as the number of UAVs. The priority for the calculation is the order given to the UAVs, i.e. the UAV 1 to the last one in order.

For simplicity, it is only considered the possibility to have 1, 2 or 3 UAVs, but the solution could be extended to as many as needed.

In Figure 4.23, the path planning for 2 UAVs in free swarm formation is shown. In this case, the map used was reduced to a size of 24x24, as it will be explained in the distributed swarm formation section.

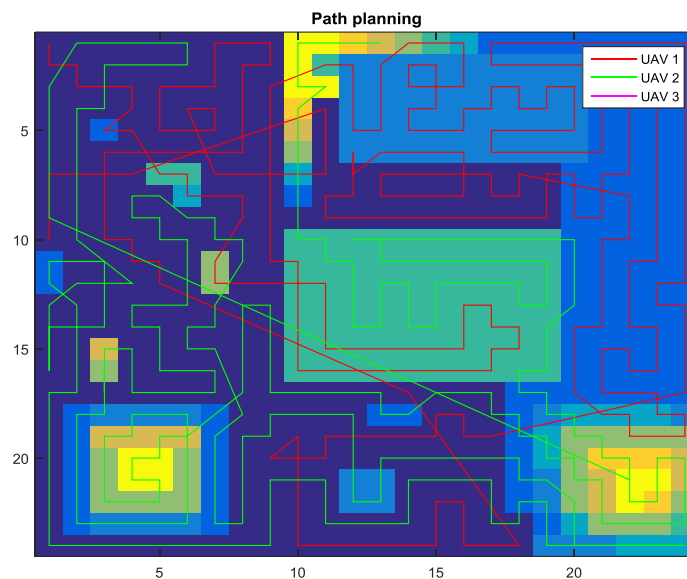


Figure 4.23. Free swarm formation of 2 UAVs path planning (by attraction)

The results obtained are  $d=676.11$ , where  $d=339.31$  corresponds to UAV 1 and 336.79 to UAV2. The weight obtained is 15752. The decreasing in the distance was expected due to the reduction of the map size, but even with that, the weight is much lower than with one UAV.

The effect in the weight is due to the parallel searching. As explained for a single UAV, the weight is calculated multiplying the order each cell is tracked by its P value, and getting the sum for all

cells. In this case, there are two cells with order 1, two with order 2 and so on, until the UAVs reach half of the number of cells.

The swarm effect also reduces the searching time because, although the distance is similar, it is shared by the two UAVs, so the maximum distance travelled is about a half than in the case of one UAV, and thus the time is half the previous one.

Regarding the path, it is interesting how the two UAVs converge in the green area in the middle of the map at the beginning. Then they separate each other and search in different high P value areas. At the end, they converge again in low P value areas.

Figure 4.24 shows the path planning for three UAVs in free formation.

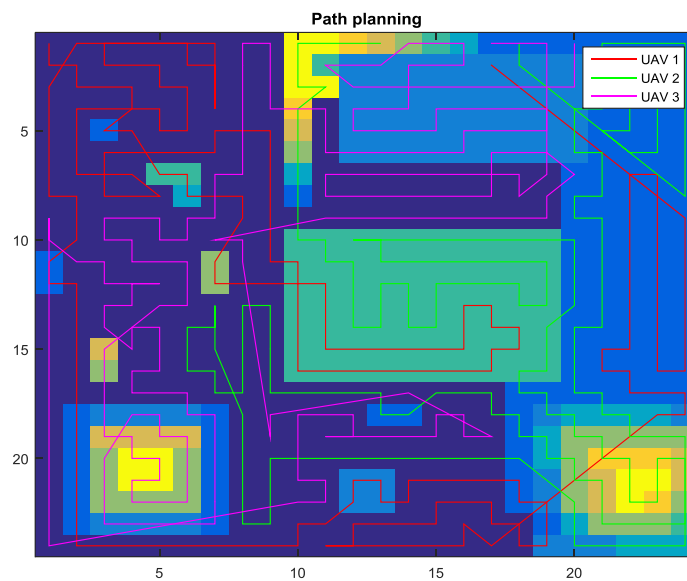


Figure 4.24. Free swarm formation of 3 UAVs path planning (by attraction)

The results obtained are now  $d=670.37$ , where 224.16 corresponds to UAV 1, 209.13 to UAV2 and 237.07 to UAV 3. The weight obtained is 11525. We can see again the effects of increasing the UAV number because the weight is lower as well as maximum distance. Moreover, in this case the convergence is not as evident as in the previous case, meaning a more distributed tracking of all zones.

In both cases, the trajectories of the different UAVs cross each other. This may not be a problem since to collision, trajectories must be at the same point at the same time. However, for this kind of arrangement, the path planning must be accompanied of an algorithm for collision avoidance between UAVs, which is not in the scope of this work.

Regarding the PSO approach, free swarm formation cannot be implemented due to the nature of the solution. As explained before, it calculates 10 waypoints for a single UAV each time, so if we have two UAVs, the first ten points would be for UAV 1, the next ten ones for UAV 2, and so on, and it would not be a real parallel searching.

#### 4.5.2 Distributed swarm formation

The other swarm formation studied in this work is a distributed one. In this case, the map is divided into several equal parts, as many as UAVs. Therefore, each UAV has an assigned area which must track.

With this formation we need to have a number of cells which is multiple of the number of UAVs. For this reason, the map was changed to 24x24, for two or three UAVs.

The path planning for 2 UAVs in a distributed swarm formation is shown in Figure 4.25.

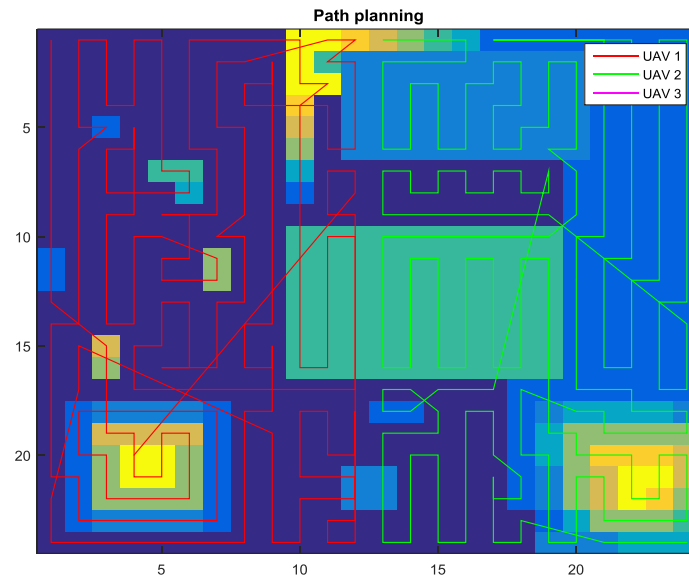


Figure 4.25. Distributed swarm formation of 2 UAV path planning (by attraction)

The results obtained are  $d=660.20$ , where 347.46 units are travelled by UAV 1 and 312.73 by UAV 2. The weight in this case is 17719. The distance is almost the same than in free formation, but the difference between the two UAVs is a little bigger. The weight is also bigger than in the previous case.

Regarding the path, we can see how the two UAVs have its own searching area and do not share it. The search is then more neat, but with worse results.

The path planning for 3 UAVs in distributed formation is shown in Figure 4.26.

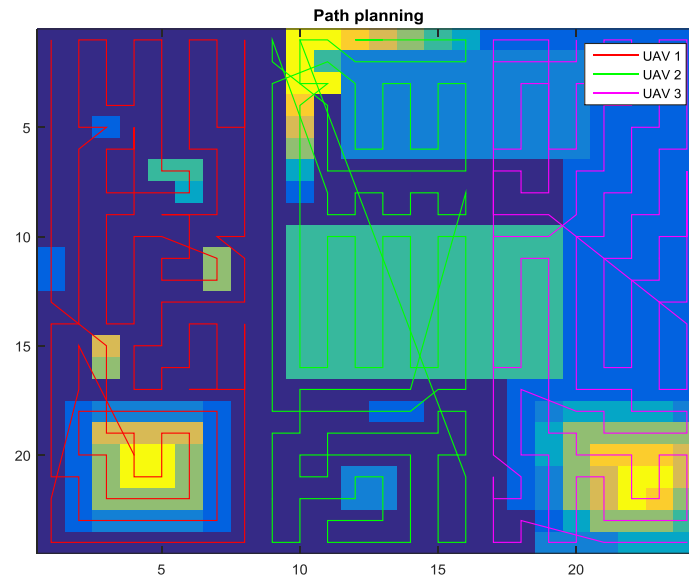


Figure 4.26. Distributed swarm formation of 3 UAV path planning (by attraction)

The results obtained are  $d=675.77$ , where 216.37 corresponds to UAV 1, 234.10 to UAV 2 and 225.29 to UAV 3. The weight is 11193. Results are similar to the two UAVs case, so the distance is similar and weight values do not differ too much. In this case, the weight is better than in the free formation, what demonstrates that optimal formation also depends on other factors like UAV number and P values distribution.

#### 4.6 Approaches comparative

In Table 4-6 we can see a comparison of the different approaches presented for all configuration studied.

As expected, the results improve when the number of UAVs is increased. This fact is due to the way the weight is calculated. As seen above, to calculate it we multiplied the order the cell is visited by the potential Risk/Occupancy. When increasing the number of UAVs, for example with 2 UAVs, we will have twice order 1, twice order 2 and so on, so the maximum number the P values will be multiplied by will be the half than with 1 UAV.

Besides, we can see the fuzzy logic method has the lowest value for the weight (3 UAVs in distributed swarm). However, the length travelled by the UAVs is very high respect to the other methods.

On the other hand, the ANFIS method does not have a weight value as low as the fuzzy logic method, but has much less distance travelled. That is due to the smooth trajectories generated by ANFIS methods respect to the fuzzy logic ones.

Finally, we can observe that the attraction method has the worst values of all methods.

Table 4-6. Approaches comparative

FORMATION		W	d	
1 UAV	Free	Attraction	31403	674
		Fuzzy Logic	28150	1542
		ANFIS	31162	893
2 UAV	Free	Attraction	16235	648
		Fuzzy Logic	14354	1622
		ANFIS	15679	932
	Distributed	Attraction	18214	661
		Fuzzy Logic	16838	1266
		ANFIS	16415	748
3 UAV	Free	Attraction	10732	737
		Fuzzy Logic	9290	1584
		ANFIS	10591	871
	Distributed	Attraction	10912	656
		Fuzzy Logic	10506	1157
		ANFIS	11155	751

## 5 Simulations

Two simulation scenarios are used with two main objectives:

1. Check the different path planning solutions presented before in a more real environment.
2. Make a comparison among the different solutions in order to know which are the best solutions and under which conditions.

The simulations are made with the characterization of two different real zones where emergency simulations have happened and SAR operations have been carried out: a forest fire in the island of La Palma, and a fisher boat sinking in the Cape of Peñas.

The scenario of the La Palma island is presented here and the one in the Cape of Peñas is shown in Annex I.

### 5.1 Simulation 1: La Palma

In August 2016, a forest fire was declared in the island of La Palma, in the Canary Islands. The fire lasted several days affecting over 4000 hectares, a 6.8% of the island surface (Figure 5.1). Fortunately, there were no civil victims, but sadly one person died during the extinguishing phase. More than 2500 people needed to be evacuated from their homes during the fire.



Figure 5.1. La Palma fire map

The steps of the simulation are as follows, corresponding to the sequence of events of the searching plan:

1. **Map characterization.** The first step is to estimate the data to be introduced in the path planning solution. The map of the fire area is the region to be covered is defined. The

grid partition is applied and the potential Risk/Occupancy value for each cell is estimated.

2. **Path planning.** The different approaches developed for different numbers of UAVs and swarm formation are obtained, calculating the trajectories associated to each case.
3. **Results.** All the cases will be analysed with the paths generated, calculating time demanded by each different solution.

### 5.1.1 Map characterization

In Figure 5.1, we can see how the fire grew throughout the days. The simulation scenario corresponds to the third day of the fire. Three days is a reasonable time to search for a person.

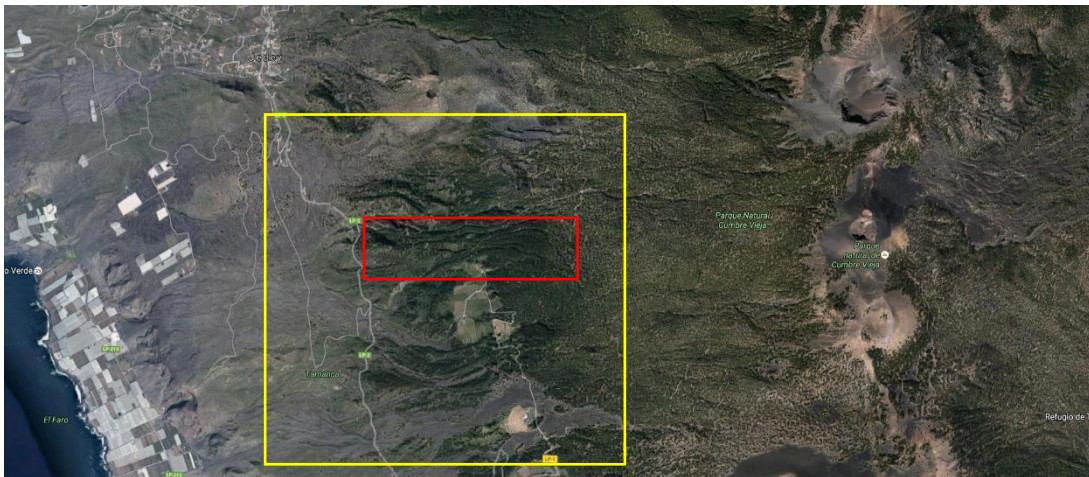


Figure 5.2. La Palma area coverage

The red rectangle (Figure 5.2) represents roughly the fire area, so we select the yellow rectangle as the area to be tracked and partitioned.

To create the grid partition, cells of dimensions 100x100 squared meters are considered. As explained before, this limit has been established, but it is totally. It depends on the characteristics of the on board camera and the UAV autonomy.

The grid partition has 24x24 cells. This is the same number as the predetermined map taken for developing the solutions. It is very convenient, because due to possible swarm formations, it is multiple of 3. The grid partition is shown in Figure 5.3.

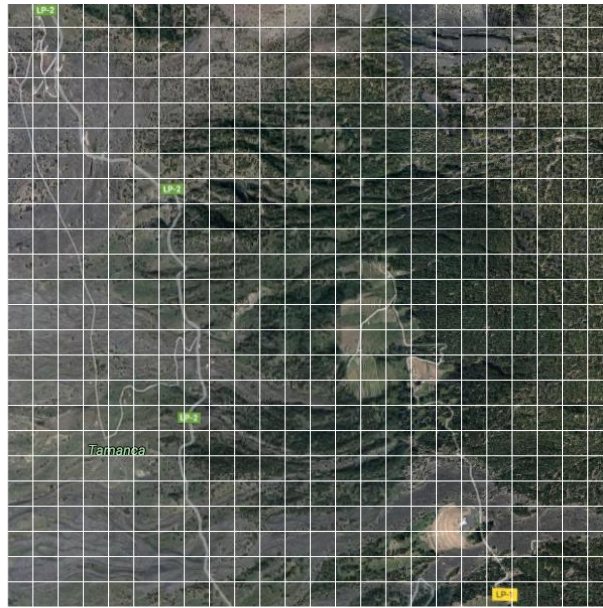


Figure 5.3. La Palma grid partition

Once the partition grid is complete, we assign the tags for the different cells, and the characteristics associated to each tag. The terrain tags are shown in Figure 5.4 and Table 5-1.

3	2	2	10	10	10	10	11	11	11	11	11	11	11	11	11	11	10	10	10	10	10
3	2	2	10	10	10	10	11	11	11	11	11	11	10	10	11	11	11	10	10	10	10
3	2	2	11	11	11	11	11	11	11	11	10	10	10	10	10	10	10	10	10	10	10
3	2	2	11	11	11	11	11	11	11	10	10	10	10	10	10	10	10	10	10	10	10
3	3	2	11	11	11	11	11	9	9	10	10	10	10	10	10	10	10	10	10	10	10
3	3	2	2	11	11	9	9	9	9	9	10	10	10	10	10	10	10	8	8	8	8
11	3	11	2	2	2	14	5	5	5	9	9	9	9	9	9	9	9	9	8	8	8
11	3	11	11	11	2	2	5	9	9	9	9	9	9	9	9	9	9	8	8	8	8
11	3	3	11	11	11	2	9	9	9	9	9	9	9	9	7	7	7	7	8	8	8
11	11	3	11	11	11	2	5	5	5	5	5	5	5	7	7	7	7	7	8	8	8
11	11	3	3	11	11	2	2	5	5	5	5	5	6	6	4	7	7	7	7	8	8
11	11	11	3	11	11	2	5	5	5	5	5	6	6	4	7	7	7	7	7	8	8
11	11	11	3	11	11	2	2	5	5	5	5	6	6	4	6	7	7	7	7	8	8
11	11	11	3	11	11	3	2	5	5	5	5	6	4	6	4	4	4	7	7	7	8
11	11	11	3	3	3	3	2	5	5	5	5	6	6	4	4	4	4	7	7	8	8
11	11	11	3	3	11	11	2	5	5	5	5	5	5	5	5	4	7	7	8	8	8
11	11	11	3	3	11	2	2	9	9	9	9	9	9	9	5	4	7	7	7	7	8
11	11	11	11	11	11	2	2	9	9	9	9	9	9	9	12	12	4	7	7	7	7
11	11	11	11	11	11	2	2	10	10	10	10	10	10	10	12	12	4	12	7	7	7
11	11	11	11	11	11	2	11	11	12	12	12	12	12	13	1	1	12	12	12	12	12
11	11	11	11	11	11	2	11	11	12	12	12	12	13	13	1	1	4	12	7	7	7
11	11	11	11	11	11	2	2	10	10	10	13	13	13	13	3	12	12	4	7	7	7
11	11	11	11	11	11	11	11	2	10	10	10	10	10	3	3	7	7	3	7	7	7

Figure 5.4 La Palma terrain tags

Table 5-1 La Palma terrain tags

	Description	Manual	Staying	Risk
1	Other	0.3	0	0
2	Main roads	0.2	0.5	0.1
3	Sec roads 1	0.5	0.3	0.1
4	Sec roads 2	0.5	0.6	0.1
5	Forest next to the plain	1	0.6	0.3
6	Plain 1	1	0.8	0.2
7	Forest type 1	1	0.3	0.4
8	Forest type 2	1	0.2	0.3
9	Hills	1	0.2	0.8
10	Forest type 3	1	0.2	0.2
11	Desert	1	0.2	0.5
12	Farm	1	0.3	0.2
13	Plain 2	1	0.7	0.2
14	SAR Team	0	0	0

Staying factor is estimated in function of the terrain accessibility and orography. That means that inaccessible areas as desert and the ones with difficult access like hills have smaller staying factors than other like roads or plains.

