Tesis Doctoral
Ingeniería Electrónica

Mission-based mobility models for UAV networks

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El tribunal nombrado para juzgar el Proyecto arriba indicado, compuesto por los siguientes miembros:

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A Marta, a mis padres, hermanos, sobrinos, abuelos, tíos, primos, amigos… a toda esa gran familia sin la que no sería quien soy.

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Resumen

Las *redes UAV* han atraído la atención de los investigadores durante la última década. Las numerosas posibilidades que ofrecen los sistemas *single-UAV* aumentan considerablemente al usar múltiples UAV. Sin embargo, el gran potencial del sistema *multi-UAV* viene con un precio: la complejidad de controlar todos los aspectos necesarios para garantizar que los UAVs cumplen la misión que se les ha asignado. Ha habido numerosas investigaciones dedicadas a los sistemas multi-UAV en el campo de la robótica en las cuales se han utilizado grupos de UAVs para diferentes aplicaciones. Sin embargo, los aspectos relacionados con la red que forman estos sistemas han comenzado a reclamar un lugar entre la comunidad de investigación y han hecho que las redes de UAVs se consideren como un nuevo paradigma entre las *redes multi-salto*.

La investigación de redes de UAVs, de manera similar a otras redes multi-salto, se divide principalmente en dos categorías: i) *modelos de movilidad* que capturan la movilidad de la red, y ii) *algoritmos de enrutamiento*. Ambas categorías han heredado muchos algoritmos que pertenecían a las *redes MANET*, que fueron el primer paradigma de redes multi-salto que atrajo la atención de los investigadores. Aunque hay esfuerzos de investigación en curso que proponen soluciones para ambas categorías, el número de modelos de movilidad y algoritmos de enrutamiento específicos para redes UAV es limitado. Además, en el caso de los modelos de movilidad, las soluciones existentes propuestas son simplistas y apenas representan la movilidad real de un equipo de UAVs, los cuales se utilizan principalmente en operaciones orientadas a misiones, en la que cada UAV tiene asignados movimientos específicos.

Esta tesis propone dos *modelos de movilidad basados en misiones* para una red de UAVs que realiza dos operaciones diferentes. El escenario elegido en el que se desarrollan las misiones corresponde con una región en la que ha ocurrido, por

ejemplo, un desastre natural. La elección de este tipo de escenario se debe a que en zonas de desastre, la infraestructura de comunicaciones comúnmente está dañada o totalmente destruida. En este tipo de situaciones, una red de UAVs ofrece la posibilidad de desplegar rápidamente una red de comunicaciones.

El primer modelo de movilidad, llamado *dPSO-U*, ha sido diseñado para capturar la movilidad de una red UAV en una misión con dos objetivos principales: i) explorar el área del escenario para descubrir las ubicaciones de los *nodos terrestres*, y ii) hacer que los UAVs converjan de manera autónoma a los grupos en los que se organizan los nodos terrestres (también conocidos como *clusters*). El modelo de movilidad dPSO-U se basa en el conocido algoritmo *particle swarm optimization (PSO)*, considerando los UAV como las partículas del algoritmo, y también utilizando el concepto de valores dinámicos para la *inercia*, el *local best* y el *neighbour best* de manera que el modelo de movilidad tenga ambas capacidades: la de exploración y la de convergencia. El segundo modelo, denominado *modelo de movilidad Jaccard-based*, captura la movilidad de una red UAV que tiene asignada la misión de proporcionar servicios de comunicación inalámbrica en un escenario de mediano tamaño. En este modelo de movilidad se ha utilizado una combinación del *virtual forces algorithm (VFA)*, de la distancia Jaccard entre cada par de UAVs y metaheurísticas como *hill climbing* y *simulated annealing*, para cumplir los dos objetivos de la misión: i) maximizar el número de nodos terrestres (víctimas) que se encuentran bajo el área de cobertura inalámbrica de la red UAV, y ii) mantener la red UAV como una red conectada, es decir, evitando las desconexiones entre UAV.

Se han realizado simulaciones exhaustivas con herramientas software específicamente desarrolladas para los modelos de movilidad propuestos. También se ha definido un conjunto de métricas para cada modelo de movilidad. Estas métricas se han utilizado para validar la capacidad de los modelos de movilidad propuestos de emular los movimientos de una red UAV en cada misión.

Abstract

UAV networks have attracted the attention of the research community in the last decade. The numerous capabilities of *single-UAV systems* increase considerably by using multiple UAVs. The great potential of a *multi-UAV system* comes with a price though: the complexity of controlling all the aspects required to guarantee that the UAV team accomplish the mission that it has been assigned. There have been numerous research works devoted to multi-UAV systems in the field of robotics using UAV teams for different applications. However, the networking aspects of multi-UAV systems started to claim a place among the research community and have made UAV networks to be considered as a new paradigm among the *multihop ad hoc networks*.

UAV networks research, in a similar manner to other multihop ad hoc networks, is mainly divided into two categories: i) *mobility models* that capture the network mobility, and ii) *routing algorithms*. Both categories have inherited previous algorithms mechanisms that originally belong to *MANETs*, being these the first multihop networking paradigm attracting the attention of researchers. Although there are ongoing research efforts proposing solutions for the aforementioned categories, the number of UAV networks-specific mobility models and routing algorithms is limited. In addition, in the case of the mobility models, the existing solutions proposed are simplistic and barely represent the real mobility of a UAV team, which are mainly used in missions-oriented operations.

This thesis proposes two *mission-based mobility models* for a UAV network carrying out two different operations over a disaster-like scenario. The reason for selecting a *disaster scenario* is because, usually, the common communication infrastructure is malfunctioning or completely destroyed. In these cases, a UAV network allows building a support communication network which is rapidly deployed.

The first mobility model, called *dPSO-U*, has been designed for capturing the

mobility of a UAV network in a mission with two main objectives: i) exploring the scenario area for discovering the location of *ground nodes*, and ii) making the UAVs to autonomously converge to the groups in which the nodes are organized (also referred to as *clusters*). The dPSO-U mobility model is based on the well-known *particle swarm optimization algorithm (PSO)*, considering the UAVs as the particles of the algorithm, and also using the concept of dynamic *inertia*, *local best* and *neighbour best* weights so the mobility model can have both abilities: exploration and convergence. The second one, called *Jaccard-based mobility model*, captures the mobility of a UAV network that has been assigned with the mission of providing wireless communication services in a medium-scale scenario. A combination of the *virtual forces algorithm (VFA)*, the *Jaccard distance* between each pair of UAVs and metaheuristics such as *hill climbing* or *simulated annealing* have been used in this mobility model in order to meet the two mission objectives: i) to maximize the number of ground nodes (i.e. victims) under the UAV network wireless coverage area, and ii) to maintain the UAV network as a connected network, i.e. avoiding UAV disconnections.

Extensive simulations have been performed with software tools that have been specifically developed for the proposed mobility models. Also, a set of metrics have been defined and measured for each mobility model. These metrics have been used for validating the ability of the proposed mobility models to emulate the movements of a UAV network in each mission.

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List of abbreviations

2D	2 dimensions
3D	3 dimensions
A2A	air-to-air links
A2GN	air-to-ground node links
A2GS	air-to-ground control station links
AANET	Aerial Ad hoc Network
ACO	Ant Colony Optimization algorithm
AODV	Ad hoc On-demand Distance Vector routing protocol
BATMAN	Better Approach To Mobile Ad hoc Networking
BLoS	Beyond Line of Sight communications
BWMN	Battlefield Wireless Military Network
CALM	Communications access for land mobiles
CoM	Composite Mobility model
CORPs	Cooperation, Organization and Responsiveness in Public Safety model
CPTD	Control Parametrization and Time Discretization algorithm
CTOL	Conventional Takeoff and Landing
DA	Disaster Area mobility model
DI-PSO	per-Drone Iterated PSO algorithm
dPSO	Distributed Particle Swarm Optimization algorithm
dPSO-U	distributed PSO for UAV mobility model
DSR	Dynamic Source Routing
DTN	Delay Tolerant Network Disruption Tolerant Network
DTNRG	Delay-Tolerant Networking Research Group
e.g.	Exempli gratia
FANET	Flying Ad hoc Network
GA	Genetic Algorithm
GM	Gauss-Markov mobility model
HC	Hill Climbing algorithm

ICN	Intermittently Connected Network
in	Inertia component weight of dPSO-U algorithm
IPN	InterPlanetary Internet
IRTF	Internet Research Task Force
IVC	Inter-Vehicular Communication
i.e.	Id est
lb	Local best component weight of dPSO-U algorithm
LM	Lawnmower mobility model
LoS	Line of sight communications
LTE	Long-Term Evolution
MANET	Multihop Ad Hoc Network Mobile Ad Hoc Network
MANET WG	Mobile Ad-hoc Networks working group
MTS	Minimum Time Search problem
nb	Neighbour best component weight of dPSO-U algorithm
NCONN	Number of connections between ground nodes and UAVs metric used for dPSO-U
NCONV	Percentage of UAVs converging to a cluster metric used for dPSO-U
NDIS	Percentage of ground nodes discovered metric used for dPSO-U
NLoS	Non Line of Sight communications
ns-2	Network simulator 2
ns-3	Network simulator 3
OBU	On-Board Units
OLSR	Optimized Link State Routing
P-OLSR	Predictive-OLSR
PR	Pheromone Repel mobility model
PSO	Particle Swarm Optimization algorithm
RBUPD	Role-Based Urban Post-Disaster
RD	Random Direction mobility model
RPAS	Remotely Piloted Aircraft System
RPGM	Reference Point Group Mobility model
RSU	Roadside Unit

RW	Random Walk mobility model
RWP	Random Waypoint mobility model
SA	Simulated Annealing algorithm
SAR	Search and Rescue operations
SCRM	Semi-Random Circular Movement Mobility model
SERVN	Serviced nodes metric for the Jaccard-based mobility model
SMS	Semi-Markov Smooth mobility model
SR	Smooth Random mobility model
ST	Smooth turn mobility model
TECONN	Time elapsed between consecutive connections among ground nodes and UAVs used for dPSO-U
TTCONV	Convergence time of the UAVs to any of the clusters metric used for dPSO-U
TTDIS	Time to discover a percentage of ground nodes for dPSO-U
TW	Three-Way Random mobility model
A2A	UAV-to-UAV links
U2G	UAV-to-ground links
UAV	Unmanned Aerial Vehicle
UAVLOC	UAV locations metric for the Jaccard-based mobility model
UDISC	UAV network disconnections metric for the Jaccard-based mobility model
V2I	Vehicle-to-Infrastructure communications
V2V	Vehicle-to-Vehicle communication
VANET	Vehicular Ad Hoc Network
VFA	Virtual Forces Algorithm
VTOL	Vertical Takeoff and Landing
WAN	Wide Area Network
WAVE	Wireless Access in Vehicular Environments
Wi-Fi	The Standard for Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WMN	Wireless Mesh Network
WSN	Wireless Sensor Network

1. INTRODUCTION

"At this point of the story, I wonder if this is the beginning of the end or the end of the beginning"

Jesús Sánchez García

Drawing a clear storyline for this thesis has been a challenging task. The reason is that the topic of this thesis is about is very broad and, sometimes, it has been difficult to put boundaries to the research lines (there was always something else that could have been studied and included). Also, the main topic is a very recent research area, and consequently, there is a lot of ongoing research. Therefore, the task of keeping up the pace of reading all the new results that researchers produce in this research area has been really daring. However, this is the beginning of this thesis, i.e. the beginning of the end (a journey of more than 4 years), or hopefully, this is the end of the beginning, i.e. having the chance to work as a professional researcher and keep on learning every day about this fascinating world of UAV networks.

1.1 Motivation

Back in 1950, nine short stories by Isaac Asimov were published as a book under the name "I, Robot" [1]. More than 50 years later, in 2004, a movie of the same name was produced, based on Isaac Asimov's stories. These science fiction stories presented a society surrounded by intelligent robots. It is obvious that nowadays we do not live in such a society as the one described in Asimov's stories. However, we do have pseudo-intelligent robots helping humans in many situations, such as the manufacturing industry [2] [3] (e.g. many products are manufactured by autonomous robotic arms), the transport industry (e.g. the first prototypes of autonomous cars are being tested but autonomous urban metro systems [4] [5] [6] have been running for several years) and also in research activities (e.g. the space exploration would have been impossible without robots [7] [8]).

Recently, and thanks to the latest advancements in electronics and control technologies, there has been a breakthrough in the development of small and medium-sized flying robots [9]. Flying robots are usually called *Remotely Piloted Aircraft Systems (RPAS)* when these are controlled by a human operator via remote control. When the aerial vehicle has mechanisms for flying autonomously, without human control, they receive the name of *Unmanned Aerial Vehicles (UAVs)*, and also a more common name, drones. Usually, a UAV is equipped with embedded systems running complex algorithms for different purposes. These algorithms allow the UAV to gather data about the environment through its sensors and make decisions accordingly to a mission objective, e.g. detecting fire on a surveyed area using infrared cameras [10] [11]. Due to the increasing availability on the market and their decreasing prices, UAVs have started to be used widely in civilian applications and therefore are not exclusive for military purposes anymore [12].

More recently, the study of UAV teams has been a very active research topic, in which UAV networks and their applications have become the focus of researchers working on the area. This research area merges concepts and techniques from areas such as networking, communications, artificial intelligence, control theory and electronics. These are commonly known as *Flying Ad hoc Networks (FANETs)* [13], *Aerial Ad hoc Networks (AANETs)* [14], or simply *UAV networks* [15]. When performing a mission or carrying out several tasks, UAV networks present several advantages in comparison to single UAV systems [13] [15] [12] [16]. Specifically, UAV teams are more robust systems as the mission objectives can be achieved even if a UAV suffers from a system failure. Also, UAV networks are capable of completing some missions more efficiently, as the mission can be divided into independent tasks and these can be carried out by different UAVs in parallel, e.g. search missions. UAV networks can be used in numerous applications, for example in construction activities [17] [18], fire monitoring [10] [11], environmental monitoring [14] [19] [20] and communication service provision [21] [22], among others. One of the most important applications of UAV networks, which is attracting the attention of researchers, is supporting emergency response operations in disaster scenarios [23] [24] [25].

According to the Annual Disaster Statistical Review [26], in 2014 a total number of 324 natural disasters occurred worldwide, claiming over 7.823 people and affecting to 140 million people. Furthermore, Figure 1 [26] shows that the disaster occurrence trends are barely predictable. These facts highlight the importance of having *emergency response teams*, also known as *first responders*, which are able to respond effectively in the presence of disasters. Apart from presenting challenges as unknown scenario areas and unexpected events, first responders and victims usually deal with the lack of communication services in disaster scenario areas. When a disaster strikes, it usually affects the communication infrastructure, leaving the disaster area with malfunctioning or non-existing communication services. The communication between rescuers is vital, as most of their tactics rely upon the knowledge of each team member status. In this situation, first responders face one of the most important tasks: to deploy an ad hoc communication infrastructure on the disaster area [27] [28].

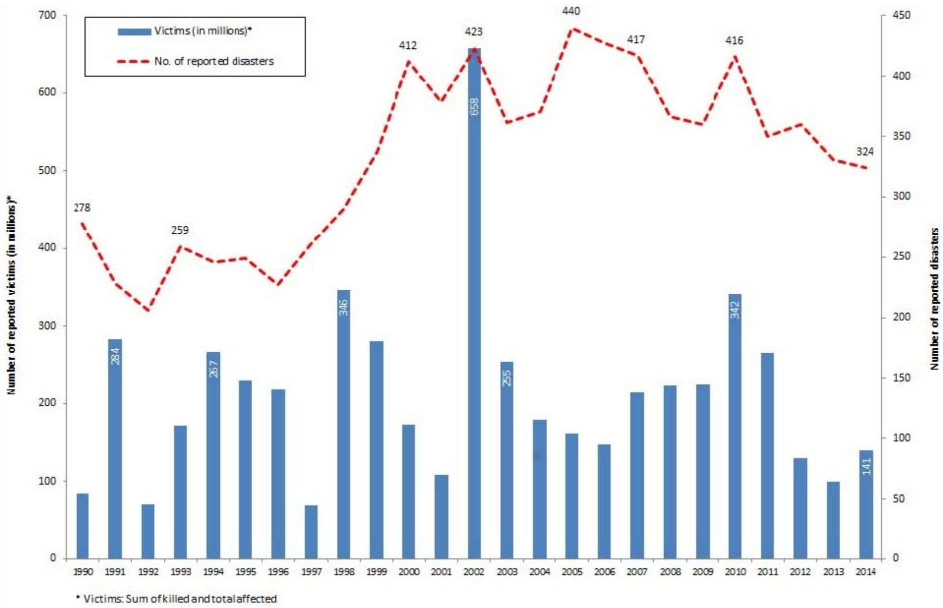


Figure 1. Disaster occurrence and victims trends

Emergency response teams have been using communication technologies in order to perform more efficient rescue operations and reducing the number of mortal victims. *Mobile Ad hoc Networks (MANETs)* brought to emergency response teams the ability to deploy multihop and tailored communication networks rapidly [27] [29]. However, the breakthrough of UAV networks has contributed to the possibility of providing better communication services within a disaster scenario area, and at the same time, having the UAVs gathering and sharing information about the disaster scenario, which can be used by both victims and first responders. This is where UAV networks play a role of paramount importance.

There are well-known situations in which UAVs have been already used in disaster relief missions [30]. As an example, in mountain rescue missions, rescue teams used UAVs in order to avoid unnecessary risks and also for supporting in ground searching tasks when an individual was reported missing. Also, back in 2005, two UAVs were used for locating victims in the area affected by Hurricane Katrina [31]. Moreover, two swimmers were rescued with the help of a drone on an Australian beach [32]. Even more, it is common to refer to emergency response professionals with the term *first responder*. Based on this, some researchers have proposed UAV networks for supporting emergency response operations under the term *zero responder* or *0th responder* [33] because of the ability of rapidly being deployed in disaster-stricken areas.