The risk has been estimated according the terrain nature as well, being riskier areas hills and desert than plains and forests.

The transit areas chosen corresponds with the roads and that can be seen in the map. WE have introduced as well a factor for other zones, which corresponds to a small construction at the bottom right area.

The emergency tags are shown in Figure 5.5 and Table 5-2.

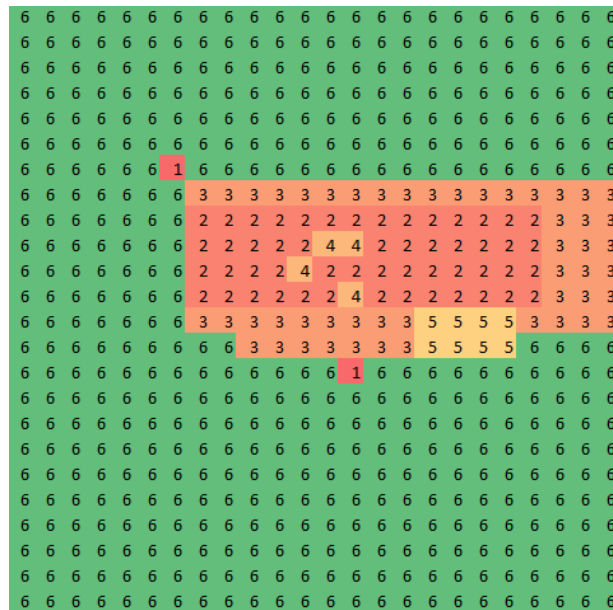


Figure 5.5 La Palma emergency tags

Table 5-2 La Palma emergency tags

		Manual	Emergency	injuries
1	SAR team	0	0	0
2	Emergency	1	0.9	0
3	next to emergency	1	0.6	0
4	Em + injuries	1	0.9	0.5
5	Next em + injuries	1	0.6	0.3
6	Not affected	0	0	0

Some historical areas have been introduced as well, as shown in Figure 5.6.

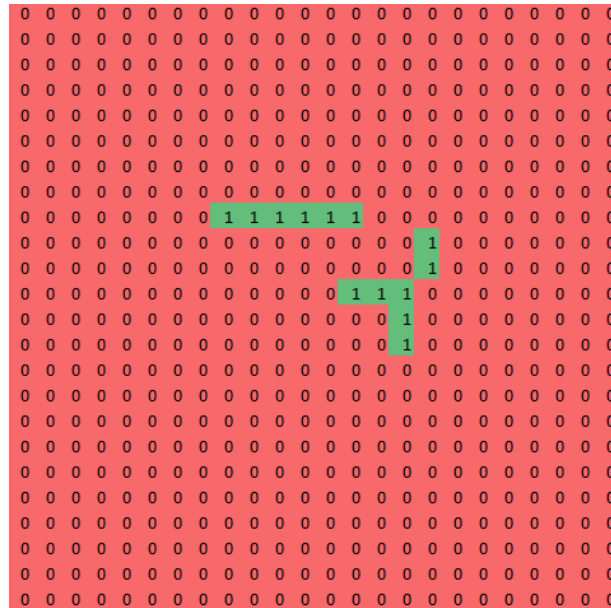


Figure 5.6 La Palma historical

Once the estimation of the inputs is done we can run the calculation of the different contributions

The terrain contribution is shown in Figure 5.7. The influence of high staying factor in the plain in the middle can be seen, and also the influence of transit factor in the roads.

The emergency contribution is shown in Figure 5.8. There are three differentiated zones, the zone that is not affected, the zone lightly affected and the affected one by the fire.

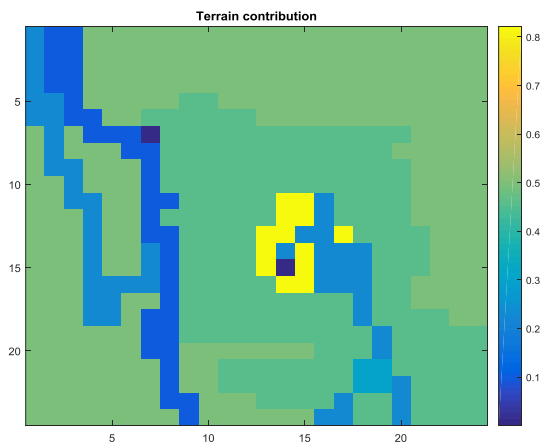


Figure 5.7. La Palma terrain contribution to potential Risk/Occupancy

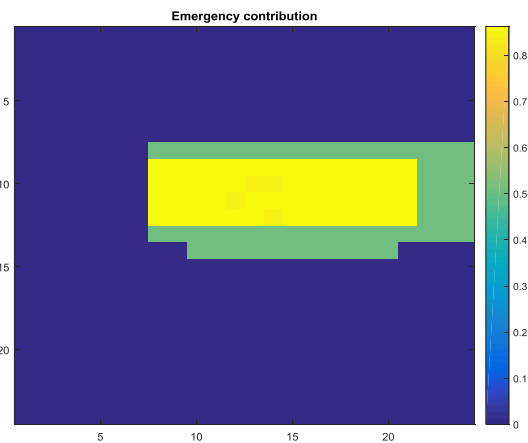


Figure 5.8. La Palma emergency contribution to potential Risk/Occupancy

Once both contributions are calculated, we combine them and we obtain the potential Risk/Occupancy map (Figure 5.9). We can see in the map the different zones that appear in the terrain contribution for the non-affected areas by the fire, and the combination of the affected one with the terrain factors.

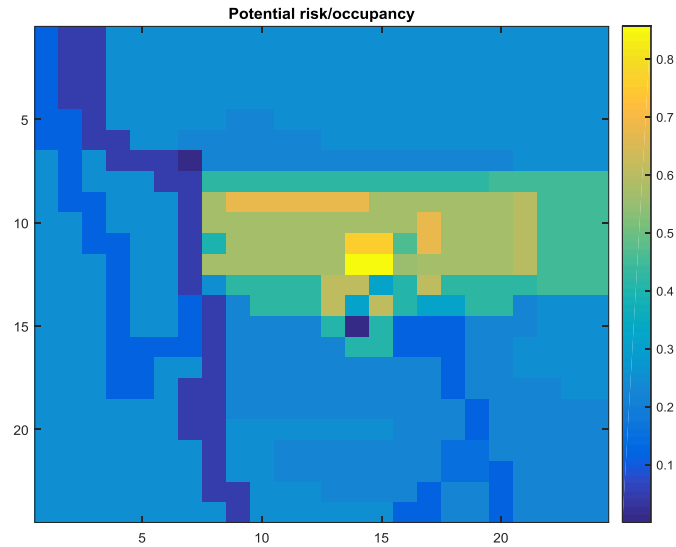


Figure 5.9. La Palma Potential Risk/Occupancy

### 5.1.2 Path planning

Once the potential Risk/Occupancy matrix is calculated, we can apply the different solutions developed for the path planning. The methods are executed for one, two and three UAVs, and in free and distributed formation.

For all the simulation, the initial points for the different UAVs are:

- UAV 1 – [1 1]
- UAV 2 – [13 1]
- UAV 3 – [18 1]

#### 5.1.2.1 Attraction path planning

**Attraction path – 1 UAV**  
**d = 680 – w = 37393**

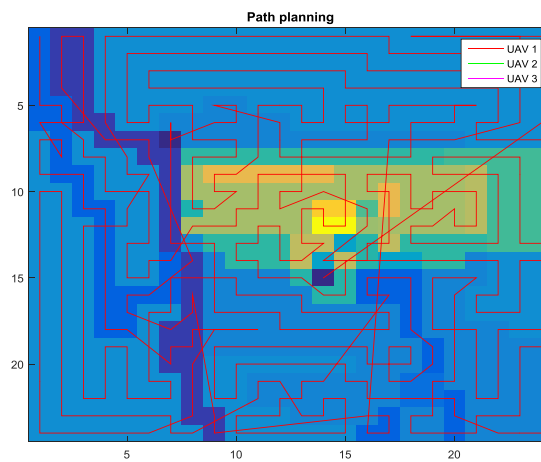
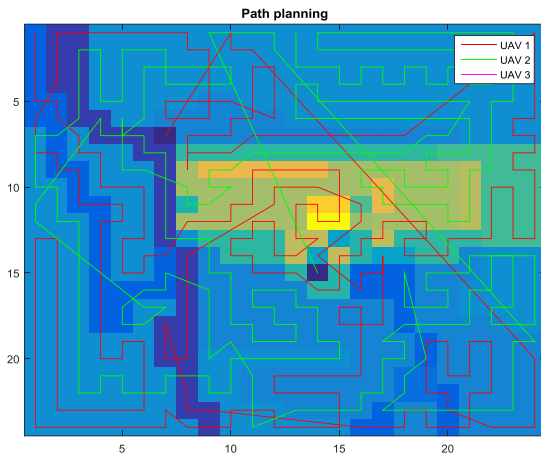


Figure 5.10. La Palma 1 UAV attraction path planning

**Attraction – 2 UAV – free formation**  
 $d = 713 - w = 19638$



**Attraction – 2 UAV – distributed formation**  
 $d = 673 - w = 20411$

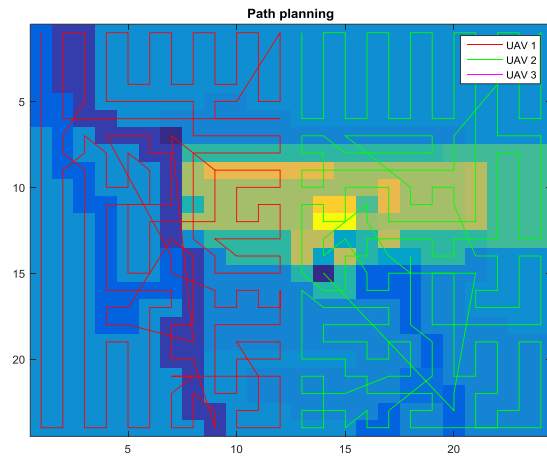
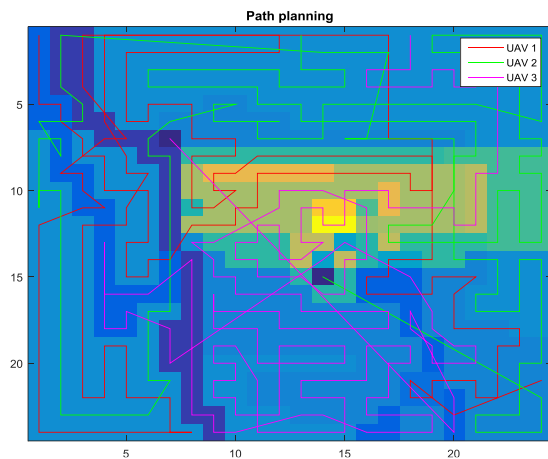


Figure 5.11 La Palma 2 UAVs, free (left) and distributed (right) swarm attraction path planning

**Attraction – 3 UAVs – free formation**  
 $d = 720 - w = 12812$



**Attraction – 3 UAVs – distributed formation**  
 $d = 678 - w = 13712$

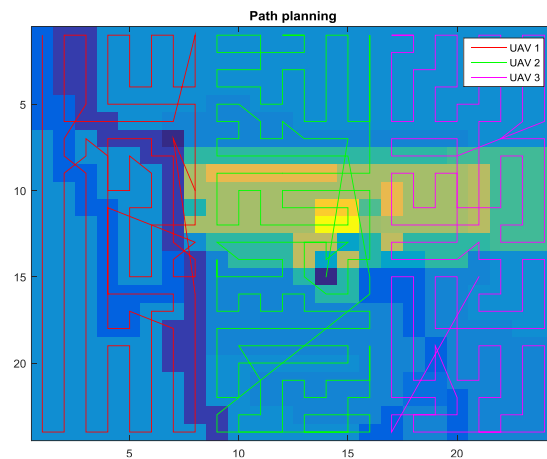


Figure 5.12. La Palma 3 UAVs, free (left) and distributed (right) swarm attraction path planning

5.1.2.2 Fuzzy logic path planning

**Fuzzy logic – 1 UAV**  
**d = 1497 – w = 35951**

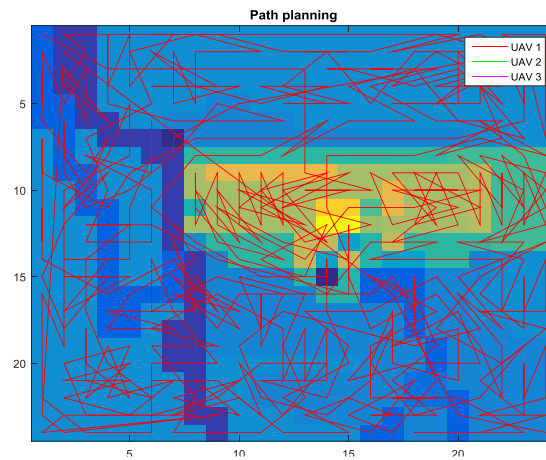


Figure 5.13. La Palma 1 UAV Fuzzy Logic path planning

**Fuzzy logic – 2 UAV – free formation**  
**d = 1550 – w = 17931**

**Fuzzy logic – 2 UAV – distributed formation**  
**d = 1212 – w = 19219**

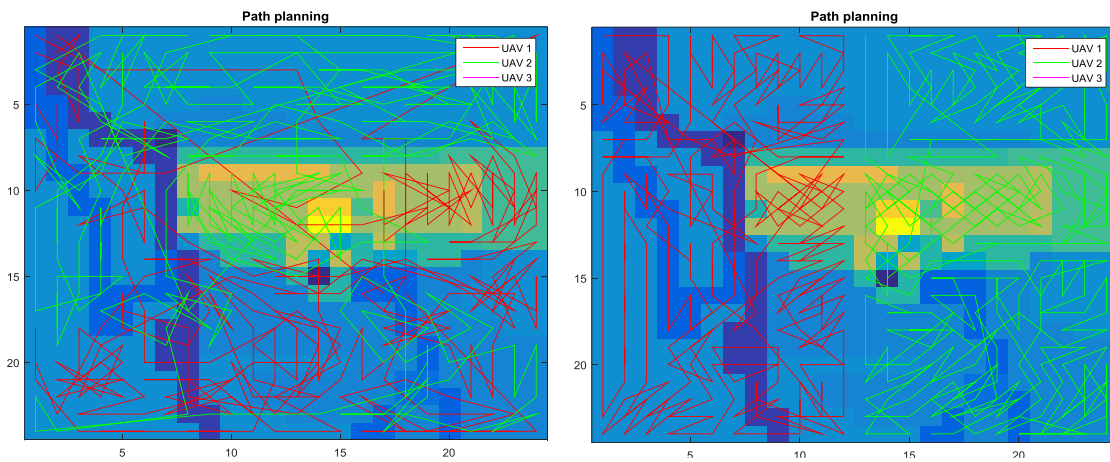


Figure 5.14. La Palma 2 UAVs, free (left) and distributed (right) swarm Fuzzy Logic path planning

**Fuzzy logic – 3 UAVs – free formation**  
**d = 1596 – w = 12137**

**Fuzzy logic – 3 UAVs – distributed formation**  
**d = 1155 – w = 13119**

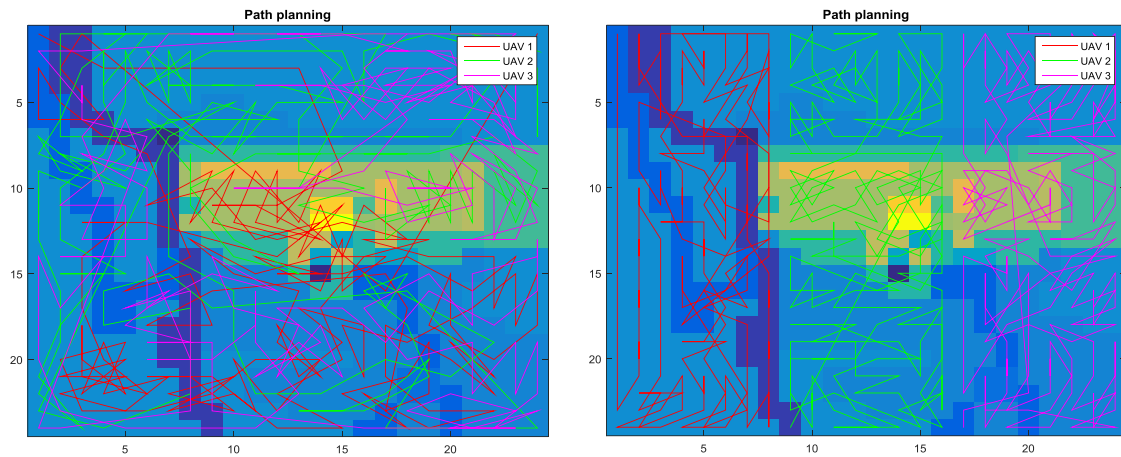


Figure 5.15. La Palma 3 UAVs, free (left) and distributed (right) swarm Fuzzy Logic path planning

5.1.2.3 ANFIS path planning

**ANFIS – 1 UAV**  
**d = 808 – w = 36284**

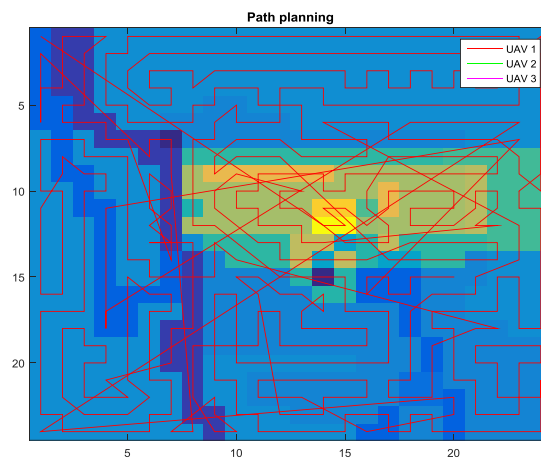


Figure 5.16. La Palma 1 UAV ANFIS path planning

**ANFIS – 2 UAVs – free formation**  
**d = 827 – w = 18579**

**ANFIS – 2 UAVs – distributed formation**  
**d = 716 – w = 19474**

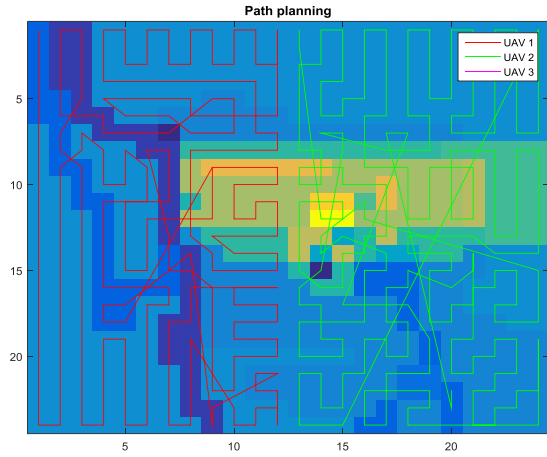
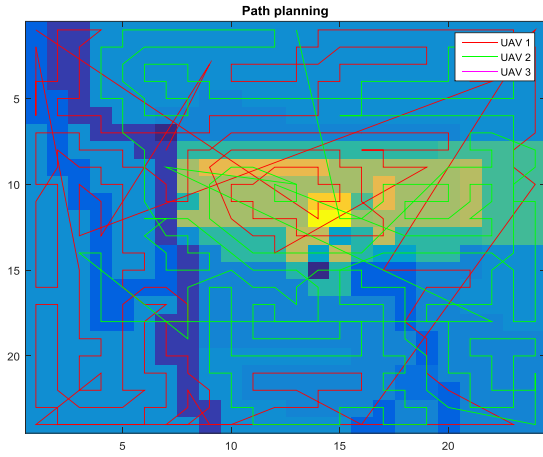


Figure 5.17. La Palma 2 UAVs, free (left) and distributed (right) swarm ANFIS path planning

**ANFIS – 3 UAVs – free formation**  
**d = 876 – w = 12520**

**ANFIS – 3 UAVs – distributed formation**  
**d = 732 – w = 13386**

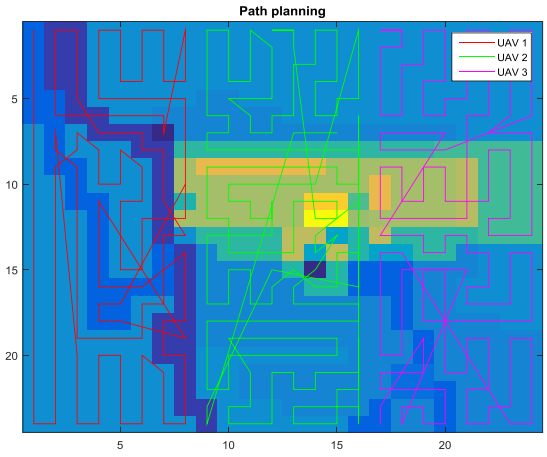
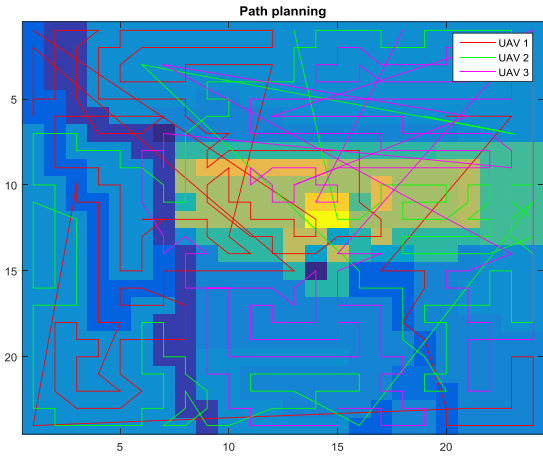


Figure 5.18. La Palma 3 UAVs, free (left) and distributed (right) swarm ANFIS path planning

#### 5.1.2.4 PSO path planning

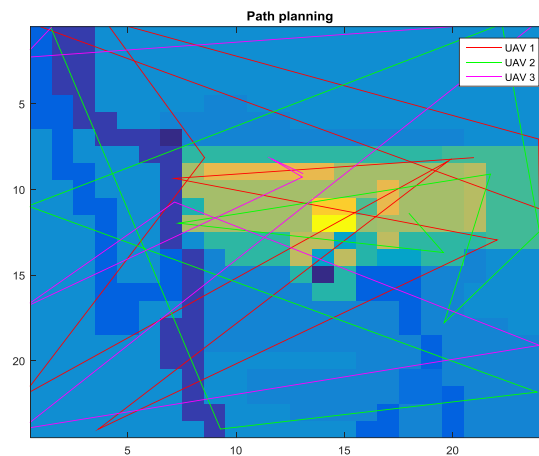


Figure 5.19. La Palma PSO path planning

### 5.1.3 Results

As mentioned at the beginning of this section, thirty missing people cases are randomly created in relation with the potential Risk/Occupancy value. The last 25 cases are obtained by uniformly distributed random numbers between 0 and 1, associated to a cell, to which the half of the potential Risk/Occupancy value of the cell associated is added, extracting the 25 higher value positions of the matrix. The first five cases are manually distributed in other areas with low P value, as exceptions (Figure 5.20).

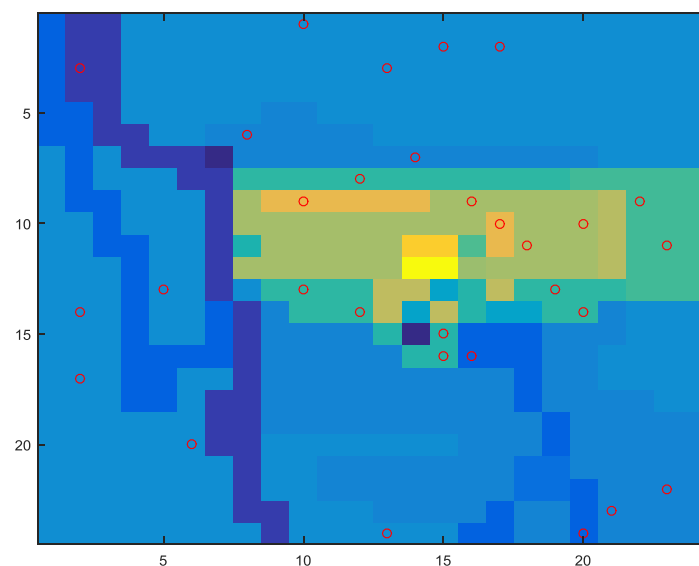


Figure 5.20. La Palma missing people cases

The results are presented as a comparison between the different swarm configurations of the same path planning method. At the end, there is a global comparison of all the methods.

The criteria are the time the UAV needs to find the people in the 30 case. To calculate this time, we need the distance and the speed of the UAV. The distances are directly obtained from the path planning algorithms. However, the speed is not available because there is not a specific UAV model selected, so it is considered as 1.

Another assumption taken into account is that when the UAV is tracking a cell, the speed is lower than when it is not tracking any cell and is only moving between different areas. To quantify this difference in the speed, the speed considered when travelling between two different cells without tracking during the flight is 3.

#### 5.1.3.1 Attraction path planning

The time results for attraction path planning are shown in Table 5-1.

Table 5-3. La Palma Attraction path planning results

Case	1 UAV	2 UAVs		3 UAVs	
		Free	Distributed	Free	Distributed
1	535.90	140.98	164.90	148.51	102.94
2	475.39	179.05	34.00	133.01	34.00
3	249.72	164.39	207.05	117.27	145.10
4	187.23	27.00	13.00	155.52	31.67
5	435.49	231.80	283.23	170.45	174.62
6	377.59	262.72	217.03	193.48	164.65
7	57.99	57.99	79.41	55.83	80.67
8	44.57	44.57	85.66	42.41	96.91
9	56.99	56.99	78.41	54.83	81.67
10	64.99	57.00	65.00	30.00	48.00
11	90.40	47.00	94.41	20.00	60.67
12	331.51	69.99	87.41	164.22	108.57
13	73.99	64.00	161.31	38.00	57.00
14	295.85	99.16	99.74	47.16	180.98
15	70.99	55.00	158.31	28.00	52.00
16	101.40	77.99	99.41	51.75	65.67
17	83.40	65.99	85.41	43.75	102.57
18	49.57	49.57	81.24	47.41	92.50
19	66.99	59.00	136.82	34.16	45.67
20	209.23	296.53	138.74	82.99	9.00
21	127.40	2.00	2.00	2.00	20.67
22	448.44	207.47	259.86	119.94	164.32
23	379.59	264.72	201.03	188.22	148.65
24	382.59	282.89	206.03	185.22	153.65
25	17.41	17.41	54.24	17.41	54.24
26	201.23	25.00	25.00	157.52	4.00
27	168.23	128.64	105.74	63.99	68.24
28	318.19	103.82	145.48	92.47	196.81
29	153.82	101.57	67.24	49.57	51.67
30	472.39	176.05	31.00	130.01	31.00
Mean	217.62	113.88	115.60	88.84	87.60
Wins	1.00	2.00	2.00	3.00	1.00
Losses	6.00	0.00	5.00	0.00	0.00
Total wins			9.00		
Total losses			11.00		

The green highlighted cells mean that this case has beaten all other path planning for the same scenario. The red ones are the worst. At the bottom of the table we can see the total number of best cases (Wins) and worst ones (Losses).

Figures 5.21 and 5.22 show the comparison of the different number of UAV for the same swarm formation. The graphics represent the time in the vertical axis, and the case in the horizontal one. We have used the tag "f1" and "f2" to identify free and distributed formation respectively.

The global tendency is as expected, that is reduce the time employed when the number of UAVs increases. We can observe as well that the first five points need more time because they have low P values, so the UAV goes there after going to the high P ones.

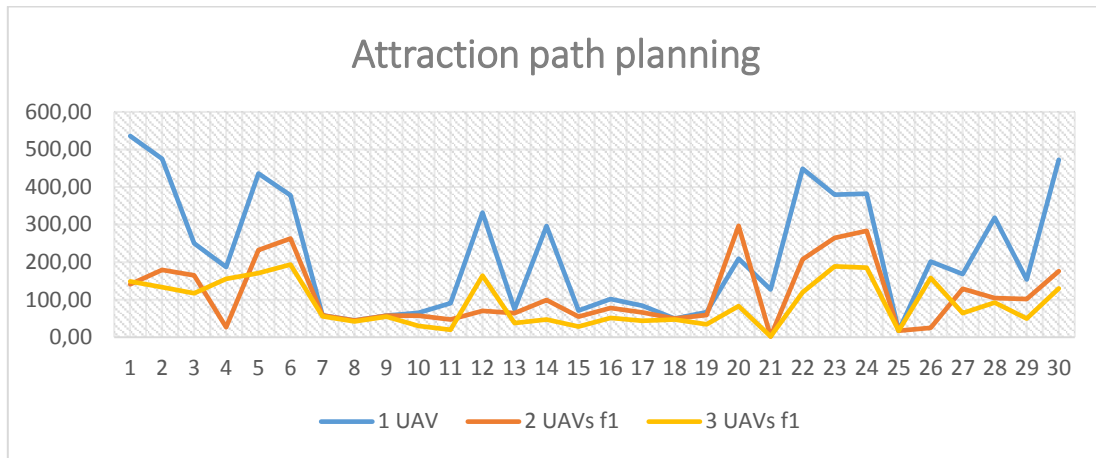


Figure 5.21. La Palma Attraction path planning results for free swarm

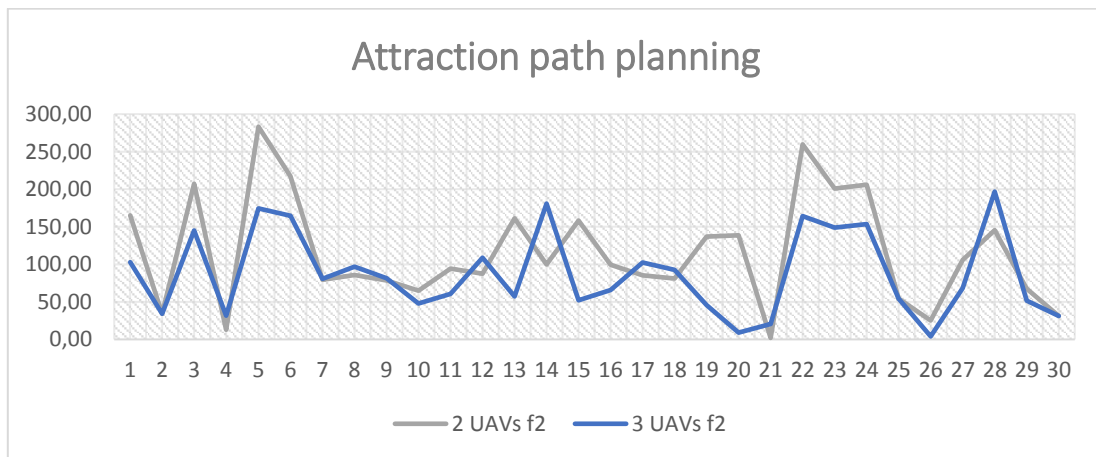


Figure 5.22. La Palma Attraction path planning results for distributed swarm

A comparison between the two swarm configurations with the same number of UAVs is shown in Figures 5.23 and 5.24. We can observe that with two UAVs the difference is not relevant, but for three UAVs we can see that, even having a similar tendency, there are much different in many of the cases, what indicates that the search of the two different distribution is done with a very different philosophy.