Therefore, as it was mentioned at the beginning of this section, the society of the future could be something similar to the one described in the book "I, Robot". With little effort, we can think of a future in which UAV networks work in parallel with first responders in rescue missions. There is a long journey to walk before we reach to that future, and yet much advancement is needed in several research fields. However, the main motivation of this thesis is to make a humble contribution to UAV networks research, in order to make the future, if possible, a better place.

1.2 Challenges

One of the main potentials of UAV networks, also known as *UAV swarms*, is the ability to carry out complex missions faster and in a more reliable way than single-UAV systems [13] [15] [12] [16]. Obviously, having multiple UAV nodes interacting with each other provides the ability to follow a divide-and-conquer strategy. Also, in the case that one UAV suffers from a failure, the rest of the UAVs can reorganize in order to successfully accomplish the mission. At the same time, organizing the tasks assigned to each UAV and coordinating each UAV movements is one of the most challenging tasks in UAV networks [15] [34] [35]. A depiction of a potential application of a UAV network is shown in Figure 2.

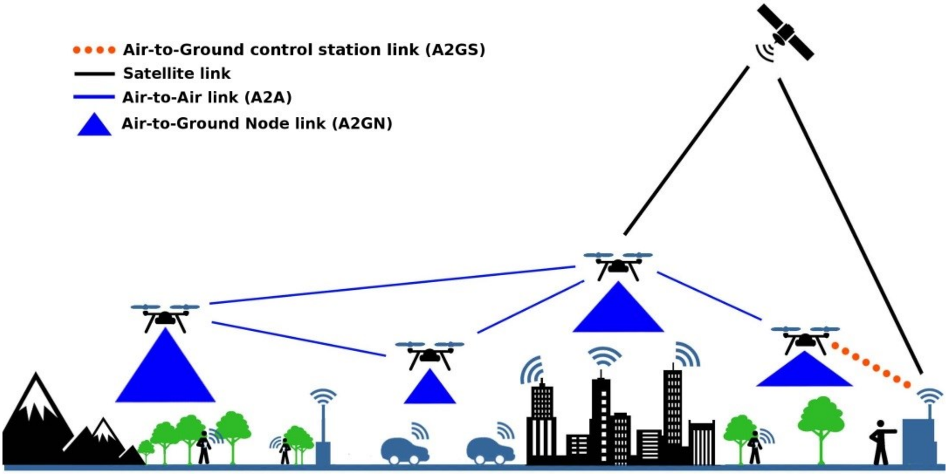


Figure 2. A potential application scenario for a UAV network

In relation to the mobility of a robot, calculating the trajectory that a vehicle has to follow in order to move from an initial position to a goal position is addressed by the *path planning* research community [35]. Usually, path planning problems generate solutions in the form of sequences of positions that the vehicle has to occupy in a specific order. When the trajectory is calculated by taking into account not only the positions but also the vehicle's motion equations, the problem includes aspects such as velocity and accelerations, among others. In this case, the problem is known as a *motion planning* problem. Path planning and motion planning research has devoted numerous efforts to multi-UAV systems research [35], embracing different task allocation strategies for such purpose [11] [36] [37]. However, path planning and motion planning research focuses exclusively on mobility aspects, leaving the networking aspects of multi-UAV systems out of the picture.

Looking at multi-UAV systems from another perspective, the *mobility models* research community focuses on studying together: i) the mobility of nodes in the network and, ii) the impact of the mobility of the nodes on the network performance. As an example, mobility models research deal with high-level trajectories in the form of sequences of waypoints, so each mobile node in the network is considered to move towards its assigned waypoint at each specific time. This approach basically creates a level of abstraction upon fundamental dynamics of the mobile nodes (e.g. vehicle accelerations) in the form of high-level mobility behaviours. Working with high-level trajectories allows analysing the UAV network behaviour as a whole, assessing the networking and communication aspects that are not addressed with enough detail in path planning and motion planning problems. When the research interest is put on the networking aspects, it is common to find works using this approach, such as [38] [34] [39] [24].

Mobility models were originally proposed for MANETs and there have been many of them. However, very few mobility models have been proposed for UAV networks [34]. UAV networks present different mobility features in comparison to MANETs and therefore adapting MANET mobility models to UAV networks is not a recommended approach. On the contrary, the design of specific mobility models for aerial vehicle networks has produced very simple mobility models so far in which the nodes in the network perform very basic mobility patterns. In addition, most of the mobility models proposed are specifically designed for *fixed-wing aerial vehicles*, reproducing smooth trajectory changes typical of this type of aerial vehicles [34], leaving unattended mobility models for other aerial vehicle types such as *multicopters*. Multicopters are able to perform sharp turns and movements due to their mechanical capabilities and therefore the fixed-wing mobility models, most of the times, are not appropriate for multicopter-like vehicles.

Moreover, UAV networks present another important difference in comparison to MANETs; they are usually used with a specific purpose in *mission-based operations* [12]. As aforementioned, there are few works that have proposed mobility models for UAV networks, but there are even fewer focusing on developing mobility models for mission-like operations. Therefore, mobility models for particular UAV network applications are identified as a major concern and thus an open research issue for the UAV networks research community [12] [34]. Nevertheless, the importance of emulating a UAV network in specific missions is of paramount importance as it is very likely that most of the UAV networks will be used in this type of operations. In addition, UAV networks are usually intended for assisting in difficult situations and in *complex scenarios* in which humans are not able to perform specific tasks or if they do they would be exposed to high risks. Complex scenarios can be defined as those presenting numerous uncertainties and varying conditions. Good examples of complex scenarios are *disaster scenarios*. In the case of disaster scenarios, some of these uncertainties are the unpredictable mobility of victims (some victims may be injured and incapable of moving, while others may be running away from the disaster area) and the possibility of sudden changes in the scenario (in the case of earthquakes and floods, building structures are affected and can collapse at any time, changing the scenario), among others.

Behind a mission-like operation, there are one or several aspects that are expected to be optimized. As an example, in an exploration mission, the time devoted to sweeping the area to be explored is expected to be minimized. Based on this, developing a mobility model that generates high-level trajectories for a UAV network can be modelled as a dynamic optimization problem. However, by taking all the uncertainties present in a complex scenario under consideration, the optimization problem may become non-manageable by using exact or optimal algorithms, i.e. taking a huge amount of time and resources for generating the trajectories for the UAV network that optimized the desired aspects. Optimal approaches also require having prior knowledge about the scenario. As a matter of fact, complex scenarios such as disaster scenarios present uncertainties that make very difficult to have reliable prior knowledge of the scenario. It is in this situation where a mission-based mobility model face the challenge of using approximation algorithms, such as metaheuristics approaches, in order to provide close-to-optimal trajectories [35] [33] [40].

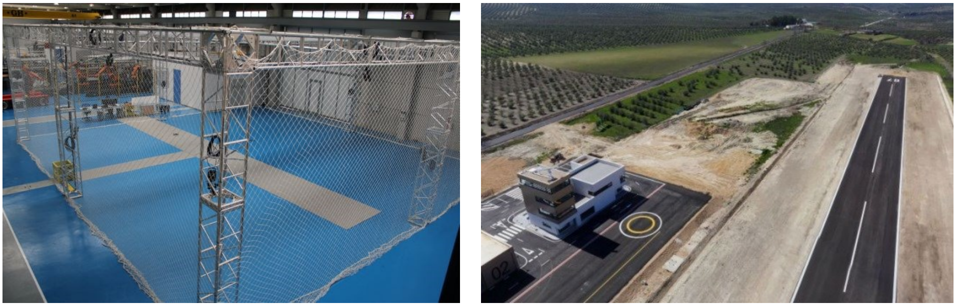
The challenge of this thesis is to develop mobility models for UAV networks performing mission-like operations. These mobility models aim to emulate the mobility of the UAV network in different missions. As there may be numerous mission types for a UAV network, this thesis considers only two categories: i) *exploration and convergence missions*, and ii) *adaptive coverage missions*. In the first category, the UAV network is used with exploration purposes. The main objective is to survey a specific area and to get information from the scenario context, e.g. the ground nodes' locations. Later on, the UAV network aims to converge to the areas in which a higher density of ground nodes (i.e. disaster scenario victims) has been detected. In the second mission category, the UAV network aims to provide reliable communication services to the ground nodes. Thus, the main objective is to periodically calculate the optimal positions of the UAVs in order to maximize the number of ground nodes under the wireless coverage area of the UAV network and also to adapt to the movements of the ground nodes on the fly. A detailed description of the problems addressed is provided in sections 3.1 and 4.1.

To summarize, the main challenge of this thesis has been to design, develop and demonstrate the feasibility of different mobility models for emulating the mobility of UAV networks performing different missions in complex scenarios. Emulating the mobility of the UAV network will allow further study and analysis of the networking aspects of the UAV network. The scenarios considered in this document are disaster scenario areas. However, the algorithms proposed in this thesis may be easily adapted for another type of scenarios.

1.3 Methods

Carrying out experiments of UAV networks in complex scenarios is very difficult. For example, a natural disaster event may occur unexpectedly and it may present many different characteristics from other events. In some cases, it is possible to develop *test-beds* in order to emulate disaster scenarios. However, setting up a physical area recreating disaster conditions can be expensive in terms of resources, personnel and money [11]. Moreover, deploying a network test-bed of several UAVs requires expensive equipment and infrastructure, such as UAV materials (e.g. the frame, the blades, replacement pieces in case of a UAV crash), maintenance equipment (e.g. fireproof bags for the batteries, a fridge for conserving the batteries performance), transportation materials (e.g. cases for storing the UAVs and for easily transporting them to the flying facilities), a flying course and a license for the specific UAV used in the experiments), access to specific flight facilities for developing the experiments with the UAVs (e.g. indoor facilities with flight safety netting or outdoor allowed fly areas like the ones shown in Figure 3), and many other resources.

For this reason, UAV networks research is usually carried out using software simulations. There are several software tools available that support research activities on UAV networks, but normally these simulators focus only a few aspects. For example, some software simulators focus on network communications and the different technologies that can be used like the well-known ns-2 [41], its evolution, which is called ns-3 [42] [43], or other simulators like OMNeT++ [44]. There are also specific scenario simulators [45] [46], also called scenario generators or mobility generators, which recreate the movements of ground nodes in different contexts, such as urban scenarios, open-space scenarios, among others. Usually, these scenario simulators allow creating abstract scenario conditions in order to evaluate an application, such a UAV network, in specific situations. There are even disaster scenario models that can be generated with these scenario simulators [47], which model the disaster area and its surroundings (the areas close to the incident site in which the emergency response teams deploy the temporary facilities for assisting victims). Also, there are simulators for multi-agent research [48] [49], which are usually used for simulating the behaviour of teams of robots in different applications.



a) Indoor flight cage for UAVs (CATEC Centro Avanzado de Tecnologías Aeroespaciales, Sevilla)

b) Outdoor flight facilities for UAVs (ATLAS Centro de Vuelos Experimentales, Jaén)

Figure 3. Examples of indoor and outdoor facilities for UAV flights

According to this common methodology adopted by the research community, and also the simulation tools available for performing research in this area, the work developed for this thesis has been supported by software simulations that emulate UAV networks movements and several communication features. Despite there are several software simulators available for free, and even a few integrated simulators of network simulators and mobility [50], none of them present all the aspects needed in order to generate trajectories for a UAV network in a mission-like operation in a complex scenario. For this reason, during the development of the research presented in this thesis, our own software simulation tools have been developed for supporting the specific requirements of modelling UAV networks mobility and the mobility of ground nodes.

It is worth mentioning that there is an ongoing effort for building a UAV network test-bed so the mobility models proposed in this thesis can be validated in real-flight UAV experiments in controlled scenarios. More information about this is provided in Appendix B.

1.4 Contributions

The main contributions of this thesis are described in a detailed manner in sections 3.5 and 4.5. However, these contributions are briefly introduced below:

- A mission-based mobility model, called *dPSO-U*, based on the *particle swarm optimization (PSO)* algorithm. The dPSO-U mobility model is able to generate the trajectories for a UAV network performing an exploration and convergence mission, meeting the following main objectives: i) exploring a large-scale scenario area for discovering the ground nodes' locations, and ii) making the UAVs to autonomously converge to the clusters in which the ground nodes are organized.
- A mission-based mobility model, called *Jaccard-based mobility model*, based on the *Jaccard distance metric*, the virtual forces algorithm (VFA) and different *metaheuristics*, such as simulated annealing (SA) and hill climbing (HC) algorithms. The Jaccard-based mobility model is able to generate the trajectories for a UAV network performing an adaptive coverage mission on a medium-scale scenario, with the following main objectives: i) provide communication services optimized according to specific aspects, such as having the maximum number of ground nodes under the UAV wireless coverage area, and ii) maintain the UAV network as a connected network.

1.5 Structure of the document

This thesis consists of 5 chapters. This chapter (chapter 1) introduces this thesis's motivation, the challenges faced, the methods used and the contributions. In chapter 2, the background and a review of the related works are included. Chapter 3 describes the work developed and the results related to the first contribution of this thesis, i.e. the mobility model for a UAV network performing an exploration and convergence mission in a large-scale disaster scenario area. In chapter 4, the work developed and the findings related to the second contribution of this thesis are presented. These correspond to the mobility model for performing an adaptive coverage mission in a medium-scale disaster scenario area. Chapter 5 describes the conclusions and future works expected to continue to this thesis. The existing relations between the chapters are shown in Figure 4.

This thesis contains two appendices A and B. Appendix A describes fundamental concepts upon which the work of this thesis is built such as the metaheuristics used and the Jaccard distance concept, among others. Appendix B is organized in two sections, the first one describes the hardware that has been used during the doctoral studies for assembling several UAVs (this is part of an ongoing effort to build a UAV network test-bed), and the second section describes the software tools developed in this thesis.

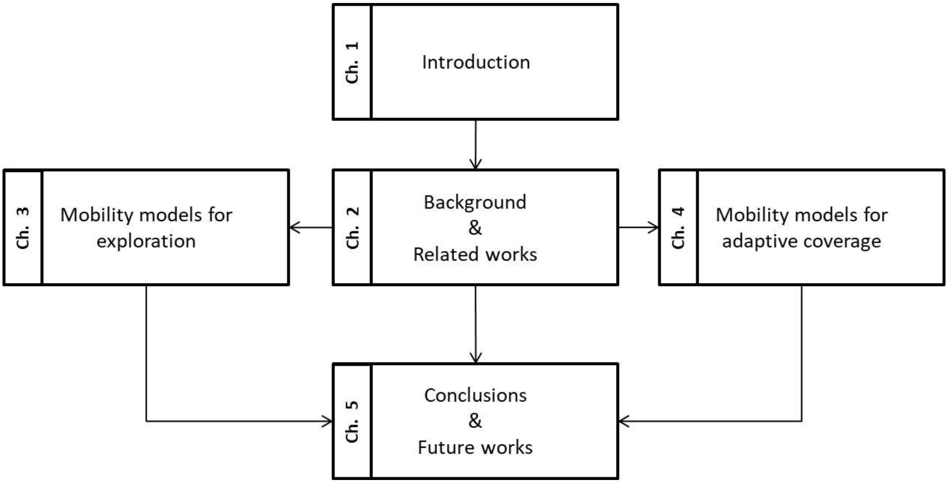


Figure 4. Relations between chapters

2. BACKGROUND & RELATED WORKS

"To develop a complete mind:
Study the science of the art; Study the art of the science.
Learn how to see. Realize that everything connects to everything else."

Leonardo Da Vinci

The research area in which this thesis falls brings together aspects from different disciplines such as electronics, computers science and robotics, among others. In an attempt to provide easy access to the context of UAV networks, the first section of this chapter introduces the reader to the main aspects of this research area. The second subsection dives deeper into *UAV networks mobility*, specifically in UAV networks mobility models and organizes the literature reviewed. Also, this section contains related works on the topics of *disaster scenario models*, as this is an area related to the work developed in this thesis.

2.1 Background

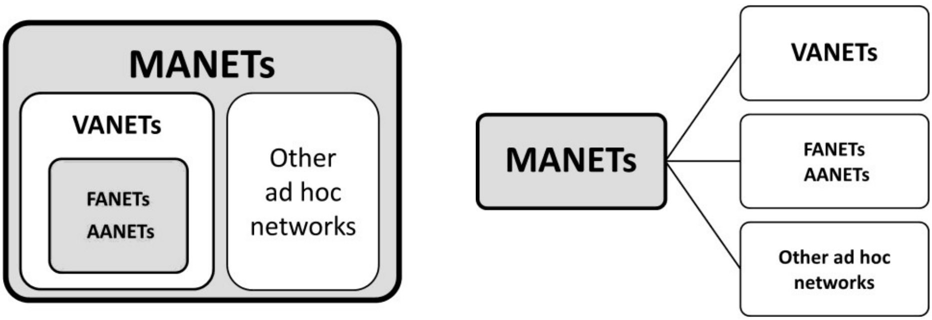
In this section, UAV networks are presented to the reader, in order to provide a big picture of the main aspects related to this topic. This section starts with an introduction to UAV networks. Secondly, it describes several topics of importance for researchers working in this area, namely: i) the type of vehicles that are used as network nodes, ii) the wireless communication technologies that commonly appear in UAV networks applications, iii) the routing algorithms used in UAV networks, iv) the mobility strategies used, and v) a compilation of common applications, with special attention to those related to emergency response operations and disaster scenarios. In order to support the reader coming from another research background, a brief introduction to multihop ad hoc networks is provided in Appendix A.

2.1.1 UAV networks

Aeroplanes have always been able to communicate wirelessly with ground control stations. Nevertheless, the emergence of small size aerial vehicles able to fly autonomously, commonly known as UAVs or drones, have paved the way for the newest paradigm within the family of mobile ad hoc networks: Aerial Ad Hoc Networks (AANETs) [51] [52] [53] [12]. This paradigm is also found in the literature under the names of Flying Ad Hoc Networks [13] [54] (FANETs), or simply UAV networks [15]. In some other cases, the terms Unmanned Aircraft Systems (UAS) [30] [55] or UAV swarm are used to refer to UAV networks [55] [14] [56]. The terms UAV network and AANET will be used interchangeably in this document from now on.

These networks have attracted the attention from the research community and also from final users and even governments such as the European Union [57], USA [57] and China [58], among others. Aside from the governments' interests in UAV networks, the focus has not been put only in military applications. One of the main advantages of this networking paradigm is the accuracy of the mobility of the UAVs, as these are able to move to specific locations in a short time frame while avoiding almost any kind of obstacle, and even able to hover (in the case of multicopters), maintaining a static position on the air during a specific amount of time. These aspects highlight one of the main keys of UAV networks, the ability to adapt the network topology to the scenario conditions, in order to optimize specific aspects [13]. These abilities make UAV networks suitable for many civil applications and, as an example, AANETs have been proposed many times as suitable candidates for being deployed in disaster relief operations. That is the reason why one of the AANETs most important civil applications are emergency response operations [14] [25] [59] [60].

The origin of the UAV networks, AANETs or FANETs is not clear though. Some works describe UAV networks as a subgroup of VANETs, which at the same time is considered a subgroup of MANETs [13]. On the contrary, others consider VANETs as a similar but at the same time different networking paradigm with a very specific application area, while MANETs remain as a generic-purpose networking paradigm [61]. This would make AANETs a specific networking paradigm by itself, being treated independently from VANETs. These different perspectives about AANETs inception are shown in Figure 5. The uncertainty about UAV networks origin has made the research community to study them from several points of view in the last decades. However, an important number of works have focused on the AANETs concept by itself and analysing the advantages and disadvantages of these networks such as [12] [62] [13] [15] [63] [64].



a) AANETs as a subgroup of VANETs b) AANETs as an evolution of MANETs

Figure 5. Different perspectives of AANETs origin

Two high-level categories of UAV networks are proposed in [62]: i) *single UAV networks*, and ii) multiple UAV or *multi-UAV networks*. In UAV networks, the term node is usually used to refer to a UAV. From the cooperative systems point of view, the single UAVs network concept refers to a network with one or more nodes in which UAVs do not cooperate with each other. This means that each UAV is acting independently and without any knowledge of the rest of UAVs that belong to the network. On the contrary, a multi-UAV network implies that there is a direct collaboration between the UAVs forming the network, i.e. each node has some knowledge of the network and its neighbours and makes use of this information when making a decision.

2.1.1.1 Nodes

UAV networks can be defined as a MANET built upon flying nodes, and more specifically, upon UAVs, in the case that the nodes are able to move autonomously. The most common types of UAVs used in UAV networks are two: i) *fixed-wing* and ii) *rotary-wing UAVs* [65]. Fixed-wing UAVs are aeroplane-like vehicles (Figure 6a). These UAVs are characterized for performing Conventional Takeoff and Landing (CTOL) operations, like passenger planes. On the contrary, rotary-wing UAVs (Figure 6b) are able to perform Vertical Takeoff and Landing (VTOL). These can hover in specific locations, maintaining a position in the air during the desired time frame, like typical passenger helicopters. Rotary-wing UAVs are also able to perform sharp turns describing less smooth trajectories than those that are typical of fixed-wing UAVs. In less frequent occasions, a UAV network may be built upon zeppelins or even balloons [66] [67].

a) fixed-wing UAV by the Advanced Center for Aerospace Technologies (CATEC)
© Fundación Andaluza para el Desarrollo Aeroespacial (FADA)

b) Rotary-wing UAV
© ACE-TI research group (University of Seville)

Figure 6. Examples of fixed-wing and rotary-wing UAVs

2.1.1.2 Wireless communication technologies

Typically, a UAV network is built from three types of communication links: i) UAV-to-UAV links also known as *air-to-air links (A2A)*, ii) UAV-to-ground user links, also known as *air-to-ground nodes links (A2GN)*, and iii) UAV-to-ground station link, also known as *air-to-ground control station links (A2GS)* [12]. These communication links are depicted in Figure 2. The UAV-to-UAV links are the communication links established among the UAVs participating in the network and one of the main interests in the UAV networks research. These A2A communication links are normally obstacle-free and LoS (Line-of-sight communications), which makes these links more reliable than typical ground-to-ground links present in MANETs [68]. However, some terrains like Manhattan scenarios may present obstacles (e.g. skyscrapers) affecting A2A links [69]. When the communication link is not LoS, these are known as Non-Line-of-Sight (NLoS) or Beyond-Line-of-Sight (BLoS) [70].

UAV-to-ground user links refer to links between the UAVs and *ground nodes* to which the UAV network is providing communication services [55]. This type of links is also mentioned in the literature as *connectivity to ground personnel* [12]. These A2GN links clearly benefit from the fact that a UAV can fly to a specific position and establish a LoS link, or even adapt the UAV antenna direction in order to maximize the quality of the communication link [68] [19]. Finally, the UAV-to-ground station links (A2GS) are considered separate from the A2GN links because of the heterogeneity of the wireless technologies used. Typically, in a UAV network, a few UAVs are equipped with long-range wireless communication devices for communicating with a control station. Usually, this communication link is called as the control link as it usually carries critical data for the UAV monitoring and operation [70]. A *ground control station* is considered a facility in which a human team receives the data acquired by the UAV network, and even provides high-level commands to the UAVs in order to control the behaviour of the network. The control station may be located in the surroundings of the UAV network deployment (at a distance of the order of a few to tens of kilometres), or separated by a longer distance (in the order of hundreds of kilometres).

The wireless communication technologies used in the UAV network depend on the specific communication link: A2A, A2GN or A2GS. For A2A links common wireless communication technologies are the standards of the *IEEE 802.11 family* [71] [72] [73]. Other alternatives such as proprietary radio frequency communication links [74] can be also found in these links. Also, low data rate wireless technologies such as the IEEE 802.15.4 which would include ZigBee, Xbee or similar ones [75] [76] can be used for these links. Although there is not much literature on UAV networks using IEEE 802.15.1 (Bluetooth), advancements on this technology may leverage its usage in A2A links [77] [78].

For A2GN links the IEEE 802.11 family is a common option as ground users devices are usually provided with IEEE802.11 communications, such as for example smartphones and laptops [39]. Also, low data rate wireless technologies can be used in the case that the information to be transmitted is lightweight; such as for example when the ground users are sensors collecting specific data that need to be forwarded to another location for further processing [79]. Depending on the application scenario, it may be possible to find IEEE 802.15.1 (Bluetooth) A2GN links in future UAV networks [77] [78].

In the case of A2GS links, if the ground control station is close, technologies such as IEEE 802.11 may be used [80] [81] [71]. However, if the ground control station is separated a few kilometres from the UAV network or even more it may be required to resource to licensed technologies like cellular communications (such as GSM, UMTS or LTE), WiMAX (IEEE 802.16) [12] [82] or even satellite communications [83]. It is important to mention that cellular communications and most WiMAX standards occupy a licensed region of the radio frequency spectrum and require an existing infrastructure for its proper operation [12].

2.1.1.3 Routing

UAV networks routing research has inherited many protocols from generic MANETs. MANET algorithms for routing packets can be classified into two main categories: i) broadcast, and ii) ad hoc routing algorithms. On the one hand, in broadcasting algorithms, a source node forwards the packet to all or to a subset of its neighbour nodes. *Broadcasting algorithms* can be organized in different subcategories [84], depending on the selection of the neighbours to which a packet is forwarded. These categories are: i) simple flooding, ii) probabilistic, iii) area-based, iv) counter-based and, v) neighbour knowledge scheme. On the other hand, *ad hoc routing algorithms* actually have mechanisms for discovering the path for transmitting a packet from a source to a destination node. The most common taxonomy for ad hoc routing algorithms has two subcategories [85] [86]: ii) *proactive*, and iii) *reactive*. Proactive protocols are those that proactively maintain a routing table in each node and therefore use this table information for routing a packet. A reactive algorithm does not usually have a routing table and needs to trigger a route discovery mechanism right before sending a packet. Other taxonomies such as the one described in [87] propose other categories such as geographic routing [88], also known as position-based routing or geometric routing. *Geographic routing* algorithms require the knowledge of the location of the nodes and use this information to route packets by sending them to nodes closer to the node destination location.

Examples of routing protocols used in UAV networks are the well-known Ad hoc On-demand Distance Vector routing protocol (AODV) with slight variations [89] [81] [90], Optimized Link State Routing (OLSR) and Predictive-OLSR (P-OLSR) [91] [90] [73] [92], Dynamic Source Routing (DSR) [93], Better Approach To Mobile Ad hoc Networking (BATMAN) [90], and geographical routing algorithms [94] [95], among others. As it happens with generic MANET routing, there is not a prevailing routing protocol for UAV networks, and depending on the application conditions the same protocol may perform better or worse. Apart from the MANET routing protocols adapted to UAV networks, there have been several efforts in designing and implementing UAV network-specific routing algorithms such as the Aeronautical Routing Protocol (AeroRP) [96] [97] or the Mobility-Aware Routing and Mobility Dissemination Protocol (MARP/MDP) [98].

It is also common to find some UAV network applications following the *Delay Tolerant Network (DTN)* paradigm as well. DTNs routing is somehow in a less mature stage than MANET routing and the majority of research has focused on VANETs. Some UAV networks routing approaches use simple DTN forwarding mechanisms based on the basic store-carry-and-forward. In this group, we can find works such as [99] [100] [101] in which UAVs are used as message ferries between disconnected network segments. However, these works do not provide detailed information on the forwarding mechanism used. In [102] autonomous UAVs use the data triage method to classify and exchange messages according to specific priorities while providing communication services to a disaster scenario area. Other works, such as [22], implement the bundle mechanism proposed by the DTNRG (IRTF DTN research group) with the aim to extend communications to rural areas or developing regions. Also, geographic routing protocols have been proposed for aerial networks following the DTN paradigm. This is the case of [103] which proposes the routing algorithm called Location-Aware Routing

Opportunistic Delay-Tolerant network (LAROD) together with the location service called Location Dissemination Service (LoDiS) for a UAV network in a military reconnaissance mission. Some others use approaches extracted from natural processes, such as the work described in [104] which apply concepts derived from modern molecular biology (i.e. genome) in order to connect heterogeneous networks with UAVs following a DTN approach.

2.1.1.4 Topology

Previous to the deployment of an infrastructure-based network, a specific topology is chosen in order to meet the application requirements. Selecting the appropriate topology for a network is of paramount importance as the network performance and its reliability highly depends on it. Examples of well-known topologies are star, ring, daisy-chain, mesh and tree topologies, among others.

UAV networks are *infrastructure-less networks* in which nodes are mobile and therefore: i) there is not a pre-defined topology, and ii) the topology may change over time [13]. The mobility capability of UAVs is one of the main advantages of AANETs. However, the great advantage of UAV mobility comes with a price because the mobility and the relative position of a node with each other strongly affect the network performance. Thus, generating specific trajectories for the UAVs that allow meeting the application requirements and, guarantee a minimal network performance at the same time is one of the main challenges of UAV networks.

Among the common topologies used in UAV networks, we can find: i) star, ii) multi-star, iii) flat and, iv) hierarchical topology [15]. Star topologies consist of a UAV network in which all the UAVs connect through a central entity. This entity is usually a ground control station. In multi-star topologies, there are ad hoc communication links between a subset of UAVs and at the same time, each UAV acts as the entity through which a star topology is built with other UAVs. Flat topologies are those in which all nodes are considered peers and there is not a node that acts as a central entity for connecting others. UAV networks can also present hierarchical topologies in which the nodes of the network are organized on different levels. A two-level hierarchy is typically found in UAV networks. The lower-level nodes perform specific tasks directly related to the mission accomplishment. On the contrary, the higher-level nodes are commonly provided with long-range communication capabilities (cellular communication or satellite) and act as a gateway interconnecting the UAV network with other networks or directly with a ground control station [13].

Usually, the UAVs that belong to a specific hierarchy level are equal in terms of hardware and software and perform similar tasks. However, in specific cases, there may be UAV networks composed by different UAVs (with different equipment and capabilities) in which each UAV contribute to the network with its specific abilities. This has been proposed in surveillance applications with different UAVs in which each of them was assigned a different area size to patrol, according to its sensors performance and it flying capabilities [105] or in disaster management operations [11].

Moreover, the mission requirements may force the UAV network to have a dynamic topology, which means that the topology may change during the mission execution. According to [106] there are three categories for a UAV network topology: i) constant, when the network topology does not change, ii) unconstrained, when the topology may change and the nodes are allowed even to disconnect from the network, and iii) constrained, in which the topology may change over time but the nodes have to maintain connected network, i.e. no nodes may disconnect from the network.

2.1.1.5 Degree of autonomy

UAVs are *autonomous vehicles* by definition and therefore, when it comes to UAV networks, a certain degree of autonomy is assumed. However, the level of human interaction in UAV networks may vary from one application to another and it depends on the application requirements. Common tasks in well-known scenarios can be performed by fully autonomous UAV networks, but complex missions and unknown scenarios may require human operators supervising the UAV network behaviour or even taking the control of specific tasks for the sake of the mission [106]. Disaster relief operations are an example of a complex mission which may require a certain degree of human decisions.

Usually, the literature on UAV networks [70] [106] differentiates between 3 categories when referring to the degree of autonomy: i) autonomous, ii) semiautonomous or man-on-the-loop, and iii) non-autonomous or man-in-the-loop (please note the slight difference between the "on" and "in" prepositions between the semiautonomous and the non-autonomous cases). Autonomous systems are those able to perform tasks without direct real-time control from a human operator on the ground. This means that the UAVs are provided with abilities to interact with each other and with the environment in order to successfully accomplish the mission assigned. In semiautonomous systems, the UAVs also perform most of its actions autonomously but there are always one or several human operators supervising the behaviour of the UAVs ready to take over control in the case of necessity. The non-autonomous category implies that one or several pilots are operating the aerial vehicles with a radio transmitter. In this case, the UAVs are also referred to as RPAS.

Apart from the previous classification, the degree of autonomy of a UAV network may be categorized according to the specific aspects that are controlled by a human operator. For example, a UAV network may present some human-controlled aspects such as the mobility or the communications aspects, among others, while some other aspects are fully autonomous. Also, in some cases, a human operator may decide to perform a human-controlled action on a specific node of the network or over a subset of the UAVs but not on the entire network [106]. Examples of a human operator action on specific nodes may be making an aerial vehicle to fly towards a specific location, or controlling specific routing aspects of a UAV such as prioritizing a specific type of network traffic over another. Examples of human actions over a group of UAVs may be to make the UAV network formation centroid to move towards a specific direction.

2.1.1.6 Mobility

A broad picture of UAV network mobility is provided in this section, not specifically centred in mobility models but from a more generalist point of view. The navigation capability of a UAV is known as the ability to follow the assigned *trajectory* [107], also known as *point-to-point motion* [38]. There are various research topics that study how to generate UAVs trajectories, namely path planning, motion planning and mobility models. Motion planning [35] [108] is the most generic research topic among the aforementioned. Its aim is to find a valid trajectory, a sequence of positions along with motion details (i.e. speed, acceleration) associated to each position, to make a mobile entity to move from its initial state to a destination state [35]. In motion planning, a state refers to a specific configuration (i.e. a vector of parameters defining the position and orientation of the vehicle) coupled with the derivative of the configuration (i.e. velocity, among others). Path planning [109] can be considered a subset of the motion planning problem in which the focus is put mainly on the trajectory as a sequence of *waypoints*, without considering motion constraints. Path planning approaches usually use simpler vehicle models for calculating the trajectories. The simplest model considered in path planning problems uses a point to represent the mobile vehicle and motion capabilities with no constraints (e.g. a vehicle can move at very high speeds and accelerations). Although vehicles, in reality, do have motion constraints, path planning approaches use these abstractions in order to calculate the trajectory.

Mobility modelling can be considered a research topic that emerged in parallel to MANETs and has shown important research activity since then. It focuses on capturing the mobility attributes of a set of network nodes in a specific scenario [34]. The main aim of mobility models is to provide a mobility behaviour that can be used later to *analyse networking aspects*, such as network connectivity, node degree and routing algorithms performance, among others. Mobility models also use simple mobile entities' models (i.e. a vehicle is usually represented as a point in the space) and simplified motion equations as the focus is put on the network performance analysis. It has been demonstrated that mobility models have an important effect on routing protocols performance [110] [34]. As the mobility behaviour of network nodes can be very different from one scenario to another (e.g. robots performing exploration tasks of an unknown area or several robots following a mobile target) mobility models' objective is to *emulate* the mobility of the network nodes in specific application scenarios. This does not mean that there are not generic mobility models such as the popular *Random Waypoint (RWP) mobility model* [34] [111], it only means that application-specific mobility models are more approximate to the mobility of the real nodes than generic models.

In the case of a UAV network, all motion planning, path planning or mobility models can be used for calculating the UAVs trajectories, depending on the interest sought (i.e. a precise motion, a set of trajectories decoupled from motion data or the mobility behaviour for pursuing research on networking aspects, respectively). In any case, the approach selected has to consider that a UAV network consists of multiple vehicles.

Regarding the type of approach for generating multiple vehicle trajectories several categories can be found such as centralized, decentralized, and distributed [112] [113] [114]. In centralized approaches, a central node, either a UAV or a ground control station, is responsible for most of the mobility decision-making [115]. In decentralized approaches, there is not a unique central entity and usually, each node can make decisions using exclusively its local information, without exchanging data with other nodes. Distributed approaches are like decentralized ones, with the difference that nodes do share their local information with each other. In random approaches, the nodes move with random direction and speed. The network nodes are even free to decide when to change their current direction and speed.

Centralized approaches are less reliable because a failure in the central node will compromise the entire mission. Decentralized approaches do not suffer from the reliability problem, but the mechanism of sharing information between nodes is not exploited. Distributed approaches have both advantages, they are reliable and they take advantage of the nodes' information sharing mechanisms [116] [117] [118]. Although it is difficult to imagine an application in which a team of UAVs is moving randomly, some degree of randomness may bring benefits to the objectives of a UAV network. These approaches are usually known as uncontrolled mobility. The benefits that partially random approaches may bring to UAV networks mobility are even more feasible in the case of UAV networks with numerous nodes [34].