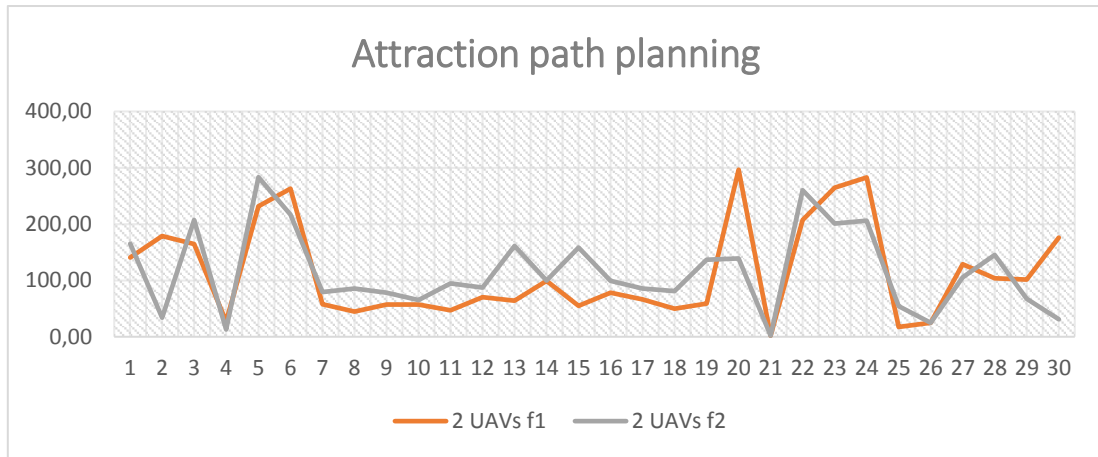


Figure 5.23. La Palma Attraction path planning results for 2 UAVs

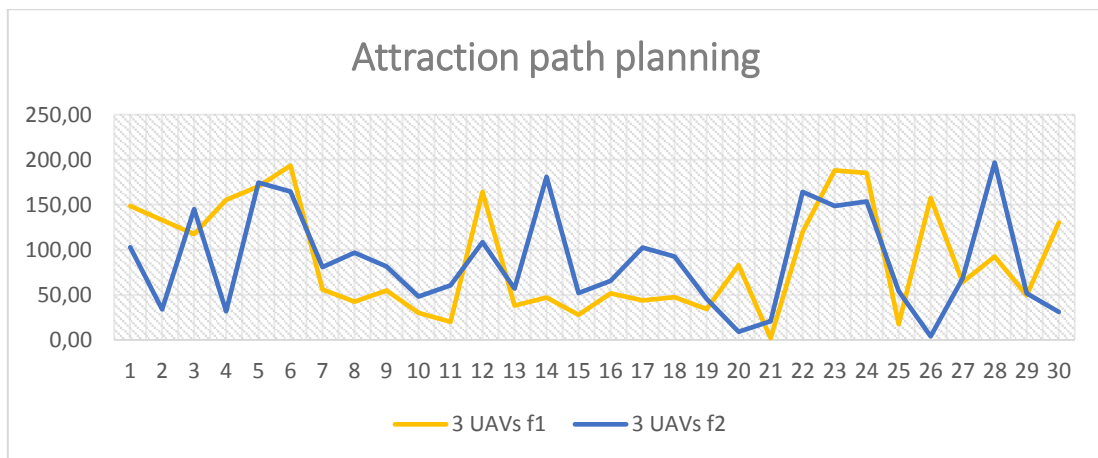


Figure 5.24. La Palma Attraction path planning results for 3 UAVs

To finish the comparison, in Figure 5.25 the mean time values are summarized.

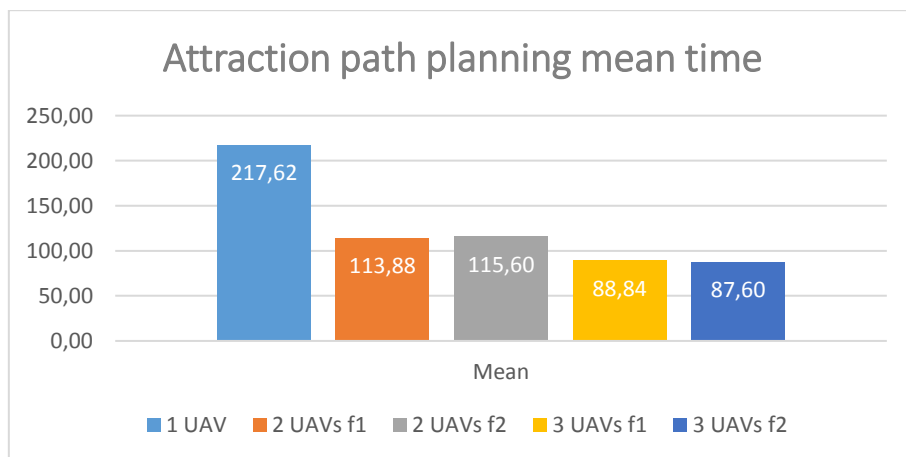


Figure 5.25. La Palma Attraction path planning mean time

### 5.1.3.2 Fuzzy logic path planning

The results obtained with the fuzzy logic path planning are shown in Table 5-2.

Table 5-4. La Palma Fuzzy Logic path planning results

Case	1 UAV	2 UAVs		3 UAVs	
		Free	Distributed	Free	Distributed
1	537.05	300.12	238.48	193.28	151.70
2	309.61	173.77	31.24	103.08	29.08
3	341.59	167.38	111.11	127.20	122.58
4	499.39	121.62	81.67	71.35	154.03
5	456.74	250.38	241.71	162.14	122.85
6	429.01	264.63	226.41	179.12	85.16
7	159.33	73.03	56.52	113.65	57.58
8	105.85	39.40	137.25	44.56	54.09
9	162.33	94.74	141.57	119.63	47.19
10	51.35	21.91	36.14	11.30	10.06
11	69.44	41.56	39.51	25.60	33.48
12	124.41	65.78	144.98	104.40	42.17
13	50.35	25.11	27.70	14.18	13.79
14	229.55	52.70	166.63	34.71	20.43
15	46.30	30.31	18.86	10.12	18.43
16	78.10	47.93	40.26	36.13	30.99
17	119.35	49.45	55.03	101.34	43.91
18	102.54	36.09	92.06	38.78	52.01
19	54.52	12.46	17.92	3.35	44.21
20	544.69	156.63	210.13	83.26	6.90
21	10.20	10.20	2.00	10.20	18.02
22	212.60	139.64	181.94	93.63	83.27
23	423.28	255.32	209.31	161.62	83.41
24	418.18	262.80	214.64	168.42	93.96
25	299.30	162.33	54.60	90.77	55.36
26	554.41	123.62	94.04	75.54	4.00
27	511.76	215.45	221.99	137.12	92.89
28	484.51	213.39	78.43	92.12	151.87
29	39.90	24.62	90.17	36.85	21.18
30	311.48	168.10	28.90	104.95	26.75
Mean	257.90	120.02	109.71	84.95	59.05
Wins	0.00	0.00	2.00	3.00	9.00
Losses	11.00	0.00	1.00	0.00	0.00
Total wins			14.00		
Total losses			12.00		

In this case, there are more winning configurations. The worst ones are almost exclusively associated to the 1 UAV configuration. The better ones are related to several agents' configurations. That means that this method is inefficient for one UAV, but its efficiency is highly improved when increasing the number of UAVs.

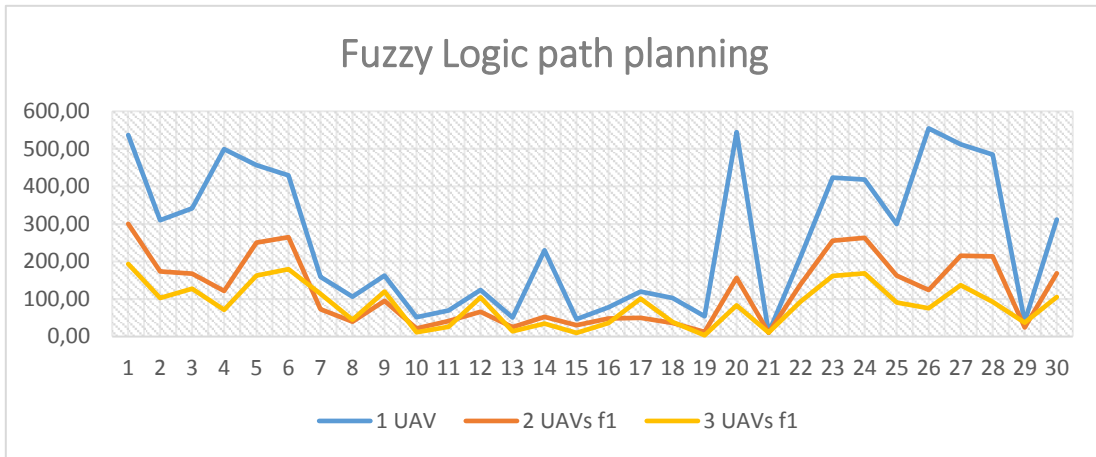


Figure 5.26. La Palma Fuzzy Logic path planning results for free swarm

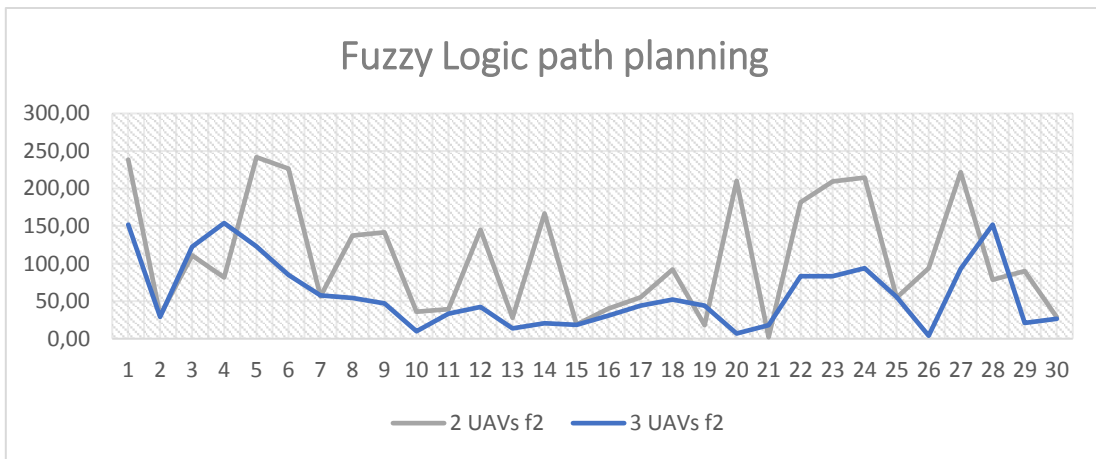


Figure 5.27. La Palma Fuzzy Logic path planning results for distributed swarm

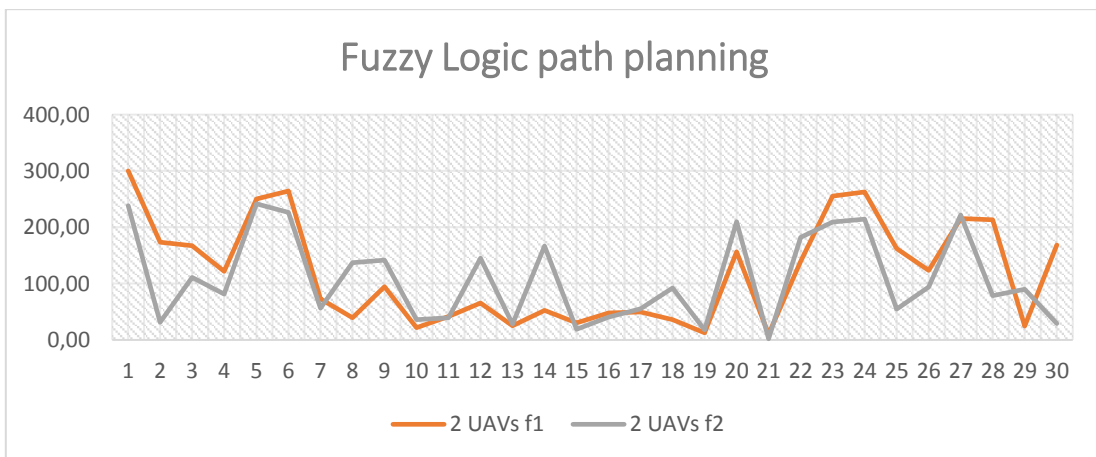


Figure 5.28. La Palma Fuzzy Logic path planning results for 2 UAVs

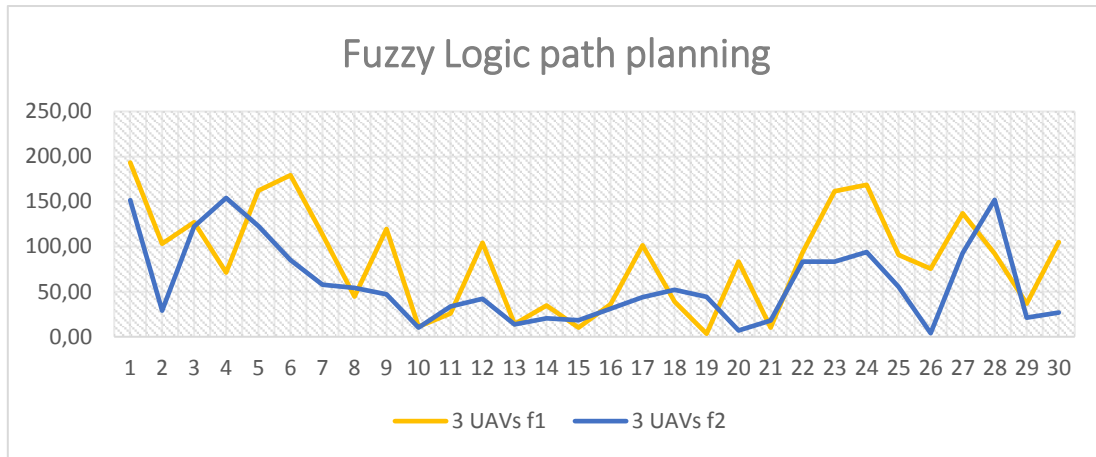


Figure 5.29. La Palma Fuzzy Logic path planning results for 3 UAVs

Figures 5.26 to 5.29 show the results comparison. We can observe similar aspects with the attraction method. In this case, we have an improvement in the searching time for the distributed configuration with three UAVs. The average time is represented in Figure 5.30.

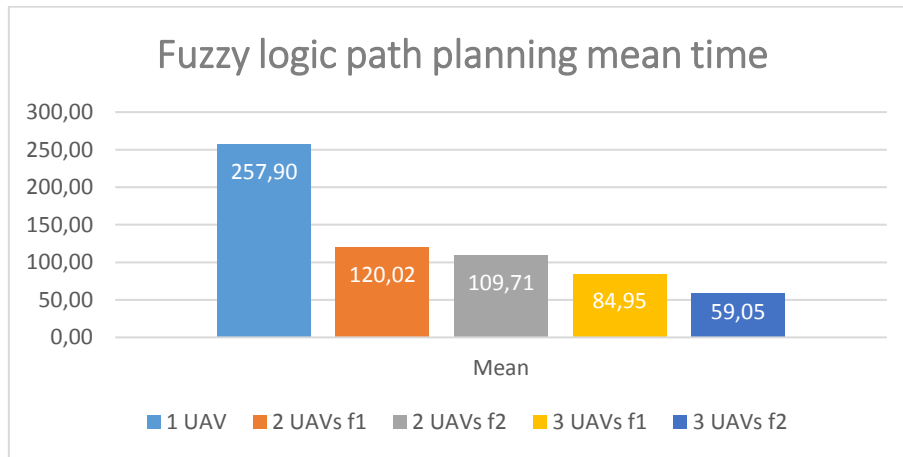


Figure 5.30. La Palma Fuzzy Logic path planning mean time

### 5.1.3.3 ANFIS path planning

The results obtained for the ANFIS path planning are shown in Table 5-3.

Table 5-5. La Palma ANFIS path planning results

Case	1 UAV	2 UAVs		3 UAVs	
		Free	Distributed	Free	Distributed
1	517.85	256.36	167.84	121.62	104.27
2	407.07	86.75	34.00	94.96	34.00
3	448.23	114.74	210.00	128.70	166.52
4	292.91	221.61	41.43	62.99	76.18
5	633.76	278.82	142.46	197.38	198.01
6	208.17	285.49	278.01	209.03	186.36
7	250.17	76.31	15.76	84.22	119.41
8	77.83	42.39	85.66	21.92	14.35
9	249.17	77.31	14.76	85.22	118.41
10	12.92	7.14	22.76	7.14	48.00
11	53.43	48.99	84.10	24.16	60.67
12	89.58	72.57	110.51	30.97	105.81
13	15.92	10.14	80.43	10.14	57.00
14	95.18	34.50	99.74	35.41	36.35
15	18.92	13.14	67.43	13.14	52.00
16	160.84	57.15	91.10	22.41	65.67
17	83.58	26.97	106.51	26.97	103.81
18	256.00	39.78	81.24	81.47	17.35
19	47.43	29.50	63.43	18.16	31.35
20	136.43	174.29	132.74	58.66	49.35
21	318.15	212.53	36.43	62.13	71.18
22	219.17	99.31	223.19	107.22	183.68
23	186.84	252.95	264.68	195.03	146.47
24	189.84	255.95	269.68	198.03	151.47
25	389.07	103.91	54.24	95.38	54.24
26	290.91	223.61	55.43	55.13	2.41
27	121.43	190.12	144.40	43.66	68.24
28	110.43	58.92	161.90	34.16	210.05
29	70.59	34.95	67.24	14.68	23.35
30	429.23	133.74	31.00	109.70	31.00
Mean	212.70	117.33	107.94	74.99	86.23
Wins	0.00	3.00	2.00	8.00	3.00
Losses	8.00	0.00	0.00	0.00	0.00
Total wins			16.00		
Total losses			8.00		

This method is the best one. However, the same problem presented with fuzzy logic appears.