Another classification that can be applied to trajectory generation approaches considers two categories: i) offline, and ii) online (or dynamic). Offline methods refer to these cases in which the trajectories of the UAVs are generated previously to the mission development. The UAVs are expected to follow the assigned trajectories as accurately as they can and the only variations allowed are those related to unexpected events such as avoiding an obstacle. Offline approaches usually require having some knowledge of the scenario prior to the trajectories generation [108]. Online methods refer to those approaches where the trajectory generation is performed during the mission time. In online methods, the UAVs may have some initial trajectories; however, these trajectories get modified during the mission course. Online approaches are also known as sensor-based planning [108].

2.1.1.7 Applications areas

UAV networks have a lot of applications. In each application field, UAV networks may be used to carry out *generic tasks*, which are those commonly found in different application fields, or *application-specific tasks* which are those that highly depends on the application and its scenario. As an example, a generic task would be searching for a specific target, which can be found in military operations (locating an enemy) and in emergency response applications (finding victims), among others. In the case of application-specific tasks, examples are destroying a target (military applications) or measuring a specific chemical substance in the air (environmental applications), among others.

Also, it is common that UAV networks overlap with other ad hoc networking approaches depending on the application for which they are used. For instance, when AANETs are used for monitoring the environment (either the air or the ground) they share the main purpose of Wireless Sensor Networks (WSNs) [19] [119] [14] [63] [120]. When AANETs are deployed over an area as a way of extending connectivity, the UAVs can be considered as mesh routers in a Wireless Mesh Networks (WMNs) [59] [39] [81]. Several works have proposed Delay Tolerant Networks (DTNs) in which nodes are Unmanned Aerial Vehicles (UAVs) [99] [100] [101] [121].

In this section, the most common applications areas for UAV networks are summarized, providing examples of research works for each application area. The aim is not to provide an exhaustive description but to briefly introduce the areas that have received more attention from both the research community and the industry.

2.1.1.7.1 Military

UAV networks and UAVs, in general, were first used for military purposes. Although UAV usage in military missions is common, military research is not usually disclosed. However, there is some public research carried out on the field of UAV networks in military missions, such as [122] [123] [93]. It is usual that military forces participate also in emergency response operations and therefore some research works may cover both applications. However, there are always specific tasks that are exclusive for military applications such as warfare operations UAVs, and thus this section is usually considered as a separate one from emergency response applications.

2.1.1.7.2 Environmental monitoring

UAV networks bring multiple possibilities to environmental monitoring applications. In these applications, a UAV network usually carries sensors with capabilities for measuring air substances. Another possibility is to embed cameras in the UAVs so they can monitor the ground and detect specific events such as the quality of the soil or the health of the trees in a forest, among others. An interesting approach is to integrate UAV networks measurements together with remote sensing data from a satellite, in order to obtain added value information. Examples of works dealing with this type of applications are [14] [19] [20] [100] [101] [124].

Those works using UAV systems for agriculture applications can be also included in this category as the main objective is to monitor natural processes, for example, the growth of crops. Most of the solutions proposed for agriculture scenarios are single-UAV systems as it has been described in works such as [120] [125]. Despite this fact, there is an increasing interest in taking advantage of the potential of multi-UAV systems in agriculture applications as it has been demonstrated in [126].

2.1.1.7.3 Logistics

Using UAVs for logistics is attracting the attention of the research community and also the industry. Delivering goods in parcels to hardly accessible places (e.g. where no highways or roads infrastructure is available) can be easily overcome with UAVs. Rural areas and post-disaster scenario areas are examples of these hardly accessible locations. Also, highly populated urban areas might suffer from congested roads and this can delay the delivery of important goods (e.g. medication or medical resources). Although this application category does not always require the UAVs to work as a network, it is desirable to have a UAV network if possible [12] [127] [128].

In addition, UAVs can be used for monitoring a factory inventory and transporting items between different locations of the factory [129] [130] [131]. This could increase production efficiency and also avoid casualties in the workplace. This specific application has been described under the name of *intra-logistics* in some reports [132]. Examples of works focusing on using UAV networks for logistics are [133]. There are also multiple companies currently working on UAV projects for logistics [134] [135] [136].

2.1.1.7.4 Emergency response

The ability of UAV networks for establishing a rapidly-deployed network which is also able to adapt to very different scenarios is of great potential for emergency response operations. Research focusing on this application area usually uses the term of *UAV networks for disaster scenarios*. The benefits of UAV networks in this case range from the capability of surveying the area affected by the disaster in a short amount of time, discovering victims, giving first aid information or supporting first responders rescue tasks. Examples of these research works are [137] [23] [39] [25] [24] [102] [138] [11] [139] [30].

2.1.1.7.5 Value-added communication services

Apart from the previous application areas, there is a heterogeneous body of work centred on providing communication services to specific scenarios. Within this category, there are research works and even companies working on extending Internet access to rural and isolated areas. This is the example research works as [22]. Well-known companies have worked in similar projects, such as the solar-powered UAV designed under the project Aquila [140] [141].

Other research works focus on using UAV networks for providing value-added services, for instance, guaranteeing communication services in high demand scenarios (e.g. supporting temporarily specific network infrastructure suffering from high traffic loads) or providing increased robustness to some other networks that may need to strengthen some aspects (e.g. reduce propagation delay, increase delivery ratio or even heal some network issues temporarily). Examples of this type of research works are [104] [142].

2.1.1.7.6 Civil engineering

Other researchers have worked on UAV systems for civil engineering applications. Within this category, applications such as infrastructure monitoring, topography and construction can be considered, among others. The benefits of using UAV networks in this type of applications are several ,such as reducing the risks of specific tasks (e.g. monitoring a tall infrastructure without the need of workers to climb to the infrastructure) or reducing time (e.g. generating a 3 dimensional map of the terrain in short time with a team of UAVs). Examples of these works are [17] [18] [143] and [144]. Teams of UAVs working on load transportation can be also considered adequate for construction applications such as those described in [127] and [128]. A team of UAVs may be able to transport dangerous loads with a high level of accuracy, avoiding the need of operators being close to the load and thus reducing the risks.

2.1.1.7.7 Other

Beyond the categories described above, UAV networks can be found in a considerable number of applications, such as film shooting or photography. Due to the versatility of UAV networks and the continuous advancements in this research area, it is expected that the number of applications will increase in the next years.

2.2 Related works

This section presents the literature reviewed and taken as a reference for carrying out the research work described in this thesis. The literature reviewed has been organized various subsections: i) UAV network mobility algorithms, ii) UAV network missions for disaster scenarios and iii) disaster scenario models.

2.2.1 UAV network mobility algorithms

Within the numerous aspects that can be studied in the field of UAV networks, mobility is one of the aspects that have attracted the attention of the research community. UAV mobility can be addressed from different perspectives such as path planning, motion planning, and mobility models. As aforementioned in section 2.1.1.6, these three research topics have a different manner to address the problem of calculating the trajectories for UAVs [35]. A trajectory is defined as a sequence of positions that a vehicle has to visit in order in order to move from its initial position to a goal position. Path planning approaches find the optimal trajectory that makes the vehicle to move from the start to the goal without any consideration of the time, velocity or accelerations. Motion planning takes into account the vehicles motion equations with more detail and each point in the trajectory is associated with a specific timestamp and a state of the vehicle (including position, orientation, velocity and acceleration, among others). Depending on the application requirements, motion planning and path planning may use vehicle models with different level of details (the simplest one represents the vehicle as a point in the space) [35].

In a similar way, *mobility models research* aims to imitate the mobility of the mobile nodes that form a network. The final goal of mobility models research is to analyse the networking properties of the network. For reaching this goal, a mobility model needs to capture the mobility attributes of the nodes with enough realism for analysing the networking aspects. Mobility models have been extensively used in networking simulation works and it has been demonstrated that the specific mobility model used has an important impact on the performance of the network [34] [110] [103]. At the same time, the mobility model needs to be an abstraction of the real mobility of the nodes, so the research focus can be put on the networking aspects without devoting more efforts to generate nodes real trajectories. For this reason, it can be said that mobility models research overlaps with some of the interests of motion planning but with the difference of generating trajectories in a simpler manner and with more abstract vehicle models. Examples of research works using simpler trajectories and abstract vehicle models are [38] [34] [39] [24], among others. In these works, trajectories are defined as a sequence of waypoints. These trajectories are also called *high-level trajectories* within the literature. When high-level trajectories are used, each vehicle is assumed to have mechanisms for performing basic movements such as moving from one position to another or even detect-and-avoid an obstacle while following a trajectory.

The most popular mobility models found in the literature are usually those developed for MANETs. A common classification for MANET mobility models can be found in [34]. This classification is summarized in Appendix A for the sake of the reader. The first research works on aerial mobility models appeared several years later than most of the MANET models. The reason behind this situation is that the aerial networks, such as the UAV networks, emerged as a new multihop ad hoc network type only a few years ago. Adapting the MANET mobility models available in an attempt to capture the mobility attributes of aerial networks has been an approach followed by numerous works. As MANETs are generic purpose networks, the majority of the mobility models associated is also generic, i.e. these do not usually represent movements associated with nodes carrying out specific tasks. Other research works, proposed new mobility models specifically developed for aerial networks trying to emulate basic movements of aerial vehicles, such as smooth turns that are typical from fixed-wing aerial vehicles. Finally, some researchers have proposed mobility models which capture with more detail the mission-like nature of UAV networks. According to this, the aerial mobility models can be organized in two main categories: i) *non-mission-based mobility models* and, ii) *mission-based mobility models*. These categories are described in the following sections. According to the classification given in Appendix A.2, there is another detail worth mentioning, which is that most of the mobility models proposed in UAV network research are synthetic. Synthetic mobility models do not use real vehicle mobility traces to generate the trajectories but formulate mathematical expressions that yield artificial trajectories which emulate the reality.

2.2.1.1 Non-mission-based mobility for UAV networks

The non-mission-based category includes those mobility model adapted from MANET research and also the mobility models that emulate simple fixed-wing vehicle movements. One of the first groups found in the non-mission-based mobility models category are the well-known *random models* such as the Random Walk (RW), Random Waypoint (RWP), and Random Direction (RD). The RW, RWP and RD mobility models are very common in the mobility models research, possibly because these models are really easy to implement. However, random models present the problem of generating sharp trajectory changes such as prominent turns and sudden speed changes. These trajectories are not adequate for fixed-wing vehicles as these are not able to perform abrupt manoeuvres. On the contrary, these trajectories may represent realistic trajectories for rotary-wing vehicles such as multirotors. However, the trajectories generated by these models are mainly random and without clear intent or objective of carrying out a specific task. Due to the fact that aerial vehicles (fixed-wing or rotary-wing) are mainly used for specific tasks and mission-based operations, these random mobility models are not adequate for representing the trajectories of a UAV network. Other works using random mobility models such as the RWP or slight modifications of it for aerial vehicle networks are [145] [96] [97].

Among the MANET-adapted mobility models, the group of the *temporal dependence models* present some features that are appropriate for aerial vehicles. Examples of temporal mobility models are the Gauss-Markov (GM) random mobility model and the Smooth Random (SR) model [146]. These models have the advantage of not generating abrupt trajectories as random models do. However, both the SR and GM model use stochastic processes and random variables to control the specific time at which a speed or direction change event occurs. This implies that these models present some inappropriate features for representing aerial vehicles mobility, namely: i) the GM model has difficulties to produce rectilinear trajectories and, ii) there is no control over the specific time at which a speed or direction change occurs. Based on the aforementioned aspects, it is clear that these models could not represent fairly aerial networks mobility. Some variants of the GM and SR models have proposed models that offer smooth trajectories and at the same time, some control over the mobility changes events, such as the Semi-Markov Smooth (SMS) mobility model [146]. An improved solution aiming to emulate aerial networks mobility with higher realism is the Improved semi-Markov Smooth (ISMS) mobility model proposed in [53]. The ISMS is described as a mobility model that overcome the problems known as sudden stop and sharp turns that the RWP produces for fixed-wing aerial vehicles. Other works using Gauss-Markov based mobility models for analysing routing protocols performance on aerial networks are [147] [148] [149].

Several works can be found within the group of mobility models that are specific for aerial networks and propose non-mission-like mobility. As aforementioned, these are models that propose different approaches for emulating simple fixed-wing aerial vehicles movements. Among these works, an example is the Smooth Turn (ST) mobility model [150] [151]. The ST model focuses on reproducing the smooth turns that are typical of fixed-wing aerial vehicles. In order to achieve this, a node in the network selects a destination position located along a perpendicular line to its current trajectory. Once the destination is selected the node starts describing a turn around the selected location. This process is repeated iteratively. This model may be considered as a special case of the TW model which is described in the next section. Another example that emulates aerial vehicle network mobility in a simple manner is the work described in [152] in which the authors propose the Restricted Random Walk model (RRW). The RRW model consists of a leader node that moves according to the RW mobility model, while the rest of the nodes simply follow the leader movements with a restricted set of directions and maintaining the leader speed. The RRW is used to analyse the connectivity of aerial vehicles and the nodes' communication range needed in order to maintain a connected aerial vehicles network. Although this model generates trajectories similar to a flight formation of a team of aerial vehicles, the leader moves according to random mobility defined by the RW model. This is the reason for considering this work as a non-mission based model.

Also, *multi-tier mobility models* [34] are those in which each aerial vehicle of the network follows a different mobility pattern which is not related to the mobility of the other nodes. In these models, a few nodes can move according to one of the aforementioned models while others move according to a different one. This model aims to emulate the heterogeneity of aerial vehicles in reality. As emulating the heterogeneity is the main objective of this mobility model, it is considered a non-mission-based model.

It is important to remark here that among the several works for aerial mobility models introduced in this section, almost all of them focused on reproducing trajectories typical from fixed-wing aerial vehicles [34]. However, some aerial vehicles such as multicopters are able to perform sharp turns and abrupt movements due to their mechanical capabilities and this has not been considered in the research works on aerial vehicles mobility models.

2.2.1.2 Mission-based mobility for UAV networks

Opposite to the non-mission-based category described in the previous section, the mission-based mobility refers to those approaches with the goal of representing the mobility of aerial vehicles that perform a specific mission. It is obvious that the mobility of the vehicles will vary depending on the mission type, e.g. the mobility of a team of aerial vehicles performing an exploration mission will be different to those performing the mission of providing communication services over a specific area. However, in both cases, the aerial vehicles share the behaviour of moving to specific positions and performing a specific task or action.

Among the mission-based mobility models, there are works that have proposed mobility models for aerial vehicles performing very *simple missions*. The Semi-Random Circular Movement Mobility Model (SCRM), the Three-Way Random (TW) mobility model and the Pheromone Repel mobility model (PR) are good examples. The Semi-Random Circular Movement Mobility Model (SCRM) [153] generates circular trajectories for the aerial nodes of the network. Each node selects a random speed and flying angle to describe the circular trajectory around a fixed centre location. This random selection can be made once or several times per round. When the node completes one round it selects a new radius for describing a new circular trajectory. This process is repeated iteratively. This mobility model has been proposed for aerial networks performing Search and Rescue (SAR) missions in which a team of aerial vehicles monitor a defined area in search for a target while describing circular trajectories. The SCRM model assumes that the SAR mission is accomplished by describing circular trajectories. However, in reality, SAR missions usually require more complex behaviour than simple circular trajectories.

The Three-Way Random (TW) [103] mobility model uses constant parameters for the speed and the turn radius of the nodes. In addition, a Markov chain is used for representing the probability of the node next movement, which can be one of three possible modes, namely: i) going straight, ii) turning right, and iii) turning left. The authors in [154] propose a mobility model using a Markov process that randomly decides whether to maintain a straight direction, turning right or turning left, which is a similar approach to the TW mobility model. This strategy is used to represent the behaviour of the group of UAVs in a simple exploration or reconnaissance application.

The Pheromone Repel mobility model (PR) is used in [154] for a group of UAVs in a reconnaissance mission. The PR model uses information shared among the network nodes for calculating the next movement of each node. The information shared among nodes corresponds to virtual pheromones representing whether a specific subdivision of the scenario was previously visited by another node and if the visit occurred recently. It is typical in the PR model to have the scenario divided into cells. Also, the PR model uses some techniques for sharing the pheromones information among the nodes, such as pheromones information broadcasting or a dynamic map containing the information of the pheromones associated with each cell. The main aim of this mobility model is to minimize the time spent in exploration. This mobility model has been validated with simulations, using 10 UAVs.

The Flight-plan based mobility model [98] uses pre-defined trajectories and each node of the network is assigned to one of these trajectories. This mobility model is typically used to model the mobility of aerial vehicles that know the trajectory to be followed in advance, such as commercial aeroplanes. This model has the only intention of emulating the aerial vehicles traffic in a specific area, i.e. the only task that the aerial vehicles are assigned is to fly from an origin to a destination location. This model can be considered a special case as there is not a clear mission behind the mobility model. However, as it aims to represent the mobility of a set of aerial vehicles flying from origin to destination as commercial aeroplanes do, this model is considered a mission-based one.

Apart from the aforementioned models, i.e. the SCRM, TW, PR and the Flight-plan based mobility models; there are not many other mobility models per se for aerial networks. Nevertheless, there are *other works* proposing *mobility algorithms* for UAV networks which are not specifically described as mobility models. This means that those other works have been proposed with the goal of generating trajectories and solving, for example, the path planning problem, but not from the perspective of a mobility model that will be used for analysing networking aspects. However, those use high-level trajectories for the UAVs which could be easily transformed into mobility models. Also, these works introduced below are considered in this section because they generate aerial networks trajectories for specific missions. This makes these works very interesting for the future goal of designing and implementing mission-based mobility models. Figure 7 shows the categories of mobility model for aerial networks considered in this thesis and some of the most common mobility models for aerial networks.