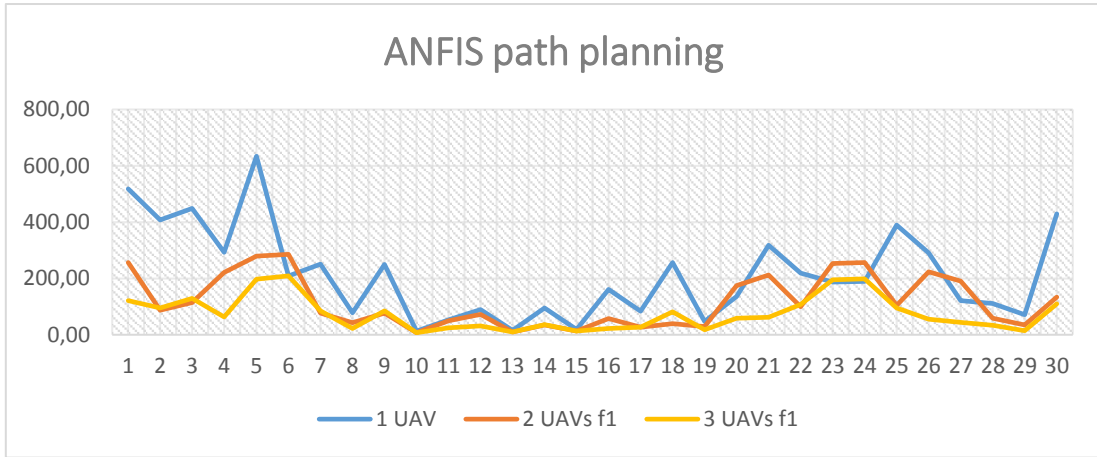


Figure 5.31. La Palma ANFIS path planning results for free swarm

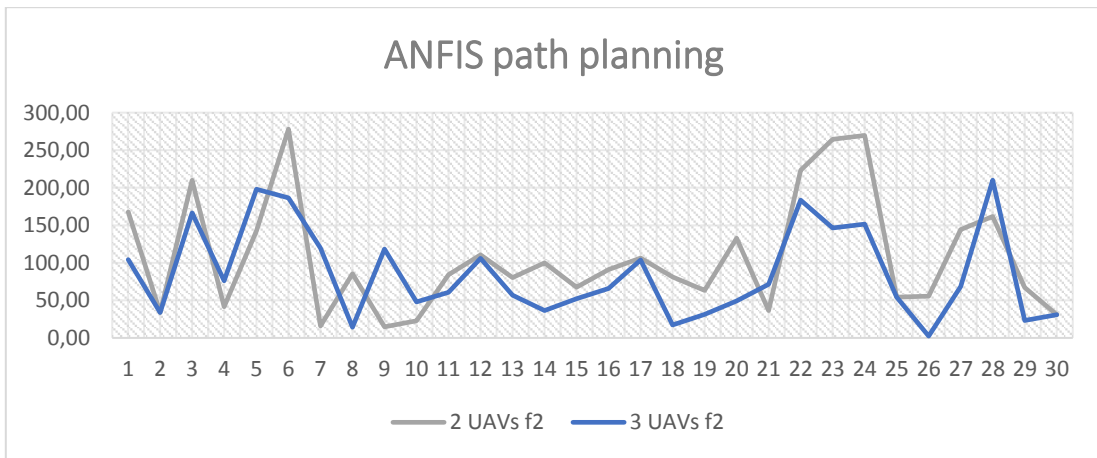


Figure 5.32. La Palma ANFIS path planning results for distributed swarm

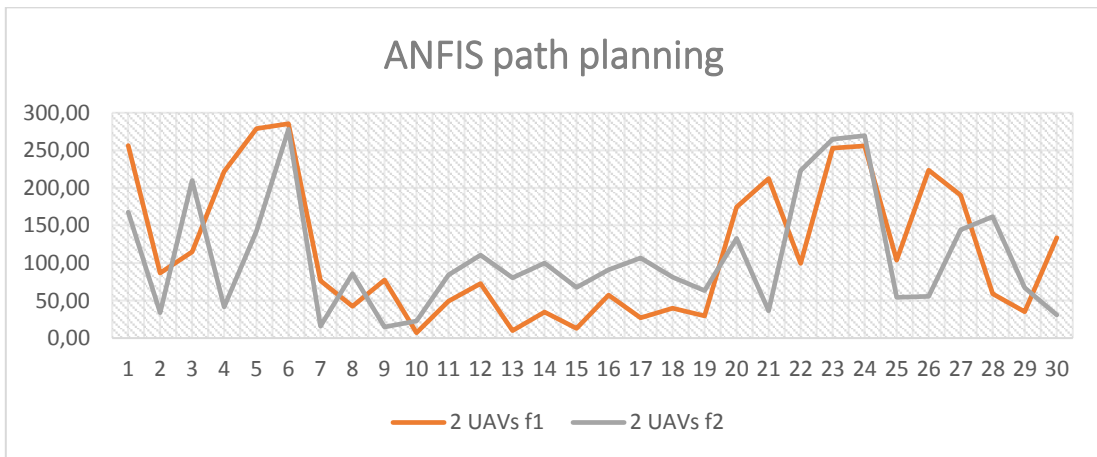


Figure 5.33. La Palma ANFIS path planning results for 2 UAVs

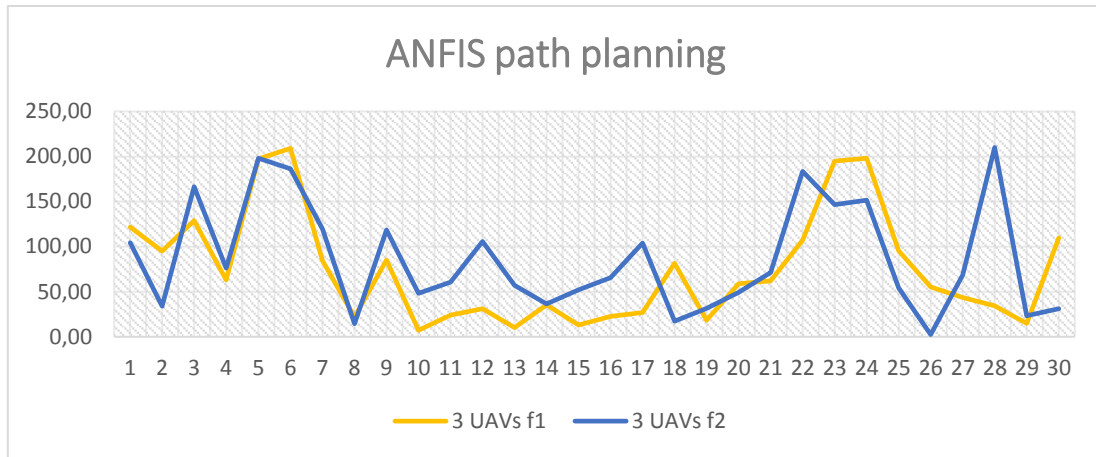


Figure 5.34. La Palma ANFIS path planning results for 3 UAVs

The ANFIS method allows to obtain better results with free swarm formation than with the distributed one. In Figure 5.35, mean time reveals that, even having some bad results with 1 UAV, it has the best average value for this scenario.

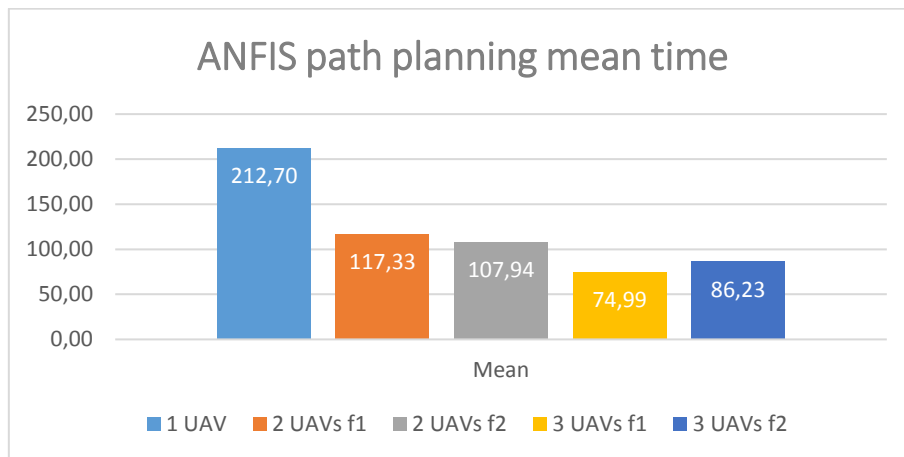


Figure 5.35. La Palma ANFIS path planning mean time

#### 5.1.3.4 PSO path planning

PSO path planning has the worst results of all. This method did not work well because the UAV travels a long distance between points in order to cover the surface with a distance/speed relation of one. Due to the continuous tracking, the UAV is very slow in comparison the other methods. All results obtained are worse than with the other solutions, even having zero values which means that the UAV did not find the person.

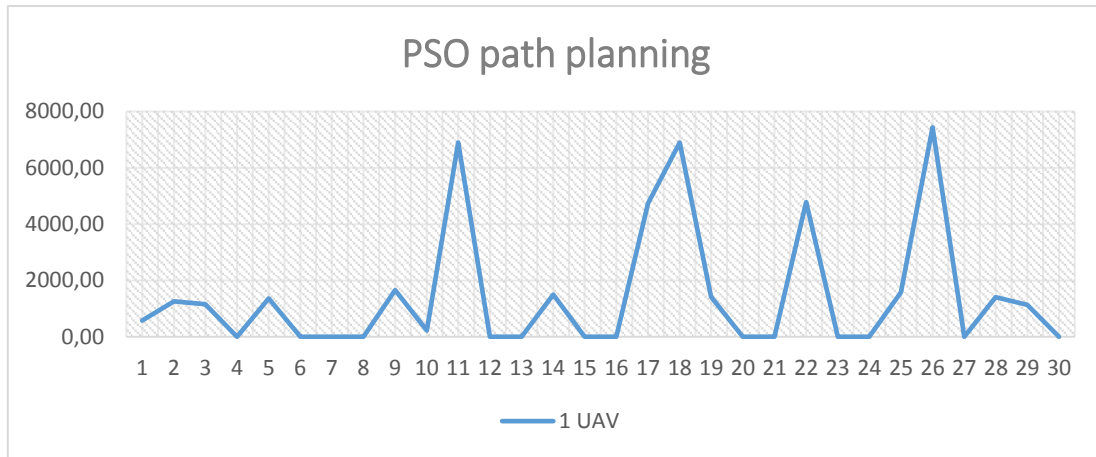


Figure 5.36. La Palma PSO path planning results

In view of the results (Figure 5.36), PSO is not taken into account for global comparison between different methods.

### 5.1.4 Global comparison

First, a comparison between the different methods is made, according to the different configurations.

In Figure 5.37 we can compare the results for 1 UAV configuration. The time results are very similar in all scenarios. We can see that, in general, ANFIS path planning is lightly better.

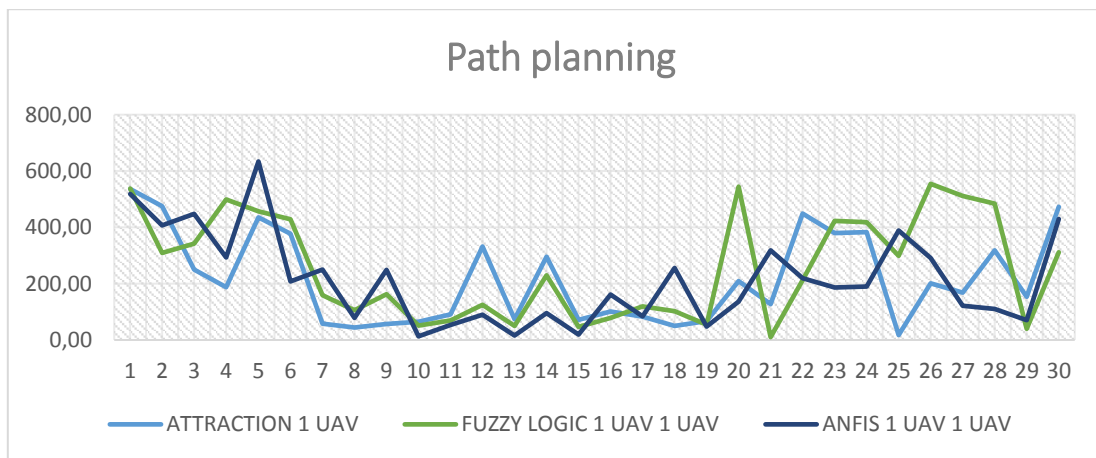


Figure 5.37. La Palma path planning results comparison for 1 UAV

In Figure 5.38, the path planning results for two UAV in free swarm formation are shown. Results are similar again, having better ones the fuzzy logic and ANFIS methods.

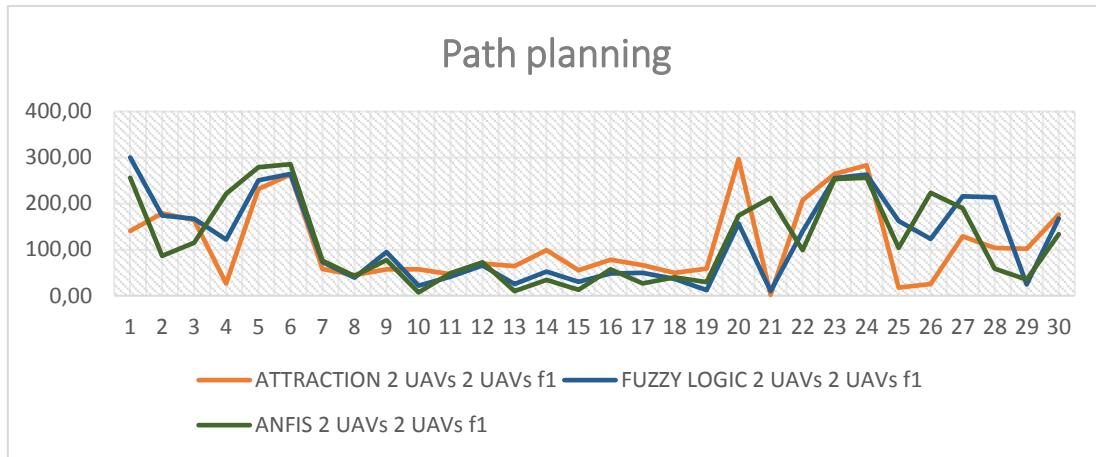


Figure 5.38. La Palma results comparison for 2 UAVs in free swarm

In Figure 5.39, configuration with 2 UAVs in distributed swarm formation is shown. The results are once similar for all methods, having the ANFIS approach a lightly better performance again.

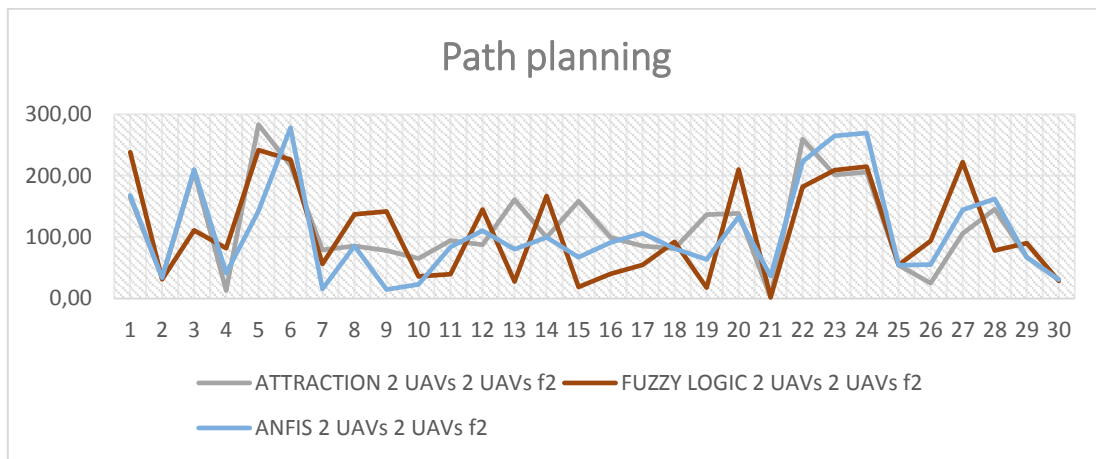


Figure 5.39. La Palma results comparison for 2 UAVs in distributed swarm

The configuration with 3 free swarm UAV is shown in Figure 5.40. The performance shown in this case is very similar as the previous configurations.

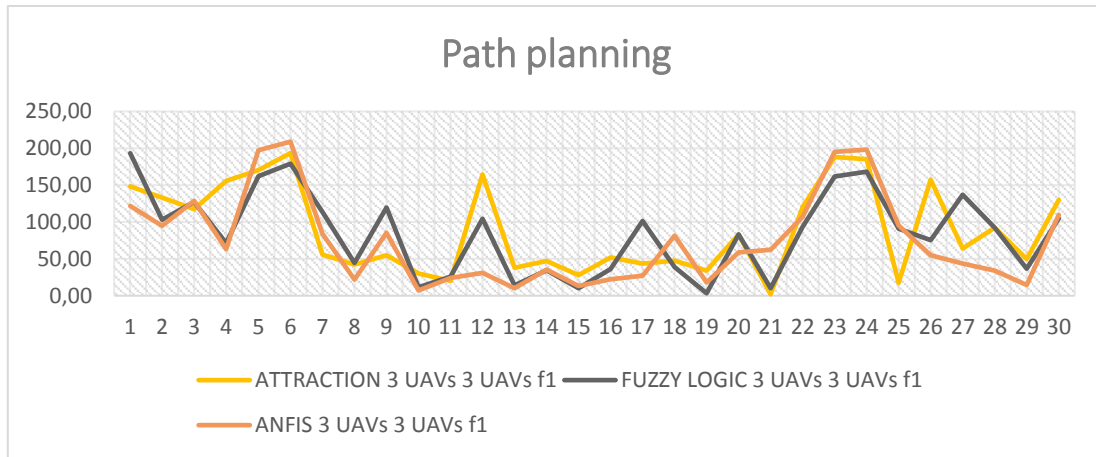


Figure 5.40. La Palma results comparison for 3 UAVs in free swarm

Finally, the configuration with 3 UAV in distributed swarm formation is represented in Figure 5.41. In this case there are a great difference between the fuzzy logic approach and the other. That demonstrates that this method work better in distributed swarm possibly because it was design for smaller maps, so when the searching area get smaller the performance of this approach improves.