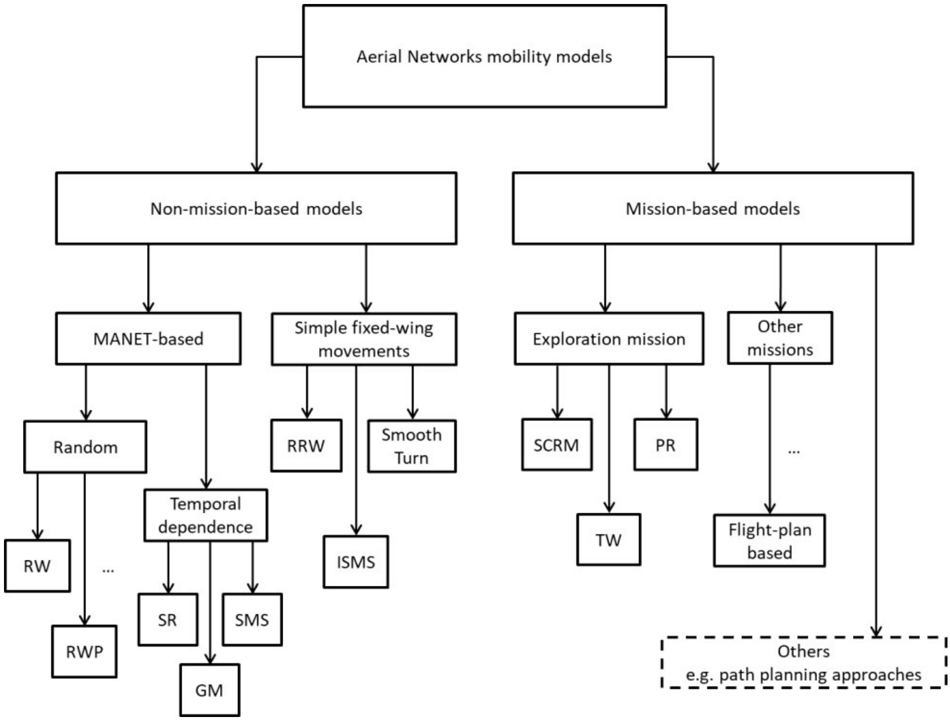


Figure 7. Categories for aerial networks mobility models

Usually, path planning approaches for exploration missions consists of sweeping the entire scenario area and involve two separate phases: i) the scenario area division in several cells and, ii) a path planning mechanism that guarantees that each cell is covered in its entirety. The scenario area division is treated with different algorithms that are not covered by this document because the proposed mobility models in chapters 3 and 4 do not use those. However, the path planning approaches are of interest here as these are usually designed to minimize some aspects (e.g. time or distance) while guaranteeing that the entire cell area is covered. Among these mobility approaches, the zigzag approaches are one of the most common in the literature [155] [156] [108]. Between the zigzag mobility patterns, the Lawnmower (LM) [155] [156] is characterized by having the vehicles to follow a rectilinear trajectory (as a virtual rectilinear lane) until the boundary of the cell or the scenario is found. Then the vehicle makes a turn and describes another rectilinear trajectory on a parallel lane adjacent to the previous one and in the opposite direction (all the virtual lanes together yield in the scenario or cell area). An example trajectory for the Lawnmower mobility pattern is shown in Figure 8. The simplest form of this mobility pattern considers that the vehicles, i.e. the UAVs in this case, make the turns outside the cell area so it is guaranteed that the area of interest is completely covered. One of the benefits of this mobility pattern is that is able to guarantee the full coverage of the area and minimize the time spent as well as the distance travelled.

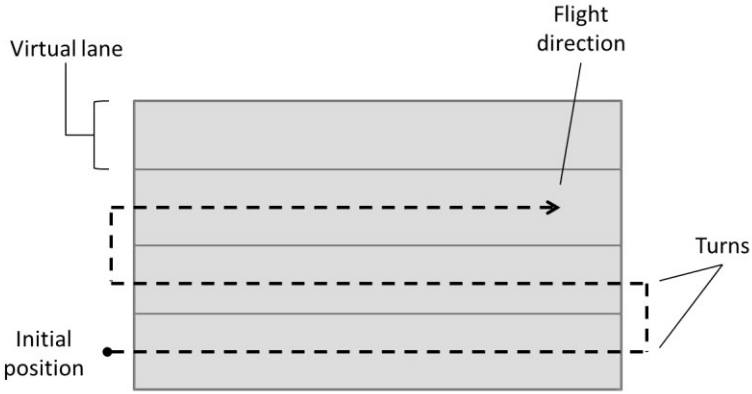


Figure 8. Lawnmower mobility pattern

A similar approach is the Zamboni mobility pattern [155] [156], which is based on the mobility of the machines used for resurfacing ice fields in hockey arenas. These machines are not able to follow a Lawnmower mobility pattern due to their large turning radio. For this reason, the Zamboni mobility pattern complies with the following approach. First, the vehicle describes a rectilinear trajectory in a virtual lane located at one of the edges of the cell area. When the vehicle reaches the cell boundary, it moves to a virtual lane (parallel to the previous one), but located in the centre of the cell area and the vehicle describes a rectilinear trajectory within this lane and in the opposite direction of the previous trajectory. After the cell boundary is reached again, the vehicle moves to a new lane located next to the first lane that was swept. Then, the vehicle follows a rectilinear line within that lane. At the time that the cell boundary is reached again, the vehicle described another rectilinear trajectory within a lane next to the one located in the centre of the cell area. This process is repeated until the entire area is covered. An example trajectory corresponding to the Zamboni mobility is shown in Figure 9.

Figure 9. Zamboni mobility pattern

Other approaches use the spiral-based patterns [155] [156] for surveillance and exploration missions using UAVs. The original spiral mobility pattern is designed for covering a scenario area while minimizing the time spent. In this approach, a UAV starts at the centre of the scenario area and describes circular trajectories while incrementing the turn radius gradually. By doing this the trajectory described by the UAV resembles a spiral curve. As an example, the authors in [39] propose a spiral track for a UAV assigned with the task of exploring a specific area in search for a point of interest. The issue with this approach is that, if the sensors used for scanning the scenario are cameras, it is difficult to get high-quality images in a trajectory that is a continuous turn, due to the aerial vehicles kinematic constraints. Also, if other directional sensors are used and fixed to the UAV frame, their measurements may be also affected by the turns. This is why rectilinear trajectories are preferred to turns because in the case of directional sensors it is easier to get better measurements in a rectilinear trajectory. An alternative that brings together aspects of the spiral pattern and the Lawnmower is the spiral-like mobility pattern. This pattern also considers a UAV starting at the centre of a cell and at the beginning the UAV describes a short rectilinear trajectory within a virtual lane aligned with the cell larger dimension. After this short flight, the UAV turns and follows a rectilinear trajectory parallel to the previous one, but on a virtual lane adjacent to the previous one and increases the flight distance a little. When this trajectory has finished, UAV turns 90 degrees and moves in a rectilinear trajectory to a lane adjacent to the first lane but located on the opposite position of the current lane. Also, the flight distance is increased again by the same amount that was increased the first time. This process is repeated until the entire area is covered. An example of a spiral-like trajectory is shown in Figure 10. The spiral-like pattern has the benefit of having rectilinear trajectories which facilitate gathering high-quality information from the ground using directional sensors. However, the multiple turns that are made within the area of interest have the same issue than the original spiral pattern. These turns yield specific regions where the directional sensors are not pointing towards the direction of interest (e.g. the ground surface).

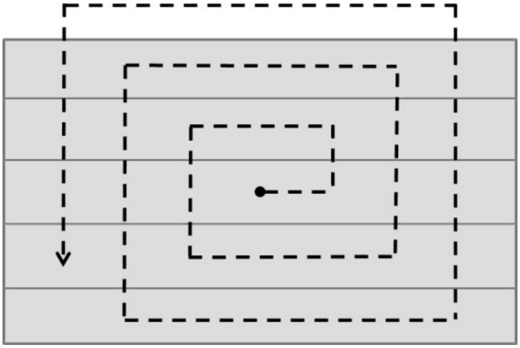


Figure 10. Spiral-like mobility pattern

It is also important to mention that Lawnmower, Zamboni, spiral and spiral-like mobility pattern usually work with pre-planned trajectories. This means that the UAVs trajectories are calculated before the mission starts. This guarantees the optimization of specific aspects such as fully covering the scenario area, minimizing the time spent or the distance travelled. However, there are missions where time is scarce and the scenario conditions are complex and may change over time. Generating trajectories for multiple UAVs for a complex scenario may lead to spending time in advance without having the certainty that the trajectories will be optimal or even efficient. An example of such complex scenarios is disaster-stricken areas. In disaster scenarios gathering information from the area affected or providing communication services to victims and first responders as soon as possible is vital.

Some other works centred in generating high-level trajectories for teams of UAVs in mission-like operations include the usage of metaheuristics. Path planning and motion planning problems complexity normally increase when mobility and scenario constraints are taken into consideration (e.g. forbidden areas, vehicle-specific kinematic constraints, avoiding collisions, among others). Considering multiple constraints is common in these problems as these usually represent a situation closer to reality. Therefore, in many cases, it is difficult or unfeasible to solve these problems by analytic means. It is in most of these cases where metaheuristics bring the benefit of providing close-to-optimal solutions to these problems and finding viable trajectories. The works using metaheuristic approaches, and the mission each one is trying to accomplish with a team of UAVs are described in the next paragraphs. Due to the fact that different metaheuristics are also used by the mobility models proposed in this thesis, such as Particle Swarm Optimization (PSO), a brief introduction to metaheuristics [157] [158] and some *nature-inspired algorithms* is provided in Appendix A.

Some of these works have used the PSO algorithm. As an example, in [115] the authors implement a PSO algorithm on a team of UAVs used for object localization and tracking tasks. The solution is tested in simulated environments and also in a real indoor scenario. One particularity is that the PSO algorithm is not distributed. The algorithm is executed by a ground station that is connected to the UAVs at any time. Thus, the solution proposed is appropriate for small-scale scenarios, but not for large-scale ones. Also, in [117] the authors propose the combination of the PSO algorithm together with a Virtual Forces Algorithm (VFA). The PSO algorithm is distributed and is used to find several zones of interest. Afterwards, the VFA is used in order to make the UAVs spread and maximize the coverage. The solution uses dynamic inertia values within the range [0.1, 0.7]. No information is given for the local and global best parameters values and no characterization of the algorithm is performed either. Also, a big number of UAVs is used, ranging from 30 to 80. Another work using the PSO algorithm is [68], in which a team of UAVs is used for improving the communication services provided by a 5G network. The drones act as relaying entities between the base station and the users. The problem addressed is finding the optimal positions of a dedicated number of UAVs for maximizing the user coverage ratio. A PSO-based algorithm called per-Drone Iterated PSO (DI-PSO) is proposed, in which PSO is employed for calculating the optimal position for each drone individually. Another example is [159], in which a team of UAVs performs a fire fighting mission in a forest-like scenario. The targets locations, i.e. fire spots, are assumed to be known before the mission starts. An auction-based algorithm is used to assign a UAV to each fire spot. Afterwards, the UAVs use the PSO algorithm together with the control parametrization and time discretization (CPTD) algorithm in order to optimally calculate their trajectories towards the fire spots.

Other metaheuristics such as the Ant Colony Optimization (ACO) algorithm has also been used in search problems. As an example, an approach to solve the minimum time search problem (MTS) using ACO-based techniques and UAVs is described in [118]. The parameter optimized is the time required to find a mobile target on the ground. The scenario is discretized and modelled as a grid of cells. Each cell is associated with the probability of the fact that the target is present in the cell. Thus, the scenario can be considered as a probability map, which is updated with the information obtained from the UAVs sensors. Other works using ACO can be found in [160] and [23], where a set of fixed-wing UAVs explores a disaster scenario with the aim of finding a first responder. The ACO algorithm is used for performing the scenario exploration. After finding the target, a reliable communication link is established between the first responder and the ground station. The novelty is having the UAVs divided into two groups. One of the groups is devoted to creating a subnetwork in which the virtual pheromones of the ACO algorithm are deposited. The second group uses these pheromones in order to find the best path from the first responder to the ground base station. A similar approach to ACO is used in [161], in which an agent-based simulation tool is developed for collaborative search task of a group of UAVs. The search mechanism is based on a pheromone-based technique similar to some of the ACO algorithm foundations. The scenario of interest is divided into cells. Each UAV leaves synthetic pheromones when it visits a cell. This pheromone mark is sent to a central controller (either another UAV running this central controller or a ground control station). The central controller uses the pheromones in order to build a map of visited cells so the rest of UAVs are able to explore the non-visited regions. The aim of the mission, in this case, is to perform a search task of a target, not to provide coverage to it.

Other works use different metaheuristics from PSO and ACO, such as other swarming approaches. For example, in [114], the authors propose a solution for exploring a geographic area with a team of small UAVs. The solution is based on a mobility model called Alpha-based. It emulates the behaviour of swarm algorithms regarding the aspect of sharing information between UAVs. Based on that information, each UAV makes a decision about following the best among its neighbour UAVs, in order to increase the exploration ability of the fleet. Three important aspects of UAV networks are considered, namely the area coverage, the network connectivity and the energy level of the UAVs. Another example is found in [162], where a UAV network is used to maintain the connectivity in a ground MANET. A swarm strategy based on the behaviour of birds flocks is implemented, which consists of three main rules: i) cohesion, which makes a UAV to stay close to its neighbours, ii) separation, that prevents a UAVs from a collision with another UAV, and iii) alignment, which makes a UAV to fly with a similar speed to the speed of its neighbours. The main aim is to make the UAVs to calculate their optimal positions in order to prevent network issues, such as bottlenecks or communication service outages.

Genetic algorithms have been also used for UAV networks mobility problems, such as in [163] [33]. A two-step solution for deploying a UAV network in a disaster scenario is proposed by the authors. The first step consists of applying a genetic algorithm as part of a global search stage, which provides suitable locations for the UAVs deployment. These positions can be calculated because certain information about the scenario is known in advance, e.g. some victims positions. Once the UAVs reach the locations provided by the GA, the local search algorithm called hill climbing (HC) is used to update the optimal positions of the UAVs, according to the new information found during the deployment. The main aim is to have under coverage as many victims as possible while maintaining a connected network.

Other nature-inspired algorithms can be also found in UAV networks mobility problems. This is the case of [104], where a set of UAVs forming a DTN have the mission of increasing the network performance in a hybrid network scenario. The hybrid network is considered a heterogeneous network made of different homogenous networks, such as cellular networks or wide area networks (WAN). The UAVs are used as relaying nodes for improving the performance within a specific network or between different networks. A technique called genome-based approach, which derives from the area of molecular biology, is used to map the nodes of the different networks and evaluate the need of a relaying UAV. The proposed model improves the data delivery rate and reduces overhead and packet delays.

Neural networks have been also proposed by some researchers for this type of problems. As an example, in [164], a UAVs team performs the mission of navigating through an unknown environment, reach a target and detonate it. The authors propose the design of a controller which uses a neural network consisting on 7 input neurons (1 encoding for the distance to the target, 3 for the angle and 3 for the distance to the closest obstacle); additionally, 15 neurons are forming the neural network core, and 2 output neurons are used. The neural network parameters are evolved by a genetic algorithm which optimizes the controller in order to maximize the success of the mission and minimize the distance travelled. Some details of the simulator used for validating the proposed controller are: i) the target location is assumed to be known a priory and it is broadcasted via satellite communications to all UAVs (centralized mechanism), ii) the UAVs generate its trajectories autonomously using the neural network controller (distributed approach), and iii) the simulator considers a 2D scenario.

Finally, a summary of the research works proposing mission-based mobility algorithms for UAV networks have been organized, at the end of this section, in Table 1.

Besides, it is worth to mention here that this thesis proposes two new mission-based mobility models. The first mobility model proposed, which is described in chapter 3, is called dPSO-U and is based on the particle swarm optimization (PSO) algorithm. The mission intended for the dPSO-U mobility model considers a UAV network performing an exploration and convergence mission. This means that the main objectives of the mission are the following ones: i) exploring a large-scale scenario area for discovering the ground nodes' locations, and ii) making the UAVs to autonomously converge to the clusters in which the ground nodes are organized. As described in Appendix A, the PSO algorithm motion equation has three main terms which represent the effect of the inertia, the local best and the global (or neighbour) best. The dPSO-U mobility model uses dynamic weights of the inertia, local best and neighbour best components for the motion equation, thus providing the algorithm with the ability to explore the scenario and then converge to a group of ground nodes. Also, a characterization of the algorithm is provided and the results according to different performance metrics when selecting different value sets of the inertia, local and neighbour best weights are shown.

Chapter 4 proposes the second mobility model, which is called the Jaccard-based mobility model. This mobility model generate the trajectories for a UAV network performing an adaptive coverage mission on a medium-scale scenario, with the following main objectives: i) to provide communication services optimized according to specific aspects (e.g. having the maximum number of ground nodes under the UAV wireless coverage area), and ii) to maintain the UAV network as a connected network. The Jaccard-based mobility model uses the Jaccard distance metric (introduced in Appendix A) and different metaheuristics, such as simulated annealing (SA) and hill climbing (HC) and is able to optimize the number of ground nodes under the UAV wireless coverage area. To the best of the author's knowledge, there are not any mobility models that have been proposed for exploration and convergence missions using the same dPSO-U approach. Also, there are not any mobility models with the mission of providing communication services that are using the Jaccard metric for optimizing communication services.

Table 1. Mission-based mobility algorithms for UAV networks

Ref.	Mobility algorithm	Mission	Optimization	Scenario
[153]	Semi-Random Circular Movement (SCRM)	Exploration and Search task	N/A (generates circular trajectories around a fixed centre location)	2D
[34]	Three-Way Random (TW)	Exploration and Search task	Minimize time spent in exploration	2D
[154]	Pheromone Repel	Exploration and Search task	Minimize time spent in exploration	2D
[155]	Lawnmower	Exploration and Search task	Guarantee full area coverage and minimize turns	2D
[155]	Zamboni	Exploration and Search task	Guarantee full area coverage and minimize turns (only for large turn radius vehicles)	2D
[155] [39]	Spiral	Exploration and Search task	Minimize time spent in exploration	2D
[155]	Spiral-like	Exploration and Search task	Minimize time spent in exploration	2D
[117]	PSO - Virtual Forces	Coverage mission of specific areas	Maximize coverage and minimize time	2D
[115]	PSO (centralized)	Target localization and tracking	Maximize target size detected by visual sensors	3D
[68]	DI-PSO	UAV placement/deployment	Maximize user coverage ratio	3D
[159]	CPTD-PSO	UAV trajectory generation	Minimize travelling distance and avoiding	3D

			obstacles	
[118]	ACO	Minimum time search of a target	Minimize time of detection	2D
[160] [23]	ACO	Search a first responder and establish a communication relay to the ground station	Successful search and reliable communication	3D
[162]	Birds flock	Provide communication services avoiding network issues	Maximize network performance	2D
[114]	Alpha-based	Exploration	Coverage area, network connectivity and energy level	2D
[163] [33]	GA - Hill climbing	Deployment to optimal positions and maintain network connectivity	Maximize the number of victims under coverage	2D
[104]	Genome-based	DTN formation and UAV allocation	Maximize network performance	3D
[161]	ACO- based	Exploration and Search task	Locate and track targets in the minimum time	3D
[164]	Neural network (trajectory generation) & GA (controller design)	Exploration and Search task	Fly to target location minimizing distance travelled	2D

2.2.2 UAV network missions for disaster scenarios

Some research works using UAV networks for emergency response operations were already mentioned in section 2.1.1.7. This subsection extends the list of works proposing UAV networks solutions for supporting emergency response missions, i.e. UAV networks for disaster scenarios. The reason for extending the number of references to UAV networks in emergency response operations is to have a clear perspective of the most common missions considered by the research community. This is not an exhaustive list and there can be some other categories that are not considered here. However, this section contents are aligned with the fact that the two mission-based mobility models proposed in this thesis have been validated considering two different emergency response missions.

One of the most important missions of UAV networks in disaster relief operations is to *provide communication services* to victims, first responders of both. Some research works focus on extending the communication range of individuals located in the disaster scenario. An example would be two or more rescuers communicating to each other from distant locations via a UAV team that acts as a multihop relay network. Examples of these works are [137] [23] [39] [102] [165] [166] [160].

Other works focus on providing communication services in disaster scenarios, not only extending the communication range of other wireless devices but providing communication or information services to the victims and/or the first responders all over the disaster scenario area. UAV networks with this objective usually extend their operations along a wide area of the disaster scenario. As these networks are probably the only communication network operating in the disaster scenario, they can be used for different purposes such as i) communicating victims and first responders with each other, ii) gathering disaster scenario information useful for the first responders (e.g. number of victims detected, obstacles, and similar details), and iii) providing first aid information to victims (e.g. directions towards a meeting point for reaching the emergency response team, emergency exit from a threat, and similar data). Examples of these research works are [59] [33] [167] [60] [168].

It is also common to perform *surveillance tasks* in disaster emergency operations. This type of tasks aims at monitoring the disaster scenario during the rescue operations of the first responders or even a time after the operations have finished.

This allows the emergency response teams to be aware of the status of potential threats that are present in disaster scenarios (e.g. the intensity or direction of a fire), to detect unexpected events (e.g. a building collapse that takes place time after the disaster occurred) or even to discover unexpected victims. Examples of these research works are [139] [156].

Another type of operations where UAV networks have been used for is tracking toxic gases plumes. These missions may fall in the category of environmental monitoring as well. However, when a disaster event affects to the facilities of a factory or a plant and toxic gases emissions contaminate the air, towns and settlements near the gases may need to be evacuated before the gases reach their population. Therefore, tracking these gases is of paramount importance and UAV networks can be used in order to gather information from the toxic clouds and even help to predict its trajectory. Examples of these works are [14] [119] [124] [169].

A similar situation as the one described for toxic gases occurs in the case of fires. There are countries in which the probability of a fire occurring during the dry season is very high. UAV networks can be used to detect a fire when it is at its early stages and help to predict the fire trajectory. This information is very valuable for firefighting professionals, so they can extinguish the fire more efficiently, with lesser risks and evacuate the villages that may be in the vicinities. Examples of these works are [10] [165].

Last but not least, *Search and Rescue (SAR)* operations are one of the most commons missions that UAV networks have been used for in emergency relief operations. Basically, a team of UAVs is able to rapidly sweep a large terrain area in search of the victims within the incident site. Knowing the location of victims before performing the rescue mission is very valuable information for any emergency response team. Moreover, when highly-equipped UAVs with costly sensors are not affordable (e.g. by an emergency response team), a greater number of smaller commercial UAVs can be used for supporting SAR operations as it is proposed in [12]. Examples of these works are [24] [25] [138] [170] [171] [165] [172] [173] [174] [156].

2.2.3 Disaster scenarios

The mission-based mobility models proposed in this thesis have been validated in scenarios modelling a disaster-struck area and a disaster relief operation. For this reason, this section introduces the reader in the most common approaches used for modelling disaster scenarios. Emergency response teams use ad hoc communications devices and networks in order to coordinate the rescue mission. For this reason, disaster relief operations, and more specifically disaster scenarios, have attracted the attention of the communications and networking research community [27] [175].

First of all, some aspects are clarified about the terminology used when referring to disaster relief operations. A disaster can be provoked by either natural causes (e.g. an earthquake) or by men (e.g. a car accident in an urban area). The area affected by a disaster is commonly known as a disaster scenario in the literature [27]. Disaster relief operations professionals are commonly known as emergency response teams, rescue workers or rescue teams [176] [177] [178] [179] [25]. Also, the term *first responder* is used often in the literature [177] [180] [33]. First responders are the individuals, either professional rescue personnel or civilians, which assist and help the victims affected by the disaster. Thus, the term first responder is more general and refers to any person which helps victims after a disaster occurred. Also, the term disaster area [181] is used sometimes to refer to the disaster scenario. However, this may lead to think of the physical dimensions of the disaster exclusively, i.e. the area or the surface affected. For this reason, the term disaster scenario is preferred because it represents a richer set of information (e.g. potential number of victims, threats, rescue personnel working on the area, etc.).

Modelling a disaster scenario refers to modelling its features (i.e. area dimensions, obstacles, people mobility, etc.). Eventually, the most complex task is to develop mobility models for victims and first responders. These mobility models mimic the mobility behaviours that individuals would present in a real disaster scenario. Examples of these mobility behaviours could be i) a rescue worker searching for victims, ii) a rescue worker transporting a victim from the disaster area to a safer place, iii) a victim running away from a potential threat, and many others. There are different approaches used by the research community for modelling disaster scenarios. The most common ones are introduced in this section.

Usually, a disaster scenario area models the area affected by the disaster i.e. where the victims are located. This area is known as the incident site [47]. In some cases, a disaster scenario model also includes the surroundings of the incident site. It is in the surroundings where some of the tactical operations of emergency response teams take place. In the surroundings of the incident site, there are different areas that can be found, such as a treatment area dedicated to providing first aid to the victims, a transport area with vehicles to move the most seriously injured victims to the hospital, among others [47]. According to these considerations, there are two categories that can be defined for classifying disaster scenario models: i) incident site scenarios [182] [33], and ii) wide area disaster scenarios [47] [177], respectively.

Apart from the previous aspects, modelling a disaster scenario is normally achieved by modelling the mobility of the victims [47]. Human mobility models can be organized into two main categories [183] [184]: i) synthetic and ii) trace-based. Synthetic mobility models are less realistic but are simpler to understand and simulate. Trace-based mobility models are considerably complex but more realistic, as they are generated from real human mobility traces. According to this, two other categories for disaster scenarios can be defined: i) *synthetic mobility* scenarios [182] [178], and ii) *trace-based mobility* scenarios [177] [184].

It is worth mentioning here that modelling the human mobility in a disaster scenario is a challenging task because the movements of the victims depend on numerous aspects [183], such as the scenario, the physical conditions of the victim (if it is able to move or not), and the psychological conditions of the victim (if it is shocked by the situation and paralyzed), among others. In addition, getting traces of victims from a real disaster scenario is a very difficult task. This would require victims recording their movements after a disaster strikes. However, emergency response teams carry communication devices and perform tactical movements when carrying out rescue tasks. Due to this, there are works that only model first responders mobility (and only a few of these use partially real traces from emergency response teams), but not victims. Other works include the mobility of the victims in their models but most of them are using synthetic approaches. Therefore, another classification can be introduced here to differentiate between the cases in which the mobility of victims is modelled or those that only model the mobility of first responders: i) victims mobility disaster scenarios [182] [177], and ii) first responder mobility scenarios [47] [185] [177] [178]. The aforementioned categories are shown in Table 2.

Table 2. Disaster scenarios aspects and categories

Aspect	Categories	Description	References
Area modelled	Incident site scenarios	It only models the area affected by the disaster	[182] [33]
	wide area disaster scenarios	It models both, the area affected by the disaster and its surroundings	[47] [177]
Mobility data	Synthetic mobility	Use synthetically generated data for simulating the mobility of individuals	[182] [178] [33]
	Trace-based mobility	Use data gathered from real individuals mobility for modelling the scenario	[177]
Individuals mobility	Victims mobility	It models the mobility of victims independently from the mobility of the first responders	[182] [177] [33]
	First responders mobility	It barely models the mobility of victims and focuses on the mobility of the first responders	[47] [185] [177] [178]

Just as a reference for the reader, some examples of the disaster scenario models found in the literature are included here. Probably, the most common and simple one is the Random Waypoint mobility model (RWP) [182]. This model has been used extensively for emulating the mobility of nodes in MANETs and also has been used for modelling the mobility of victims [33]. Another mobility model specifically oriented to disaster scenarios is the Disaster Area (DA) mobility model [47]. This model represents the movements of the first responders and, indirectly, the mobility of the victims (when they are carried by emergency professionals). This model includes both the incident site and also its surroundings. The Composite Mobility model (CoM) [178] is based on basic mobility models that are combined in order to model more complex mobility behaviours. This model considers three important factors present in real human movements: i) realistic human movements, ii) group mobility and iii) obstacle avoidance. The main drawback of this model is that it assumes that the scenario characteristics are known in advance, which may be not realistic. The CORPs model [185] (Cooperation, Organization and Responsiveness in Public Safety) introduces another level of reality by implementing events to which victims and first responders may react (e.g. a fire event attracts firefighters and makes victims run away). A more complete model is the Role-Based Urban Post-Disaster (RBUPD) mobility model [177]. This model has been designed using real disaster's data and it models victims, first responders, and vehicles such as ambulances.

3. MOBILITY MODELS FOR EXPLORATION

"El que está contento con aquello que tiene, ése sí que es feliz"

María Cristina García Villada

A UAV network is a very powerful system that is able to accomplish many different missions when deployed in a complex scenario. In an attempt to validate a UAV network behaviour in specific operations, mission-based mobility models are defined. This chapter proposes a mobility model for a UAV network performing an exploration mission in a complex scenario, i.e. a disaster scenario. The mobility model proposed pursues two main objectives. The first objective is to provide the UAV network with trajectories that favour the exploration of the scenario, with the goal to discover as many ground nodes as possible (i.e. victims). Second, after several groups of ground nodes are discovered, the proposed mobility model provides trajectories that make the UAVs to converge to these groups. This chapter is organized in the following sections: problem description, problem model, proposed solution, simulation results and discussion of results.

3.1 Problem description

The sections 2.1.1 and 2.2 have introduced the reader in the area of UAV networks that are used in different application areas. Scenarios affected by natural or man-made catastrophes, also known as disaster scenarios, are characterized by non-working or highly dysfunctional communication infrastructure. At the same time, emergency response and rescue missions professionals are in need of tools with two main objectives [27] [29]: i) gathering disaster area information rapidly, and ii) providing a communication infrastructure that supports first responders and victims communications during the rescue operation.

UAVs can fly over a disaster scenario area gathering information of high value for the first responders such as the locations of the victims and how these are organized. Also, a UAV team can provide important informative messages to the victims, such as first aid advice for injured victims or also guidance on how to get to a safe place for awaiting the arrival of emergency responders. Finally, after gathering information, the UAVs can be organized to build a flying network providing communication services in the areas where the first responders and victims need it the most, e.g. specific regions in which the victims are gathered or organized in groups. For this reason, UAV networks are a very suitable tool for these two aforementioned objectives.

Based on the aforementioned requirements of first responders and victims in a disaster scenario, the problem to be addressed in this chapter is to design and implement a mobility model for a UAV network in an exploration and coverage mission. Specifically, the mobility model has to emulate a UAV network behaviour which is carrying out a mission with two main objectives: i) *exploring* the disaster scenario area for discovering the locations of as many ground nodes as possible, and ii) making the UAVs to autonomously *converge* to the regions in which the ground nodes density is high (i.e. groups of victims, also referred to as clusters in this document), in an attempt to be prepared to offer communication services.

3.2 Problem model

With the aim of addressing the problem described in the previous section, a specific model of the problem is proposed. The problem assumes a large disaster scenario, two-dimensional, squared, and with a size of 5000 meters per side. Also, it is assumed that the victims are *organized in groups*, i.e. there are specific regions on the scenario where the density of the victims is higher. However, the victims are considered to be mobile ground nodes and therefore the shape of the groups (also called *clusters* from now on) can vary.

The model is divided into *two stages*; each stage addresses one objective of the mission. In the first stage, when the UAVs enter the scenario, the UAV network will fly over the scenario detecting ground nodes. During the first stage, the UAVs will adhere to the DTN paradigm. This means that the UAVs are assumed to establish communication links with each other in a discontinuous manner due to their mobility. Therefore, the UAVs will exchange messages with each other whenever they have an encounter. An encounter is considered the situation in which two UAVs are separated by a distance smaller than their wireless communication range. Once the UAVs have explored the scenario, the second stage starts. During the second stage, the UAVs are expected to converge to the groups of victims, i.e. to the clusters. Each UAV will converge to the specific region in which the higher density of ground nodes has been detected. Once the UAVs have converged to a group, i.e. to a cluster, the mission is considered to be accomplished.

A depiction of the two stages of the exploration mission is shown in Figure 11, where the green dots represent ground nodes (i.e. victims). The left side of the figure represents three UAVs entering the scenario area over the top-right corner, at the very beginning of the mission. On the right side, the exploration stage has finished and the UAVs have finally converged to different clusters. Please note that Figure 11 is only an example of the mobility of the UAV network and not the real mobility model behaviour, which will be later explained with more detail.

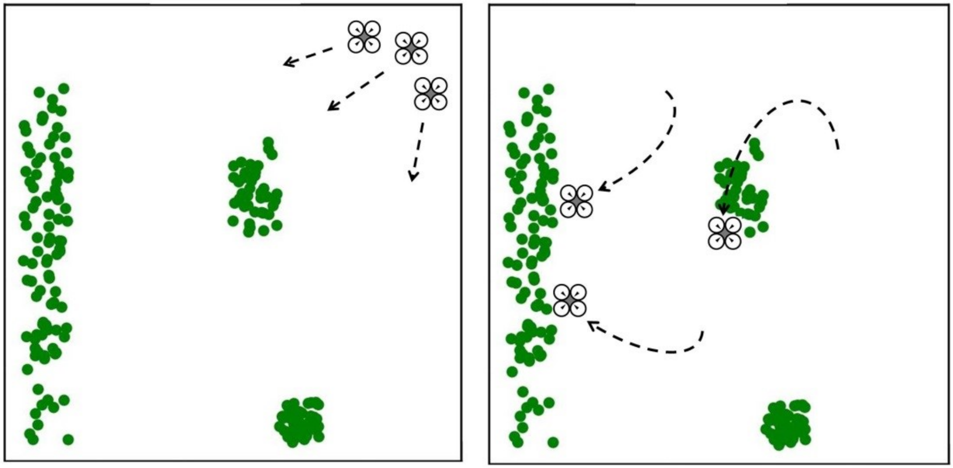


Figure 11. Mission stages: exploration (left) and convergence (right)

The trajectories described by the UAVs during both stages are generated by the mobility model proposed in this chapter and it will be explained in later sections with more detail. Therefore, the mobility model will be providing each UAV with new waypoints, in the form of a sequence of locations, i.e. a trajectory. The main goal is that the proposed mobility model emulates a UAV network behaviour in a mission with two main objectives: i) exploring the disaster scenario area for discovering as many ground nodes as possible, and ii) making the UAVs converge to the different clusters.

Further details on the considerations and assumptions made for modelling the problem are provided in this section. The first subsection describes the environment model regarding the disaster scenario and the second one provides details about the UAV network models.

3.2.1 Scenario model

This section focuses on an area affected by a large-scale disaster, where the victims are located. Modelling a disaster scenario is normally achieved by modelling the mobility of the first responders and/or the victims [47]. Considering the previous works in disaster scenario modelling such as [47] [185] and [177], the mobility of the victims is modelled in this chapter by using a simplified synthetic model. The model used is considered a first approach which will allow validating the UAV network mobility model. The following assumptions describe the disaster scenario and the mobility of the ground nodes, which in this specific case are considered victims.

3.2.1.1 Scenario assumptions

The scenario model considered in this section has the following features:

- The scenario is flat and has a rectangular shape. Similar scenarios have been proposed in other works [154].
- There are a few areas where the victims group together, which are called clusters. These clusters simulate small towns or victims settlements.
- No obstacles are modelled.

3.2.1.2 Ground nodes mobility assumptions

The model considered for emulating the mobility of the ground nodes (i.e. victims) is based on the following assumptions:

- The victims are allowed to move only within the cluster they belong to.
- Each cluster central position is static; however, its boundaries may vary due to the mobility of the victims inside the cluster.
- Within a cluster, the victims move randomly, changing their speed and direction at any time, according to the RWP mobility model [111] [186].
- The victims' speed ranges from 0.5 ms^{-1} up to 3 ms^{-1}.
- A victim may be static during a specific time frame i.e. not moving at all.

An example of the disaster scenario considered is shown in Figure 12. There are several victims' clusters, particularly 3 in this case. The nodes move over time and therefore these occupy different positions on the left and right part of the figure (positions at $t = 0\ s$ and $t = 1633\ s$).