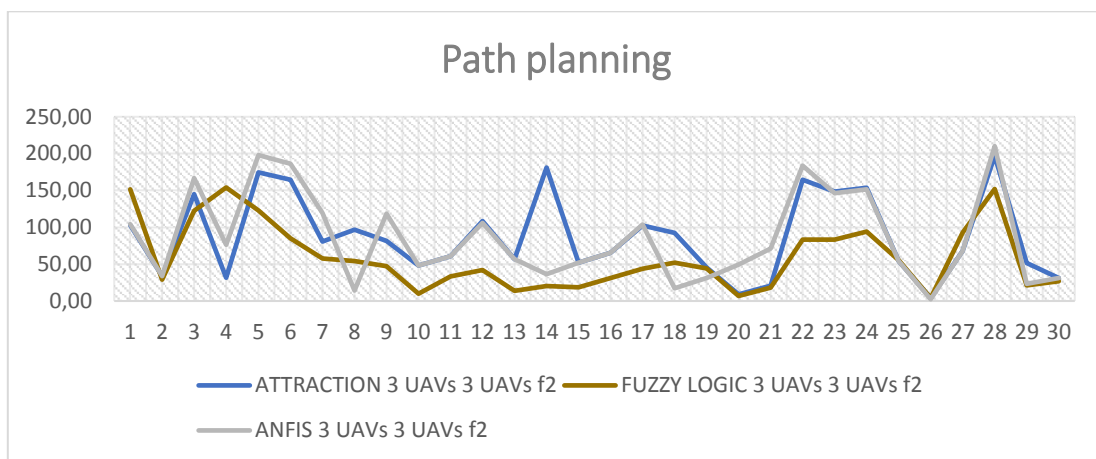


Figure 5.41. La Palma results comparison for 3 UAVs in distributed swarm

In the following next figures (5.42 to 5.44), the average time and the number of wins and losses can be compared. The mean value confirms what was observed in previous figures. The number of wins and losses indicates that ANFIS method is, in general, the best one. The fuzzy logic has also a very good performance, especially for distributed configurations. However, even having less number of wins, attraction method is the most consistent due to a small number of losses, what indicates that its results are very equilibrated.

Therefore, we can say that the best configuration for searching is 3 UAVS in free swarm formation.

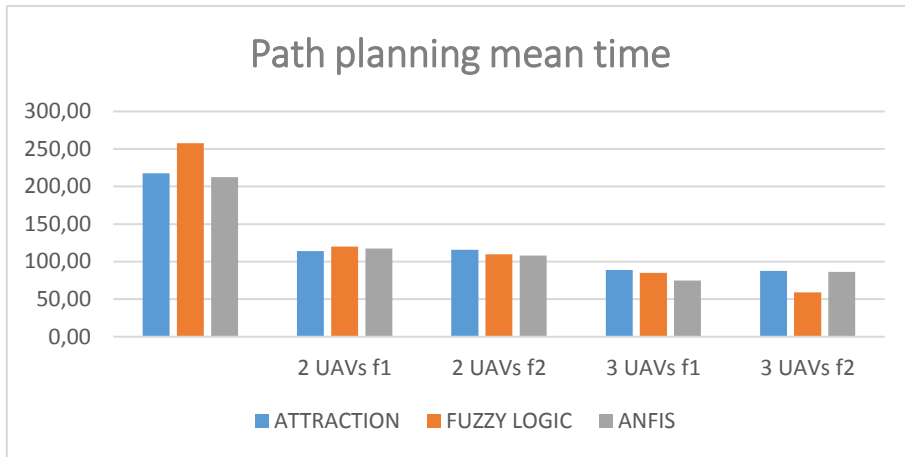


Figure 5.42. La Palma path planning mean time comparison

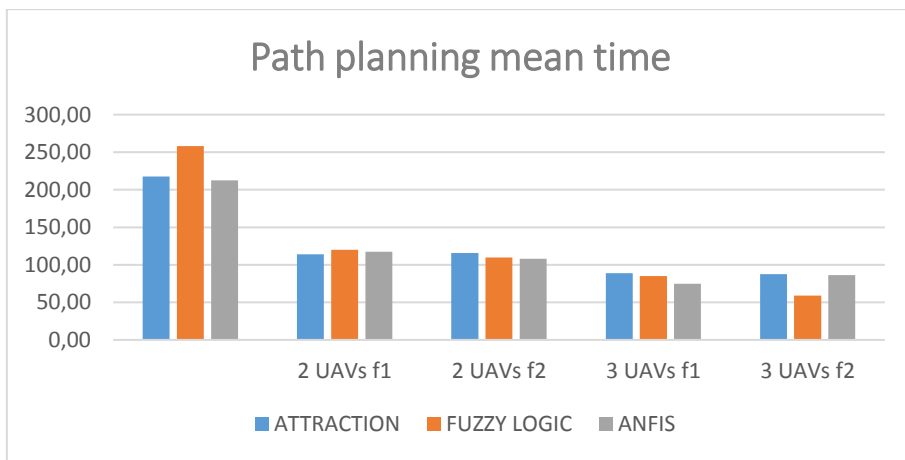


Figure 5.43. La Palma won cases comparison

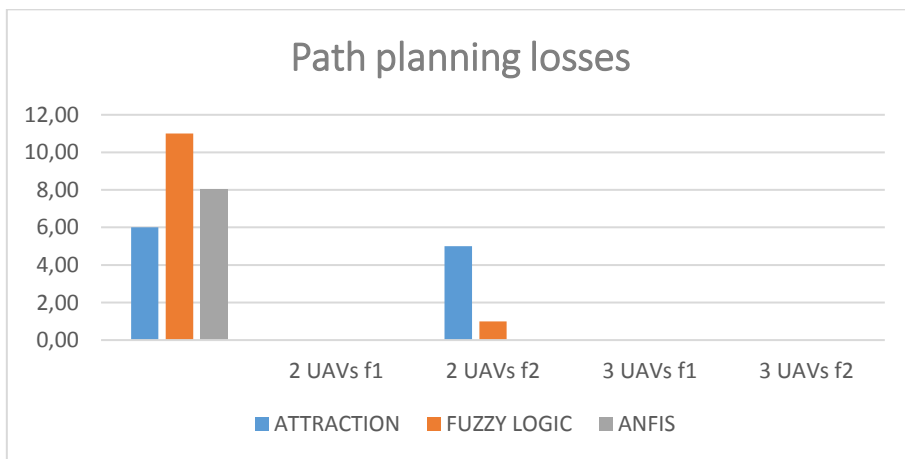


Figure 5.44. La Palma lost cases comparison



## 6 Conclusions and future work

In this work, two main proposals are presented. The first one is the map characterization according to Risk/Occupancy, and the second one is the UAV path planning for the searching.

Regarding the map characterization, the conclusion is that it helps to focus the path planning. Thanks to this P map, the path planners can trace a trajectory to minimize the risk the people are exposed to. In the simulations, a fast tracking of the higher probability risk/occupied areas can be observed, that results in a quicker finding of the people involved.

For the four path planning algorithms proposed, three of them had good results; the PSO approach did not have a good adaptation to the problem. For the other three, it has been found that the performance of the method is strongly associated to the P map. The following characteristics of each method can be concluded:

- **Attraction:** this method has kept in medium positions regarding efficiency. It performs a regular and extensive search, which implies that it does not take a lot of time finding people in low P areas, but it does not go as fast as other methods to high P values zones. This method works very well for homogenous P maps.
- **Fuzzy Logic:** It has a quite fast convergence but very irregular. However, it works well in maps with large high P areas due to its type of searching, which performs like a random search in all danger area.
- **ANFIS:** this method has been proven to be the best one. It has a fast convergence to high P values and also performs a quite regular searching. It has been the best in all environments. The main weakness is the cases with low P areas far from high P ones, where other methods have obtained better results.

In summary, we can conclude that ANFIS method is the best, but other methods could have a good performance depending on the type of searching area.

Regarding the swarm formation, a dependence on the type of path planning method for the performance of the swarm has been observed. For example, ANFIS works better with free formation, while fuzzy logic improves with distributed formation. Besides, depending on the distribution of P values, variations have been also observed. Therefore, in general, free formation is better, but it should be chosen in association with the P map and the path planning method.

Future works related with several aspects presented in this work could be the following:

- Study other factors for the map characterization and their influence on the potential Risk/Occupancy map.
- Applying the fuzzy logic and ANFIS methods in other environments and adjust inference systems for particular searching areas or different P values distribution.
- Including other data regarding the UAV such as speed or height, or even dynamics.
- Study other ways to get better results for real time, even introducing variables tracked in real time by the UAV.

- Continue with path following, obstacle avoidance and visual tracking to obtain a complete model.
- Test all the proposals in real systems.

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## Annexes

### Annex I. Cape of Peñas simulation

The Cape of Peñas is the second most septentrional point of the Iberian Peninsula, located at the central area of the region of Asturias. This cape is in the Cantabrian sea coast, opened to the Atlantic Ocean, so the rough water and heavy sea is very frequent in this area.

There have been numerous naval accidents in the Cape of Peñas area, especially with fisher boats involved. The most recent one was the boat Santa Ana in 2014 where, due to the shink, eight out of nine people of the crew died sadly. This event is the framework of this second simulation.



Figure I.1. Cape of Peñas most famous accidents

The use of UAV for SAR operation is very important in maritime environments, because the UAV can travel faster than a boat and even in rough sea conditions when maritime SAR could be suspended.

Like in the previous simulation, thirty cases will be generated. Then, a map characterization and a path planning for the SAR will be calculated. In this case PSO approach will not be taken in account.

### Map Characterization

In Figure I.2 we can see the area of the Cape of Peñas. The red rectangle corresponds the location of the accident. The yellow area is the considered for the SAR operation.



Figure I.2. Cape of Peñas area coverage

The grid partition made consists of a matrix size 21x30, made of squared cells with 50 meters side.

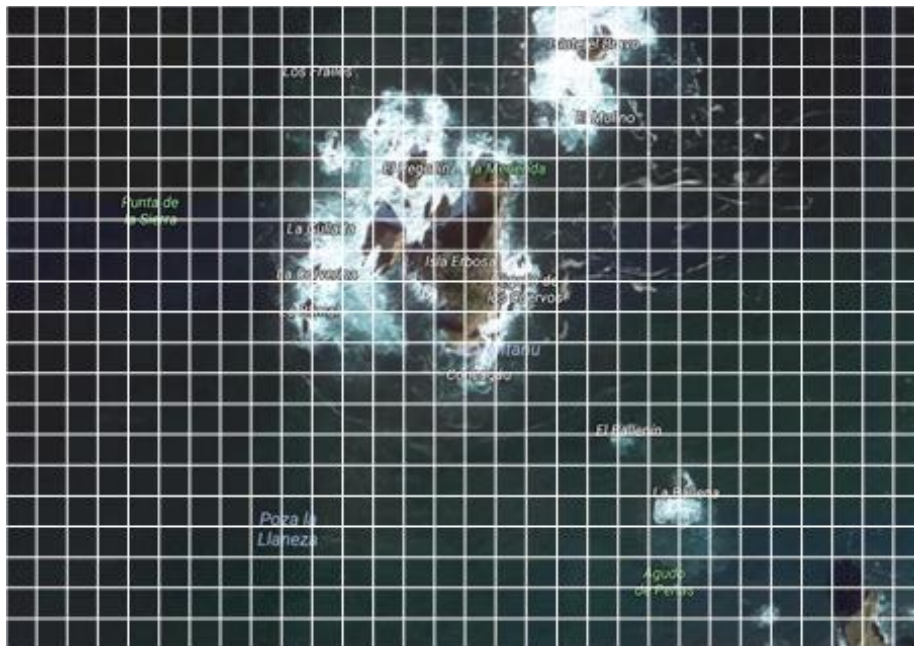


Figure I.3. Cape of Peñas grid partition

The next step is to assign the tags to the different areas and estimate the corresponding data. In Figures I.4 to I.6 we can see the tags corresponding to each contribution, and in Tables I-1 and I-2 their characteristics.

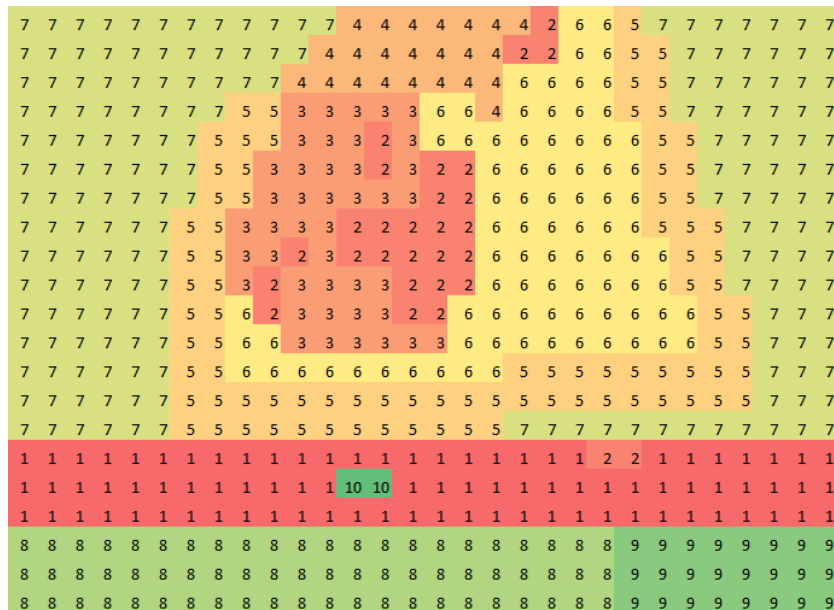


Figure I.4 Santa Ana terrain contribution tags

Table I-1 Santa Ana terrain contribution tags

	Description	Manual	Staying	Risk
1	Boat Transit	0.5	0.3	0.5
2	Rocks	1	0.5	0.7
3	Currents 1	1	0.8	0.9
4	Currents 2	1	0.6	0.8
5	Currents 3	1	0.4	0.5
6	Currents 4	1	0.6	0.5
7	Sea	1	0.3	0.5
8	Next to coast	1	0.4	0.5
9	Coast	1	0.4	0.8
10	SAR Team	0	0	0

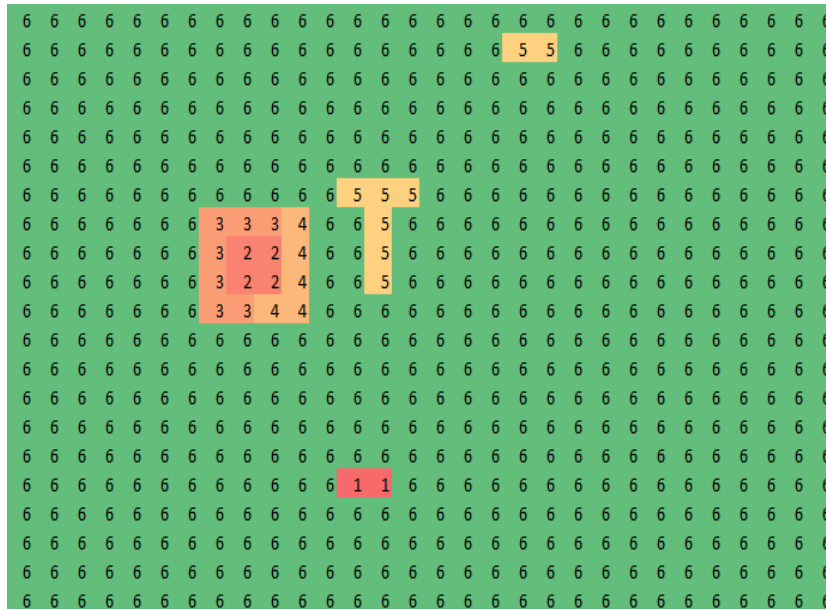


Figure I.5 Santa Ana emergency contribution tags

Table I-2 Santa Ana emergency contribution tags

	Description	Manual	Emergency	injuries
1	SAR team	0.000001	0	0
2	Emergency	1	0.9	0
3	Next to emergency	1	0.6	0
4	Em + injuries	1	0.8	0.5
5	Injuries	1	0	0.5
6	Not affected	0	0	0

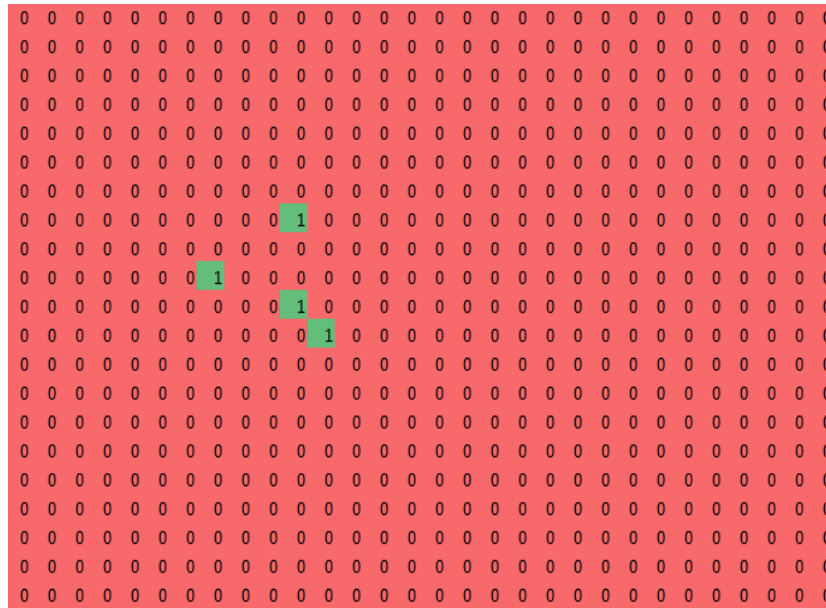


Figure I.6 Santa Ana historical

The Staying is used in this case to quantify the possible location of the people due to the sea currents. The risk value is estimated according the possibility to be damaged because of rocks or by bad sea conditions. The transit factor is chosen according the regular boats ways along this area.