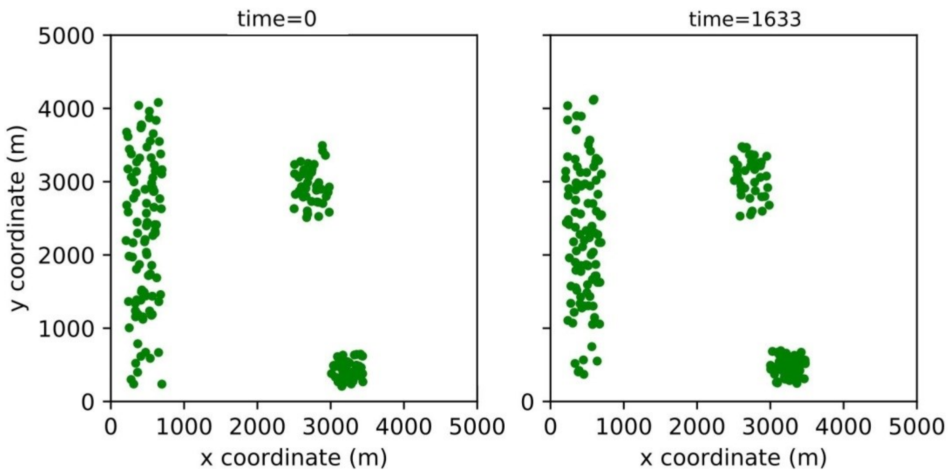


Figure 12. Disaster scenario model with victims organized in 3 clusters

3.2.2 UAV network model

The proposed mobility model considers that each UAV is an agent that behaves autonomously and communicates with its peers and also with victims. Several assumptions have been made regarding the UAVs model. These assumptions have been classified into three groups: i) the ones related to the UAV navigation, ii) those related to the communications aspects and iii) those related to the mission aspects.

3.2.2.1 UAV navigation assumptions

- The type of UAVs considered can be either a multicopter or a fixed-wing UAV.
- The UAV trajectories generated with the proposed PSO algorithm are high-level trajectories, which consist of a sequence of waypoints.
- The UAVs movement is assumed to take place in a two-dimensional space, which simplifies the UAV dynamics and avoids overloading the simulations. This assumption has also been made in other works such as [187] [156] [188].
- Collision avoidance mechanisms have been not considered [137] or simplified [160] [154] [166] in similar research works. A simplified collision

avoidance mechanism is considered in this model, which is based in the change of the flight altitudes of UAVs in case of a potential collision, as proposed in [12] [160] [166]. As the UAVs movements have been modelled in a two-dimensional space, the collision avoidance mechanism is unnoticed from the point of view of the simulations.

- The UAVs maximum speed has been set to 15 ms^{-1}. This value depends on the UAV type and, for this reason, has been set to the average speed of a standard UAV.
- The UAVs know the scenario dimensions and its boundaries coordinates in advance. However, they do not know anything else; therefore, they do not know the victims' locations nor the number of clusters.
- The UAVs start the exploration mission by entering the disaster scenario area from any of the corners.

3.2.2.2 UAV communication assumptions

- UAVs are equipped with short-range wireless communication devices that allow them to communicate with their peers and with ground nodes (victims or first responders).
- Some UAVs may also have long-range wireless communication devices with the ability to communicate with a ground base station and/or a satellite.
- The mechanism used by UAVs for detecting nodes on the ground may be by using wireless communication technologies. Potential candidates for these technologies are the IEEE 802.11 standards [39] [23] [189] [190] [191] [172] [192], due to the numerous handheld devices that offer this communication technologies [193]. Several works propose potential solutions that could be used to know the victims that are within the wireless communication range [39] [194]. Also, MANET approaches like the ones proposed in [195] [196] [197] could be used so the UAVs could "sense" the victims' mobile phones. However, the proposed approach is not limited to these technologies and other discovery mechanisms could be used such as cameras and artificial vision techniques. Also, the active behaviour of victims for facilitating their discovery with SOS signals emitted via their smartphones or similar is not discarded.

- The communication is based on the disk model assuming a 250 meters radius [163] [156]. Any pair of UAVs separated a distance smaller than 250 m will be able to establish a communication link with each other [198] [199]. Other works have considered longer communication ranges such as 500 m [23] [81] but this heavily depends on the communication equipment of the UAV [200] [201] and the multiple factors that affect to wireless communications such as antennae and transmit power among others [55]. There can be considerable variability between the wireless communication equipment from different UAV models. Besides, UAVs are resource-constrained systems in terms of payload and batteries. This affects the wireless communication devices that can be carried by the UAVs, and therefore also affects the transmission range. In the case of considering UAVs with long-range wireless equipment could have been considered for the proposed algorithm, however, a more conservative transmission range is assumed in this section for validating the proposed algorithm performance. This allows validating the proposed model in the case of UAVs with more modest wireless capabilities. Other works use alternative communication assumptions for modelling wireless coverage such as dividing the scenario area in a grid of regular cells assuming that a UAV located on the centre of a cell is able to cover the entire cell [14] [55].
- The routing mechanism considered in this UAV network is similar to the epidemic routing algorithms for DTNs [202] [104]. Specifically, the routing algorithm consists of the fact that whenever two UAVs can establish a communication link, they exchange lightweight information (the coordinates where the bigger number of victims has been detected).

3.2.2.3 UAV mission assumptions

- The aim of the UAVs is to explore the scenario, discover as many victims as possible and converge towards one of the victim groups, i.e. a cluster.
- The two mission objectives, i.e. exploration and convergence, are assumed to be performed in an amount of time that is smaller than the UAVs maximum flight time. This assumption is later confirmed in section 3.4.3.1, specifically in Figure 25.

- The assistance that the UAVs provide to the victims may be either providing emergency information (e.g. informing victims about a safe path outwards the disaster scenario) or by enabling communications (e.g. allowing the victims to communicate among themselves or with first responders in the area).

3.3 Proposed solution

This section describes the PSO-based mobility model proposed for a UAV network performing an exploration and convergence mission. The proposed mobility model is based on the PSO algorithm as it is described later on. The reader can refer to Appendix A for an introduction of the PSO algorithm in one of its most common and well-known formulation, the canonical PSO [203].

3.3.1 PSO-based mobility model for UAVs

3.3.1.1 dPSO-U description

The dPSO-U mobility model, also referred here as the dPSO-U algorithm, is based on the PSO formula shown (46) in appendix A.1, but with some modifications. In the proposed algorithm the random variables φ_1 and φ_2 from (46) have not been considered. These parameters φ_1 and φ_2 contribute to increase the exploration ability of the algorithm, i.e. escaping local maxima and identifying the global maximum in the search space. However, the main aim in this section is to generate UAV trajectories and the parameters φ_1 and φ_2 would contribute to random changes in the flight direction. These random changes would result in higher energy consumption and the effect of an unstable and drifting flight trajectory, which sometimes can be difficult to control. Due to this fact, the approach of dismissing the parameters φ_1 and φ_2 is preferred, together with including a random component when the UAV reaches the disaster scenario border and has to make a turn mandatorily. Thus, a random term is included in the proposed algorithm which has a value different to 0 only when a UAV reaches a border of the scenario.

The original PSO algorithm [204] considered two different approaches for arranging the information sharing mechanism between particles [203]. The first one, called *Gbest*, assumed that every particle is able to share information with all the particles in the swarm. The second method, called *Lbest*, considers that each particle has the ability to share information with a restricted number of particles, its neighbours. In the specific case of the problem addressed in this chapter, by considering that the particles are UAVs with short-range wireless communication capabilities, a UAV will not be able to exchange information with all the UAVs due to the communication range limitations. As it has been mentioned earlier, the network approach followed is the DTN paradigm, in which a UAV exchange information only when it has an encounter with another UAV. Therefore, the method followed will be similar to the Lbest method. This also implies that the global best is not unique. As a consequence, there will be multiple optima, one per each group of UAV neighbours that exchange information. For this reason, the approach followed considers that the term *global best* is better referred to as *neighbour best*. The term neighbour best has also been proposed in other works, such as [117] and [116], and therefore this same term is used from now on in the text. According to these changes, the particles' velocity vector of the proposed algorithm is defined in (1).

$$v_i(t+1) = \omega v_i(t) + C_1(P_i(t) - x_i(t)) + C_2(P_{ni}(t) - x_i(t)) + \varphi_b \quad (1)$$

Where the terms are as follows:

- $v_i(t)$: Current velocity.
- ω: inertia component weight.
- C_1 and C_2: represent the intensity of the attraction of a particle towards its local best (C_1) or towards its neighbour best (C_2).
- φ_b: Random value that represents the random direction that a UAV follows when it reaches the border of the scenario.
- $P_i(t)$: The local best of particle i.
- $P_{ni}(t)$: The neighbour best of particle i, i.e. the best candidate solution among particle i and its neighbours so far.

The parameters used in this section for characterizing this algorithm are ω, C_1 and C_2. These will be called *inertia weight*, *local best weight* and *neighbour best weight* respectively along section 3. In some cases along this section, the terms *inertia (in)*, *local best (lb)* and *neighbour best (nb)* may be used for simplicity.

The canonical PSO algorithm has advantages with respect to other metaheuristics such as GA [68]: i) simpler implementation due to a small number of parameters, ii) lower computational cost, and iii) faster convergence. The dPSO-U mobility model algorithm is a fully distributed implementation of the PSO algorithm applied to a UAV network, and therefore, it inherits the aforementioned advantages from PSO. This is the reason for considering dPSO-U a good candidate for solving the problem proposed in this section in terms of complexity and scalability.

3.3.1.2 Exploration optimization

The goals for the dPSO-U mobility model are to maximize the exploration of the scenario and later on make the UAVs converge to any of the ground nodes clusters. In order to use the dPSO-U as an optimization algorithm, the following aspects have been considered. The search space S considered corresponds to the area of the scenario explored by the UAVs. As the scenario considered has two dimensions, the search space consists of all the possible positions that the UAVs may occupy within it. These positions are represented by Cartesian coordinates in the form of (x, y), where x and y correspond to each of the two dimensions. Without loss of generality, this section considers the bottom-left corner as the origin of coordinates $(x = 0, y = 0)$. The size of the scenario is defined by the maximum values that x and y coordinates may take, which are defined by x_{max} and y_{max}. Based on these definitions, the search space is defined according to (2).

$$S: \{x: 0 \ \leq x \leq x_{max}\}, \{y: 0 \leq y \leq y_{max}\} \quad (2)$$

An optimization algorithm usually makes use of a fitness function to evaluate the quality of the candidate solutions. The fitness function is defined as the number of ground nodes discovered (first responders or victims), represented by the symbol d in (3), associated with a position that a UAV occupies within the scenario area (4). The aim of dPSO-U is maximizing this fitness function, i.e. finding the optimum position at which a UAV can communicate with the biggest number of ground nodes. This implementation of the proposed dPSO-U algorithm is shown in (5).

$$d = \#ground\ nodes\ discovered \quad (3)$$

$$f(x, y) = \ d \quad (4)$$

$$find\ (x^*, y^*) \in S \subseteq \mathbb{R}^2\ such\ that\ \forall (x, y) \in S, f(x^*, y^*) \geq f(x, y) \quad (5)$$

So far, the PSO-based algorithm has been introduced as a solution to an optimization problem. By following the description aforementioned, the goal would be finding the optimal solution of the search space (i.e. a position in the form of coordinates x and y) that maximizes the fitness function defined in (4). However, exploring the disaster scenario is the real goal pursued, i.e. finding several clusters and making the UAVs to converge to the clusters. The following considerations have been made in order to achieve these specific objectives.

3.3.1.3 Phases of the algorithm

In the proposed dPSO-U mobility model algorithm, each UAV will experiment three different time *phases* of equal duration, namely: i) inertia, ii) local best and iii) neighbour best.

- *in phase*: The first phase corresponds to the inertia effect. During this phase, the weight of the inertia term (1) is considerably greater than the local and neighbour effects. Each UAV starts flying with a rectilinear trajectory which is selected when entering the disaster scenario area. Each time a UAV reaches a scenario border, a new rectilinear trajectory is calculated randomly. The UAV will follow the most recent trajectory generated until a new border is reached or until the local or neighbour best phases start.
- *lb phase*: The second phase corresponds to the local best. During this phase, each UAV gets attracted by its local best. The weight of the inertia is reduced by the same amount that the local best weight increases. The addition of the weights of the inertia and local best hast to be equal to 1.
- *nb phase*: The third phase corresponds to the neighbour best effect. During this phase, each UAV is attracted by its neighbours' best candidate solution. The weight of the inertia is reduced by the same amount that the neighbour best weight is increased. The addition of the weights of the inertia, local and neighbour best has to be equal to 1.

The duration of the phases is the same for all the UAVs and corresponds to one-third of the total simulation duration. There is an exception for those UAVs that did not discover any victim nor exchanged information with other UAVs. In this case, a UAV will extend the inertia phase until it discovers some victims or receives information about victims from another UAV.

Prior to the exploration mission, each UAV is aware of the initial weight values of each term of equation (1), i.e. inertia, local best and neighbour best. For instance, UAVs will be assigned to have a top weight for inertia of 1. Thus, during the inertia phase, the UAV will only experience the effect of its inertia. When the second phase starts, the local best effect will increase gradually up to the local best top weight. At the same time, the inertia weight will decrease accordingly so at every time the addition of inertia and local best weights is equal to 1. At the third phase, the same mechanism applies; the neighbour best effect will increase gradually up to its top weight and the inertia weight will decrease accordingly. At every time the addition of inertia, local and neighbour best weights will be equal to 1. It is important to mention that once the local best reaches its top weight it does not decrease. The only weight that decreases is the inertia. A diagram describing the behaviour of each UAV in relation to the phases described in this section is shown in Figure 13.

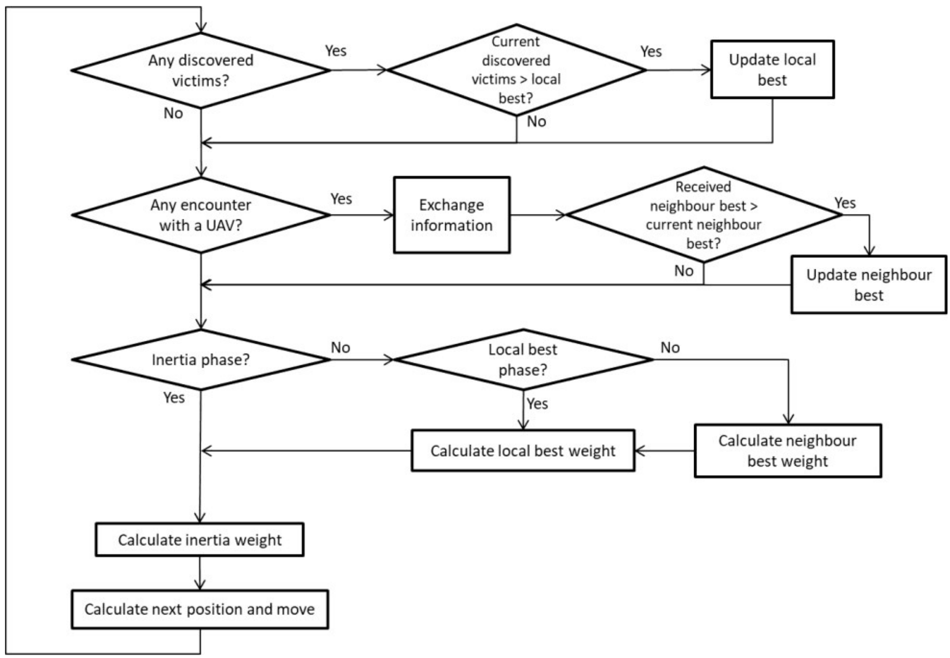
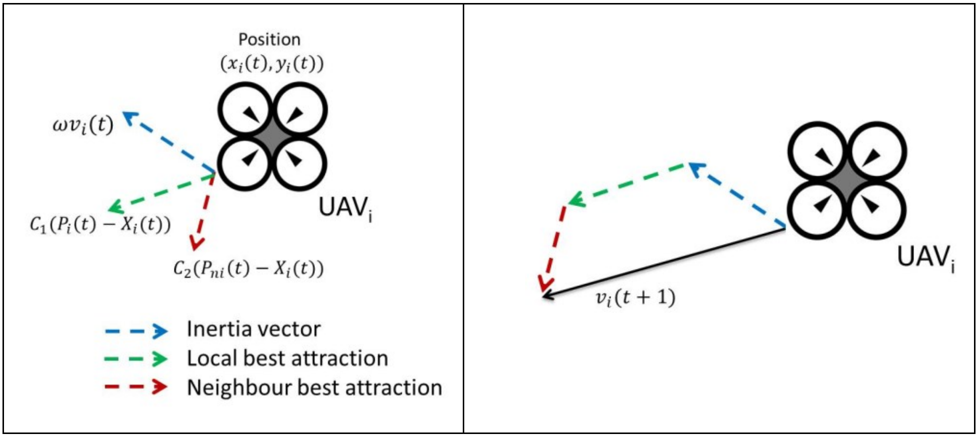


Figure 13. UAV behaviour diagram

Some details that are worth mentioning is that: i) the algorithm prioritize inertia and local best components at the first stages of the algorithm, therefore UAVs have fewer encounters at the two first stages, and ii) the last phase of the dPSO-U, the number of encounters increase as the UAVs converge to the clusters, however, the number of encounters will depend on the number of UAVs that converge to the same cluster (the case with the highest number of encounters would be having all the UAVs in the same cluster).