Finally we calculate the individual contributions and the potential Risk/Occupancy map, as shown in Figures I.7, I.8 and I.9.

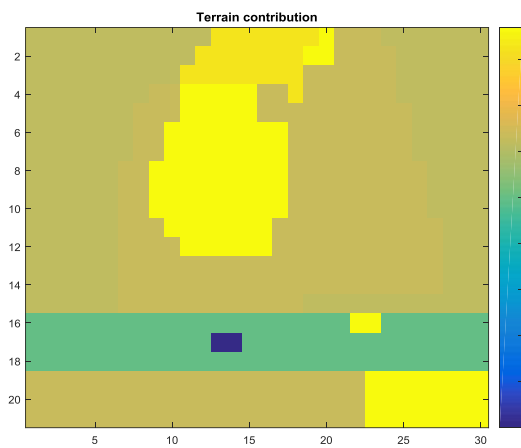


Figure I.7. La Palma terrain contribution to potential Risk/Occupancy

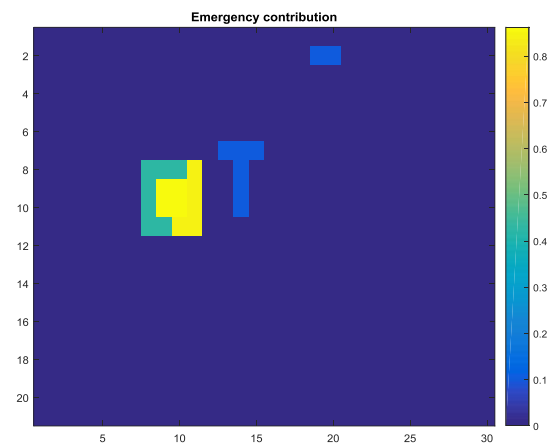


Figure I.8. La Palma emergency contribution to potential Risk/Occupancy

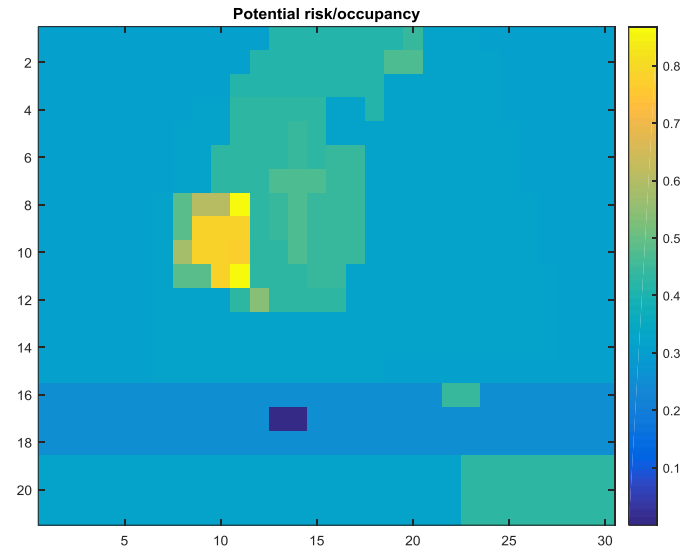


Figure I.9 Potential Risk/Occupancy map

### Path planning

Once calculated the potential Risk/Occupancy map, the different path planning methods are executed. The initial positions are:

- UAV 1 – [1 21]
- UAV 2 – [16 21]
- UAV 3 – [21 21]

### Attraction path planning

**Attraction path – 1 UAV**  
**d = 695 – w = 61881**

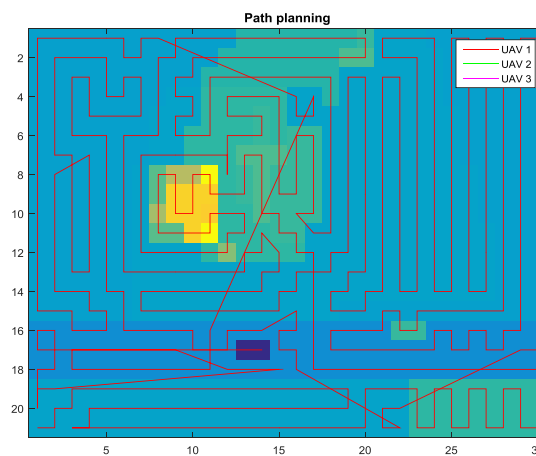
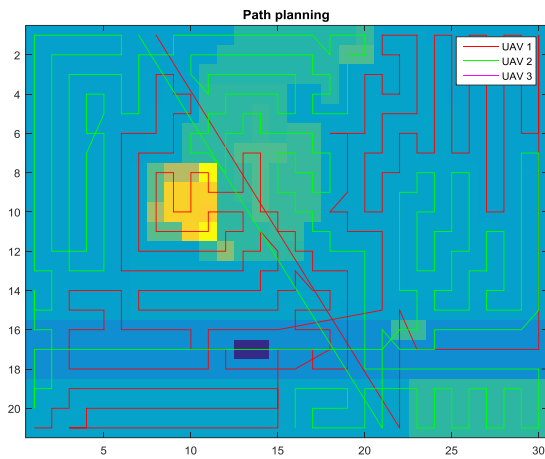


Figure I.10. Santa Ana 1 UAV attraction path planning

**Attraction – 2 UAV – free formation**  
 $d = 730 - w = 31431$



**Attraction – 2 UAV – distributed formation**  
 $d = 695 - w = 32282$

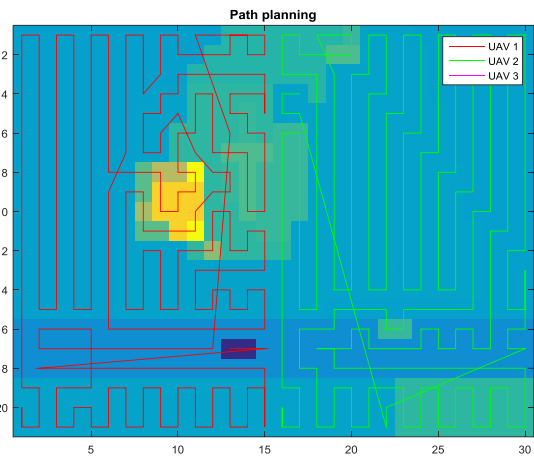
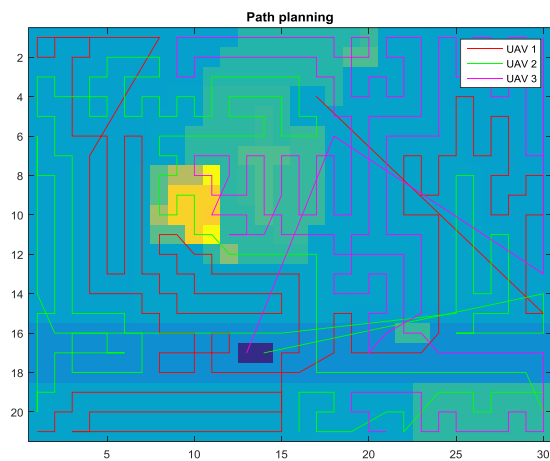


Figure I.11 Santa Ana 2 UAVs, free (left) and distributed (right) swarm attraction path planning

**Attraction – 3 UAVs – free formation**  
 $d = 753 - w = 21057$



**Attraction – 3 UAVs – distributed formation**  
 $d = 694 - w = 21615$

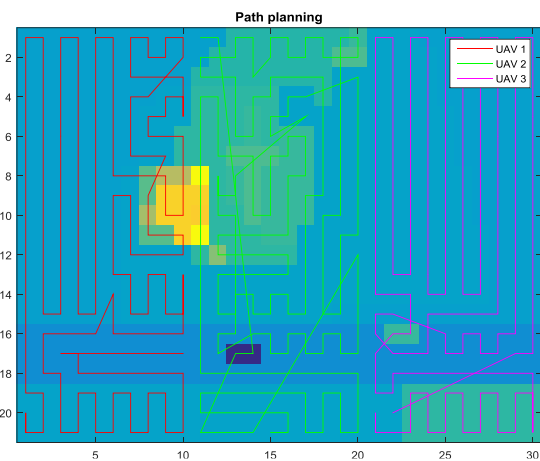


Figure I.12. Santa Ana 3 UAVs, free (left) and distributed (right) swarm attraction path planning

## Fuzzy logic path planning

**Fuzzy logic – 1 UAV**  
**d = 1715 – w = 61150**

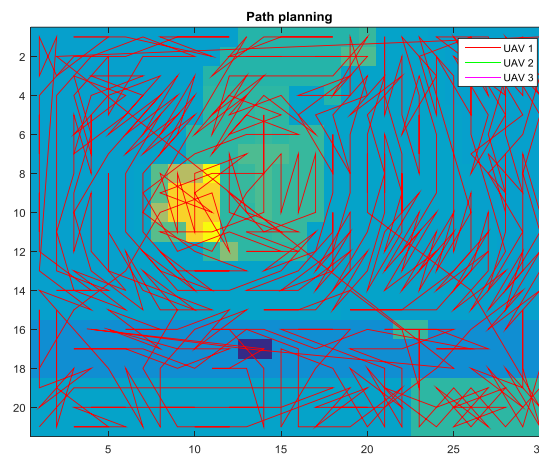
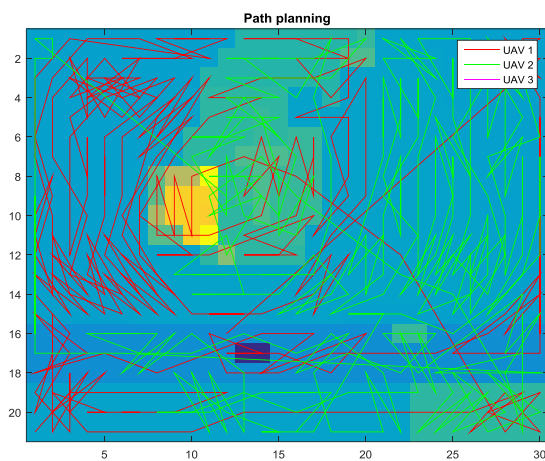


Figure I.13. Santa Ana 1 UAV Fuzzy Logic path planning

**Fuzzy logic – 2 UAV – free formation**  
**d = 1664 – w = 30631**



**Fuzzy logic – 2 UAV – distributed formation**  
**d = 1148 – w = 31245**

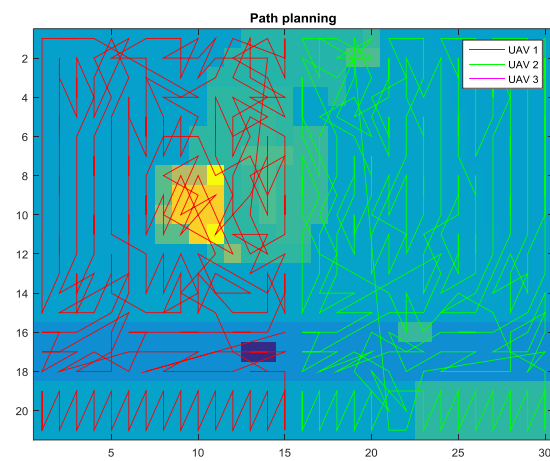


Figure I.14. Santa Ana 2 UAVs, free (left) and distributed (right) swarm Fuzzy Logic path planning

**Fuzzy logic – 3 UAVs – free formation**  
**d = 1737 – w = 20575**

**Fuzzy logic – 3 UAVs – distributed formation**  
**d = 1195 – w = 21210**

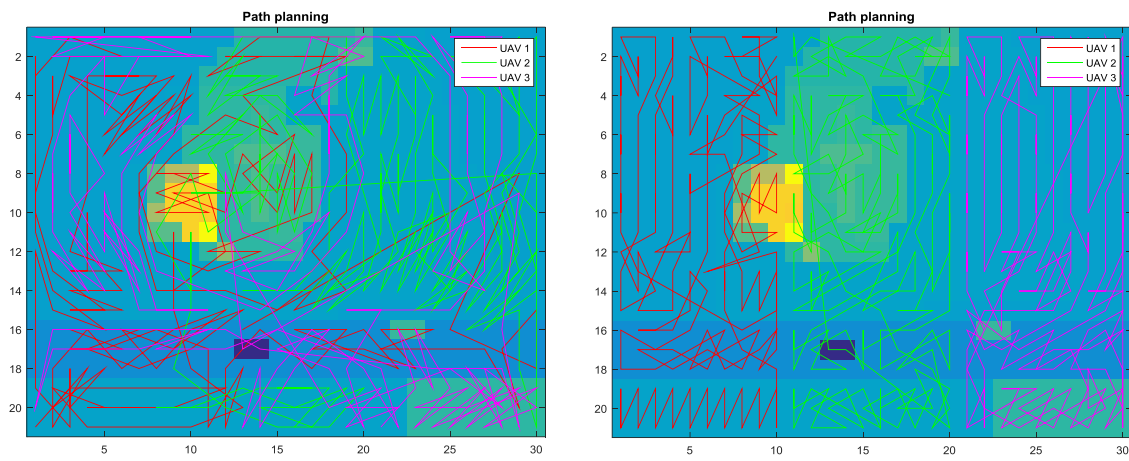


Figure I.15. Santa Ana 3 UAVs, free (left) and distributed (right) swarm Fuzzy Logic path planning

ANFIS path planning

**ANFIS – 1 UAV**  
**d = 768 – w = 61212**

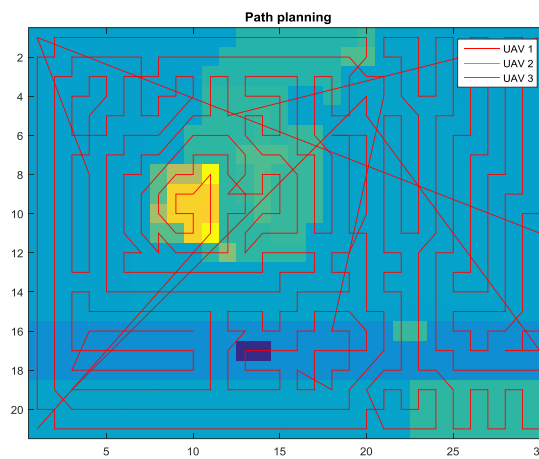
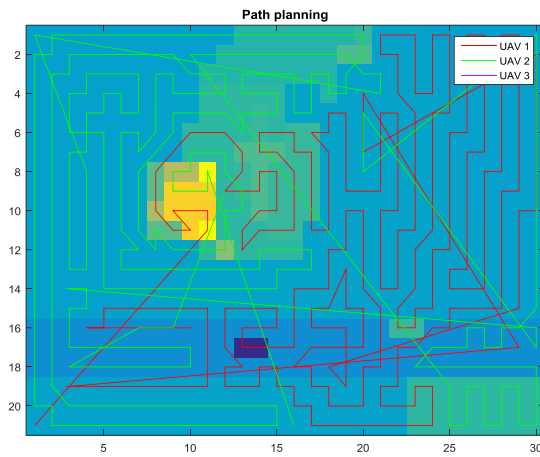


Figure I.16. Santa Ana 1 UAV ANFIS path planning

**ANFIS – 2 UAVs – free formation**  
 $d = 859 - w = 30988$



**ANFIS – 2 UAVs – distributed formation**  
 $d = 747 - w = 32142$

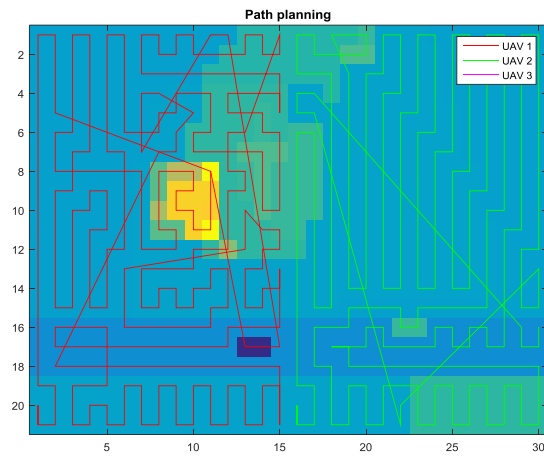
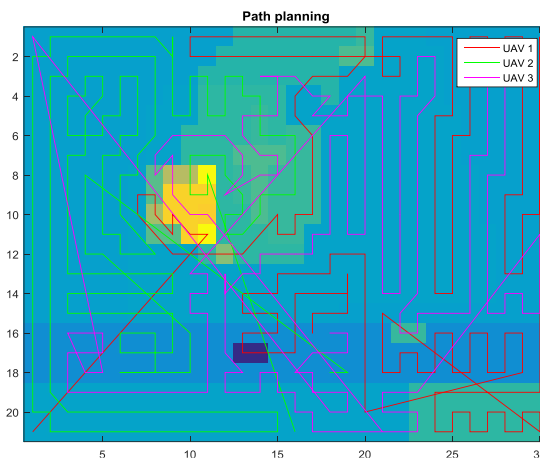


Figure I.17. Santa Ana 2 UAVs, free (left) and distributed (right) swarm ANFIS path planning

**ANFIS – 3 UAVs – free formation**  
 $d = 813 - w = 20404$



**ANFIS – 3 UAVs – distributed formation**  
 $d = 699 - w = 21224$

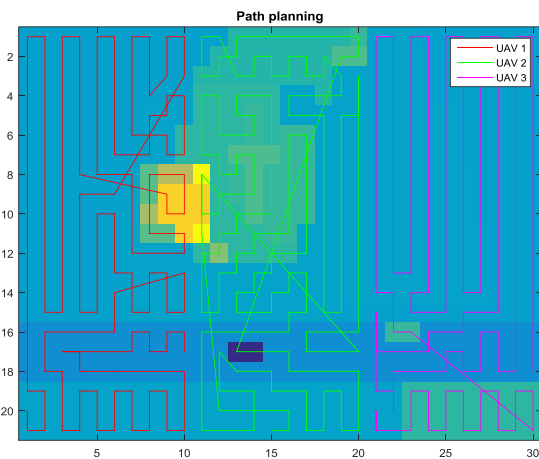


Figure I.18. Santa Ana 3 UAVs, free (left) and distributed (right) swarm ANFIS path planning

## Results

As in previous simulation of La Palma fire, thirty cases of missing people have been randomly generated (Figure I.19)

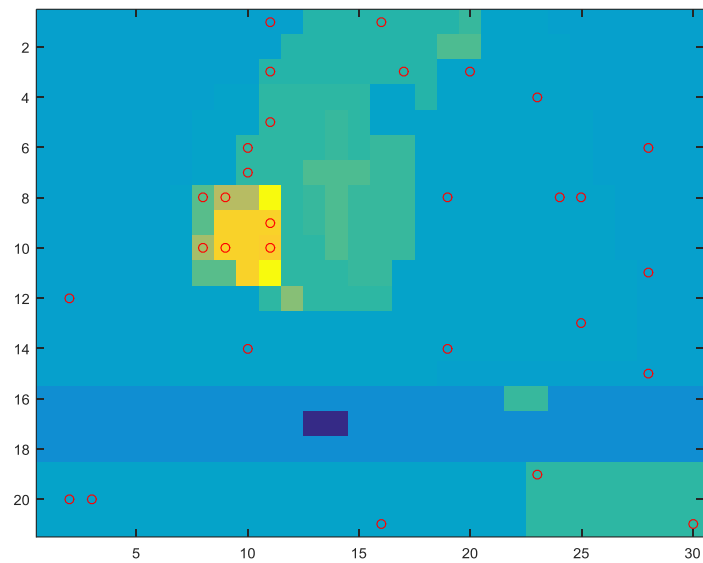


Figure I.19. Cape of Peñas missing people cases

### Global comparison

For this simulation, we only make a global analysis for all methods in order to summarize the results. So, a comparison between the different methods for the same it is shown.

In the first one, for one UAV, we can observe a similar performance for all methods. However, if we look at the first cases, the best method is the attraction one, due to a more indirect search, so the cases out of the high P areas are found faster by this approach.

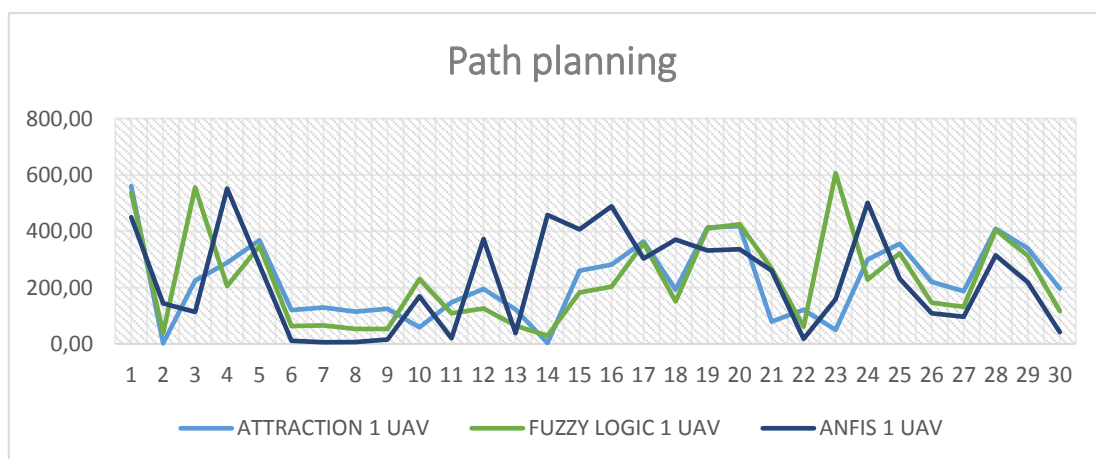


Figure I.20. Cape of Peñas path planning results comparison for 1 UAV

For 2 UAVs in free swarm, the performance is still similar, but with some better results for intelligent methods.

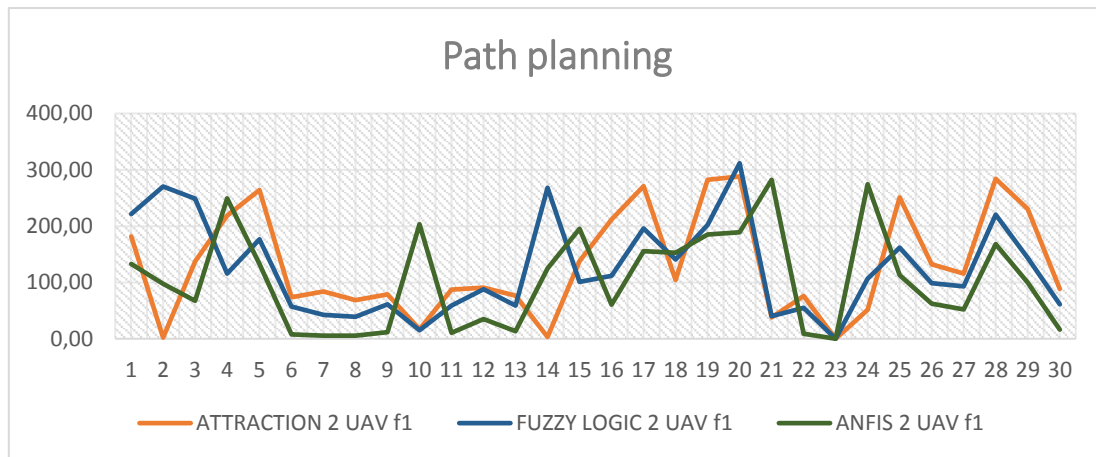


Figure I.21. Cape of Peñas path planning results comparison for 2 UAVs in free swarm

In Figure I.22 it shown the 2 UAV in distributed formation comparison. In this case, differences are more notable specially for fuzzy logic method, which is clearly the best in this configuration and confirms its good performance for distributed swarm.

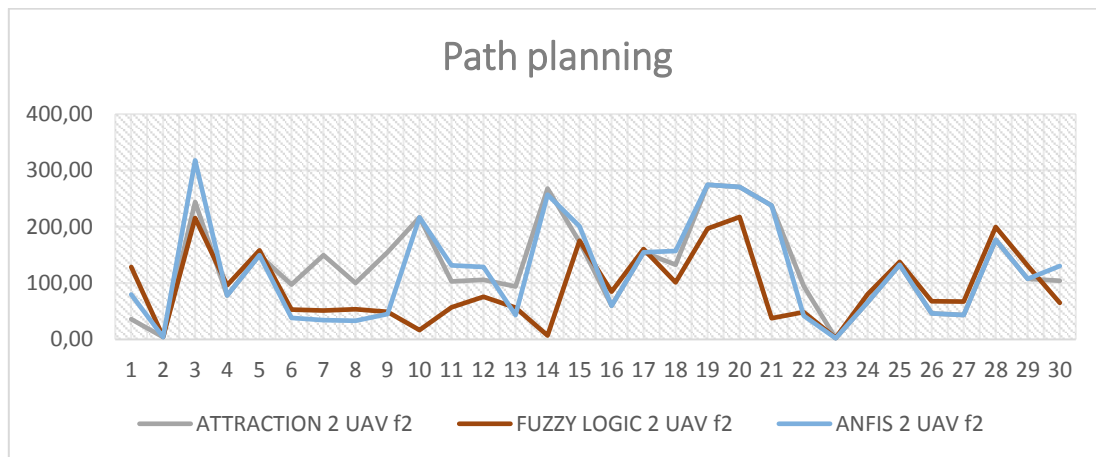


Figure I.22. Cape of Peñas path planning results comparison for 2 UAVs in distributed swarm

For 3 UAVs in free swarm, the ranking of the results is very clear, being ANFIS the best, then the fuzzy logic and the worst the attraction method.

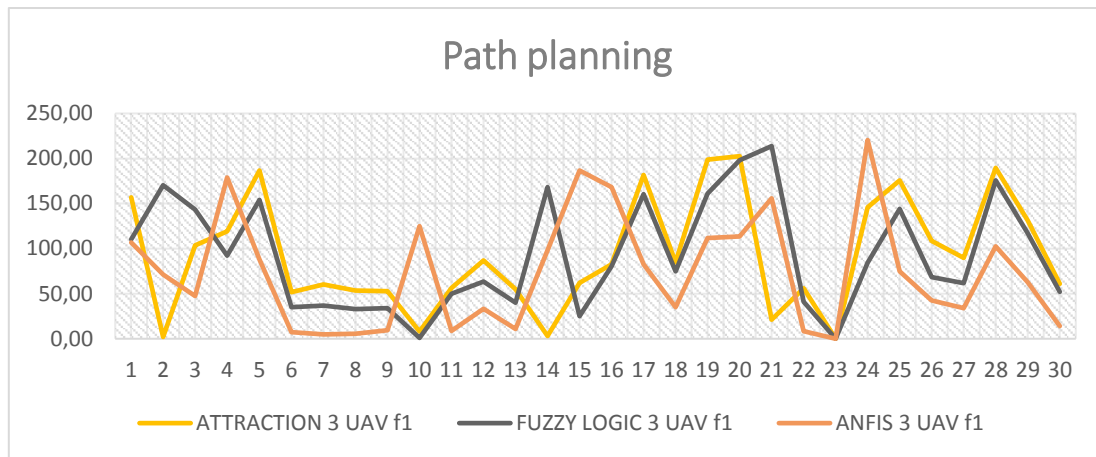


Figure I.23. Cape of Peñas path planning results comparison for 2 UAVs in free swarm

In the last configuration, again the fuzzy logic is the better method for distributed swarm.

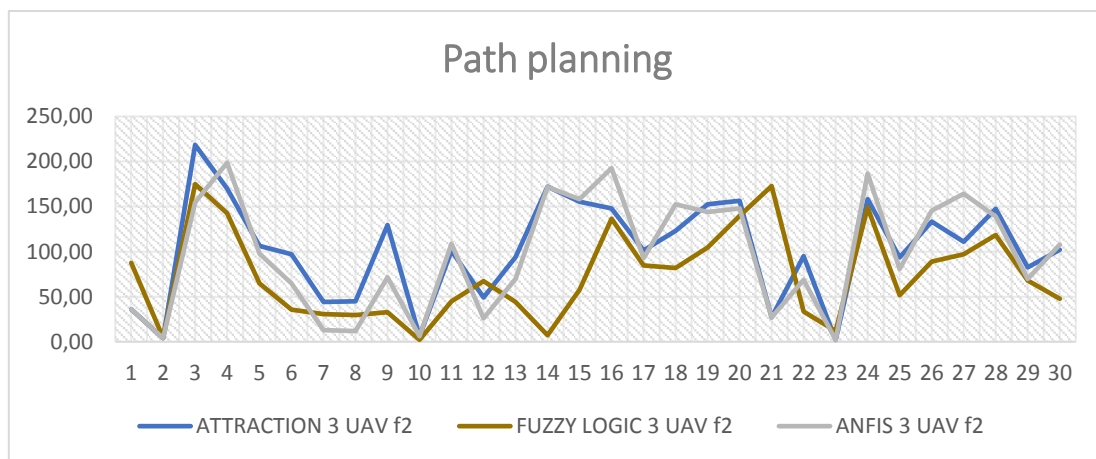


Figure I.24. Cape of Peñas path planning results comparison for 3 UAVs in distributed swarm

Finally, in the next figures are shown the average values and the win/losses comparison, confirming the results seen above.

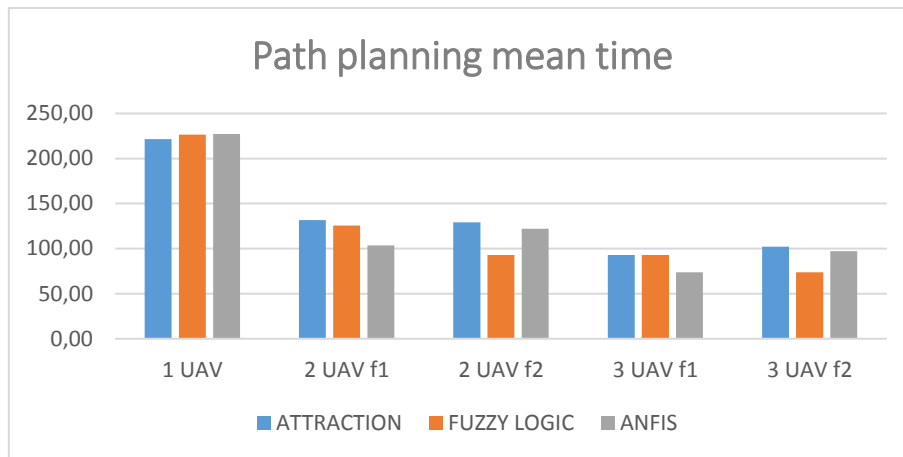


Figure I.25. Cape of Peñas path planning mean time comparison

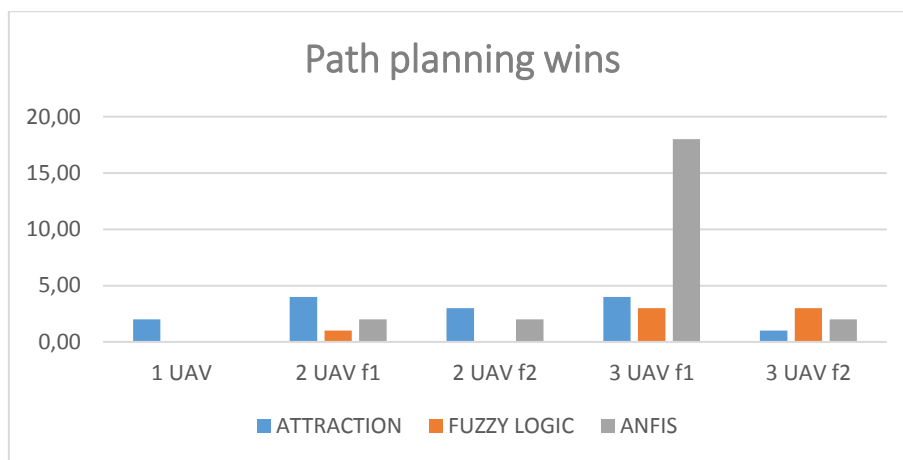


Figure I.26. Cape of Peñas won cases comparison

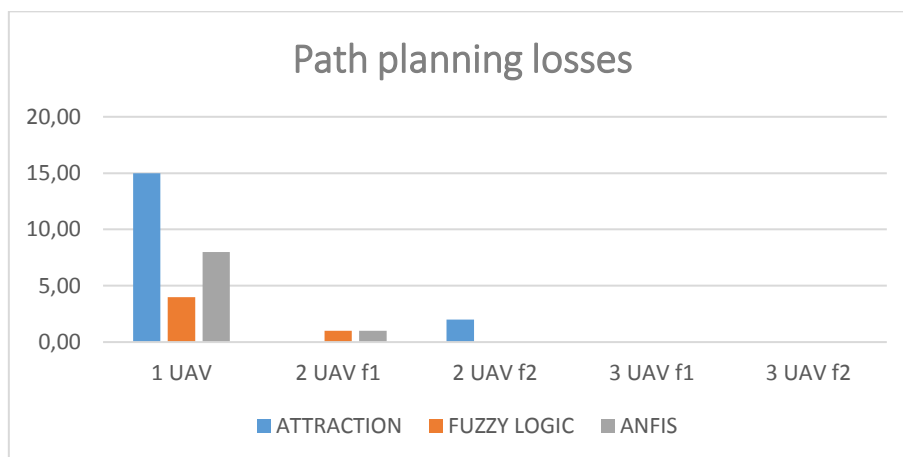


Figure I.27. Cape of Peñas lost cases comparison

The average values shows the ANFIS method having the minimum values in general, followed by fuzzy logic one. The win/losses comparison confirms the ANFIS method as the global winner

in this simulation, winning more than the half of the cases with 3 UAVs in free swarm configuration.