3.3.1.4 UAV network mobility model

The dPSO-U algorithm considers that each UAV in the network moves like a particle of the algorithm. The movement of the i^{th} UAV in the network is described by equation (1). The velocity vector of each UAV_i at a time equal to $t+1$, which is represented by $v_i(t+1)$, is defined by the addition of three vectors: i) the velocity vector $v_i(t)$, ii) a vector pointing in the direction of the local best position of UAV_i, which is represented by $P_i(t)$, and iii) a vector pointing in the direction of the neighbour best position of UAV_i, which is represented by $P_{ni}(t)$. These three vectors are weighted by the following parameters respectively: i) ω, which is the inertia component weight, ii) C_1, which represents the intensity of the attraction of a particle towards its local best, and iii) C_2, which represents the intensity of the attraction of a particle towards its neighbour best. The maximum intensity of the vectors is given by the maximum velocity that the UAV is able to reach, which is a design parameter. A fourth component that is present in equation (1) is φ_b, which represents the random direction that UAV_i follows when it reaches the border of the scenario. An example of the velocity vector of the UAV_i is show in Figure 14.



a) Inertia, local best and neighbour best attraction vectors for UAV$_i$

b) UAV$_i$ velocity vector in $t + 1$ (calculated as the addition of the vectors shown in a)

Figure 14. UAV velocity vector calculation

Examples of the UAVs trajectories at the different phases of the simulation, which were described in section 3.3.1.3, are shown in Figure 15, Figure 16 and Figure 17. The UAVs correspond to the cross marks and their trajectories are represented by the dashed lines. Each UAV is assigned a different colour in order to distinguish the different trajectories. The ground nodes are represented by points and their colours are related to the time elapsed since their last connection to a UAV. The more intense the red colour the smallest the time elapsed since the ground node had a connection to any of the UAVs. Figure 15 corresponds to the inertia phase. Figure 16 corresponds to the local best phase and it shows the first turns in the UAVs trajectories when they start to be attracted by their local best positions. Figure 17 corresponds to the neighbour best phase and it shows how the UAVs converge to the different victims' clusters. It is difficult to distinguish the cross marks that indicate the UAVs locations in Figure 17 as these overlap with the ground nodes dark red colour around them and also with the dashed line corresponding to the trajectories. However, the ground nodes dark red colour is a good signal to identify where the UAVs locations are. Each figure has been taken in different simulation iterations and that is the reason for the UAV trajectories not being equal between the figures.

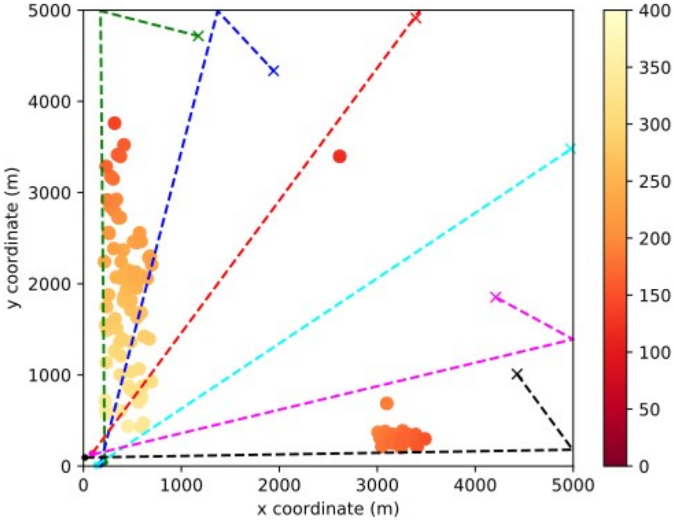


Figure 15. UAV's trajectories and nodes connection time (in phase)

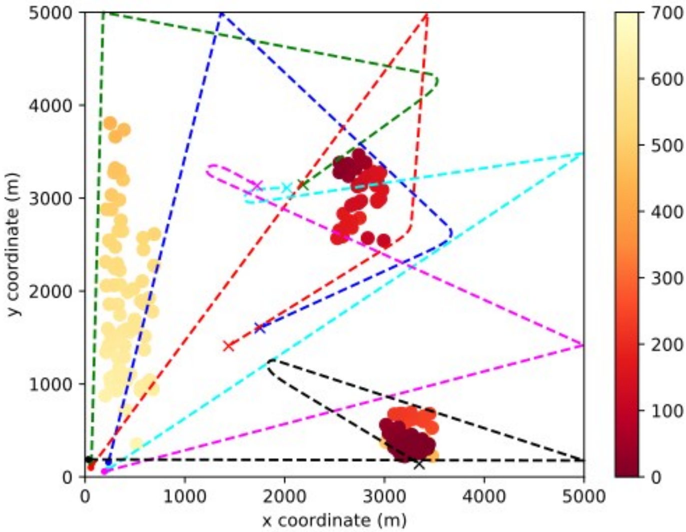


Figure 16. UAV's trajectories and nodes connection time (lb phase)

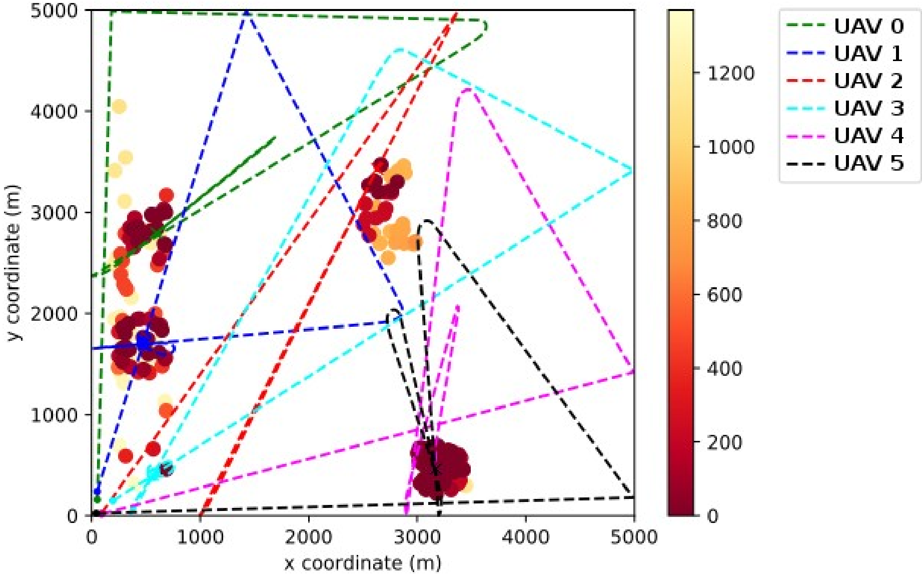


Figure 17. UAV's trajectories and ground nodes connection time (nb phase)

3.3.1.5 Comparison with the Lawnmower algorithm and stopping criterion

The Lawnmower is an optimal trajectory planning algorithm able to guarantee that the scenario area is fully covered and minimizing the vehicles turns. Using the Lawnmower algorithm to the problem described in section 3.1 guarantees sweeping the entire scenario area after a disaster has occurred. This would imply that almost all the of the ground nodes, i.e. the victims, are discovered (as the ground nodes are mobile nodes, there is the possibility of some nodes not being discovered as their locations never coincide with the wireless coverage area of the UAV network). Taking Figure 18 as a reference, after using the Lawnmower algorithm for covering the entire scenario area the UAVs would end up located at one of the scenario corners. At this point, the UAVs could share the information about the different groups of victims discovered and describe simple rectilinear trajectories towards any of the groups. The usage of the Lawnmower algorithm then represents one of the best options for solving the problem addressed in this chapter, as it meets the two main objectives: i) exploring the disaster scenario area for discovering the victims' locations, and ii) making the UAVs to autonomously converge to the clusters in which the victims are organized in. This is the reason for choosing the Lawnmower pattern as the first algorithm to be compared to the proposed dPSO-U mobility model.

In the case of using multiple vehicles following a Lawnmower mobility pattern, the vehicles can be arranged in a line formation and describe parallel trajectories in a synchronized manner. This has been mentioned in previous works such as [205] [103]. Please note that by looking at Figure 18 it may seem that some UAVs are flying longer distances than others in the turns that they perform at the scenario border. However, the turn trajectories depicted in the exterior of the scenario area are only drawn separately for distinguishing the different UAVs mobility. In reality, all UAVs following the Lawnmower approach travel the same distance.

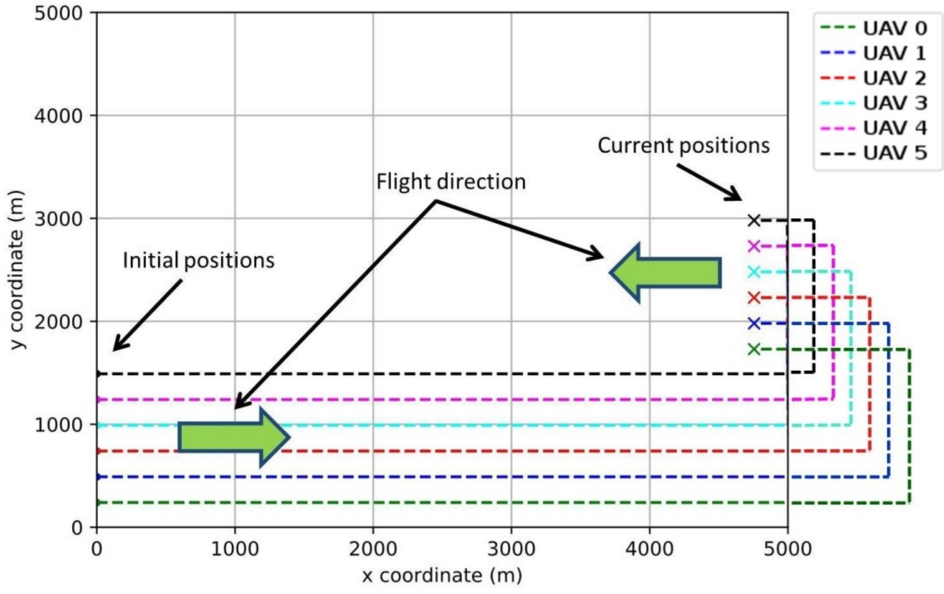


Figure 18. Example of lawn mower movement pattern with multiple UAVs

As the dPSO-U algorithm makes use of the PSO fundamentals as an optimization algorithm, it is necessary to define a stopping criterion to end the optimization iterative process. Due to the fact that the simulation results are presented in comparison to the Lawnmower mobility pattern, the stopping criterion is defined as the time $t = T_{stop}$ at which the UAV team using a Lawnmower pattern completes an entire sweep of the scenario area. As an example, the UAVs shown in

Figure 18 start to sweep the scenario at the bottom-left corner. The stopping criterion, i.e. T_{stop}, will be given by the time when these UAVs reach one of the top corners. The convergence phase of the Lawn mower approach was not included initially in the stopping criterion assuming that the dPSO-U mobility model will be able to make the UAVs converge even before than the UAVs finish an entire sweep of the scenario.

3.3.1.6 Information exchange between UAVs

In the original PSO algorithm [204], two modes of communication are considered. These modes are usually known as the *PSO topology* [203]. The Gbest mode, in which all the particles of the population are assumed to be able to communicate with each other. Therefore, each particle in the swarm shares its local best with all particles. In that case, the global best term that is shown in equation (46) corresponds to the global best of the entire search space. A second mode, called Lbest was also proposed in [204]. The Lbest mode assumes that each particle only shares information with its neighbours. A similar approach to Lbest is followed in the proposed mobility model, due to the limited communication range that UAVs have [206], as it is mentioned in section 3.2. According to this, T_t^i is defined as the topology of particle i at time t. In this section, the term T_t^i corresponds to the group of UAVs that share their own local bests information with UAV$_i$, the neighbours of particle i at time t. The UAV$_i$ neighbours will vary with time as all UAVs are constantly moving and new communication links may be established while other may be broken. Therefore, for each topology T_t^i a neighbour best candidate exists, which will be the best local best value among all the local best of the UAVs that belong to correspond to topology T_t^i. This implies that there are not one but multiple neighbour best candidates.

The information exchanged by UAVs in each encounter corresponds to a tuple that contains: i) the *maximum* value of *ground nodes discovered* and ii) the *UAV location* in which the maximum was reached. Each UAV stores its own local best and also the best among the local best values of all the UAVs it had encounters with. As an example, let's consider three UAVs with indices i, j and k, and a situation at time $t = t_1$ in which UAV$_i$ had an encounter with UAV$_j$ but not with UAV$_k$. In this case, UAV$_k$ may be aware of UAV$_i$ local best through an encounter with UAV$_j$ at a later time $t = t_2$. According to this approach, UAV$_i$ will have a neighbour best $nb_i^{t_1}$ calculated among the local bests of the UAVs which it had encounters with (both directly and indirectly) until the time $t = t_1$. This means that $nb_i^{t_1}$ may have a different value than the neighbour best of UAVj $nb_j^{t_1}$ as this depends on the encounters UAVi and UAVj had with other UAVs. In the case of UAVi having an encounter with UAVj at $t = t_1$, the UAVs will share their neighbour best values $nb_i^{t_1}$ and $nb_j^{t_1}$ with each other, and both will take the maximum of these values as the new neighbour best. This process is shown in Figure 19.

Figure 19. Neighbour best transference between UAVs (I)

Continuing with the example, let's consider that later at $t = t_2$, where $t_2 > t_1$, an encounter between UAVj and UAVk takes place. Let's also consider that both UAVs share their neighbour best values $nb_k^{t_2}$ and $nb_j^{t_2}$ with each other and $nb_k^{t_2}$ is smaller than $nb_j^{t_2}$. In this situation, UAVk will then update its neighbour best to the value $nb_j^{t_2}$ which originally came from the neighbour best of UAVi at $t = t_1$, i.e. $nb_i^{t_1}$. This process is shown in Figure 20.

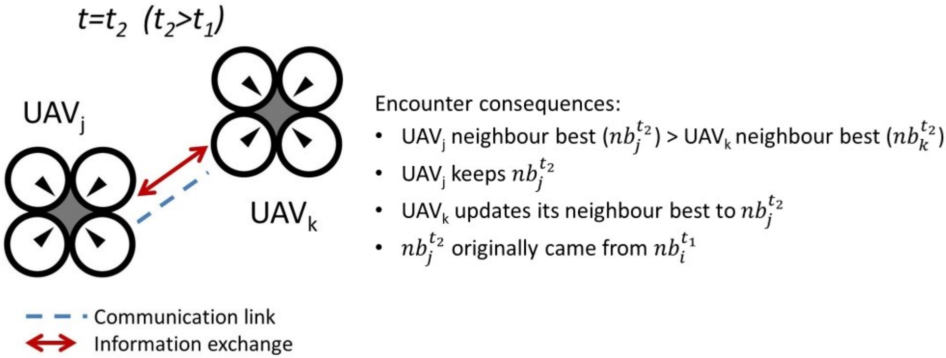


Figure 20. Neighbour best transference between UAVs (II)

3.4 Simulation results

In this section, the simulation results obtained from the *characterization* of the proposed algorithm are introduced. Later on, the algorithm behaviour is characterized and tested on scenarios with a different number of clusters, ranging from 1 up to 10 clusters. Finally, the results of comparing one of the best-performing cases of the dPSO-U algorithm against the Lawnmower planning algorithm are shown.

3.4.1 Simulation settings

The *main settings* used for running all the simulations of the proposed dPSO-U algorithm are shown in Table 3. *Simulation-specific settings* are described in the corresponding subsections included below. It is worth highlighting that all the simulations results presented in this paper were run in tailored software tools developed specifically for this research.

Table 3. dPSO-U main simulation settings

Number of UAVs	6
Number of victims	200
Number of victim's clusters	3
Cluster 1	100 victims
	Bottom-left corner: $(x_{1,0},y_{1,0})$ = (200,200)
	Top-right corner: $(x_{1,1},y_{1,1})$ = (700,4200)
Cluster 2	60 victims
	Bottom-left corner: $(x_{2,0},y_{2,0})$ = (3000,200)
	Top-right corner: $(x_{2,1},y_{2,1})$ = (3500,700)
Cluster 3	40 victims
	Bottom-left corner: $(x_{3,0},y_{3,0})$ = (2500,2500)
	Top-right corner: $(x_{3,1},y_{3,1})$ = (3000,3500)
Scenario dimensions	5000 meters long and 5000 meters wide
Simulation duration (T_{stop})	1633 seconds(an entire sweep of the Lawnmower algorithm)
Simulation step	1 second
Mobility generation tool	BonnMotion [45] with tailored modifications
Characterization	23 value sets of the PSO parameters defined in (1): - Inertia - local best - neighbour best
Iterations	20x4 iterations per each value sets of the PSO parameters: - UAVs starting at each of the 4 scenario corners - 20 iterations per each starting point

3.4.2 Performance evaluation metrics

The *metrics* considered for analysing and comparing the different mobility model aspects are presented in this subsection. These metrics are also used for the task of assessing if the proposed dPSO-U mobility model meets the main objectives of the problem, i.e. exploring the scenario and making the UAVs converge to the ground nodes clusters. These metrics are shown in Table 4.

Table 4. Performance evaluation metrics

Metric	Acronym	Description
Percentage of ground nodes discovered	*NDIS*	The total number of ground nodes discovered by the UAV network. Discovering a node is considered to be the fact of a node being under the wireless coverage range of any UAV at least once. It shows the exploration ability of the algorithm.
Percentage of UAVs converging to a cluster	*NCONV*	The percentage of UAVs that ended up within the area of a victims cluster. It shows whether the UAVs of the network were successful in meeting the secondary goal of the paper.
Time to discover a percentage of ground nodes	*TTDIS*	The time that the UAV network needs for discovering the 25%, 50%, 75% and 100% of the ground nodes.
Convergence time of the UAVs to a cluster	*TTCONV*	The time that the UAV network needs for converging to a victims cluster. The time considered is the average time calculated from the convergence time of all the UAVs in the network.
Number of node-UAV connection events	*NCONN*	The number of connection events between the ground nodes and the UAVs.
Time elapsed between consecutive node-UAV connection events	*TECONN*	The elapsed time between two consecutive connections of one node and any of the UAVs. It shows the frequency of the connections that the nodes can have with any of the UAVs.

3.4.3 dPSO-U characterization

As it has been described in section 3.3.1, the weights corresponding to the inertia, the local and the neighbour best are *dynamic* and can take values from the range [0,1]. Depending on the values assigned to each component, the behaviour of the UAV network will be different. It is important to recall that, the addition of the weights of the three terms of the dPSO-U algorithm have to yield always the value 1 at any time in the simulation. The inertia weight starts always with a value equal to 1 and its final value is obtained by subtracting to 1 the values of the local best and the neighbour best weights. An example of the inertia, local best and neighbour best weights evolution versus time is shown in Figure 21. The most important characteristic in this approach are the final values of the inertia, local best and neighbour best weights of (1). The characterization proposed in this section considers different combinations of the *final values* of the aforementioned weights.

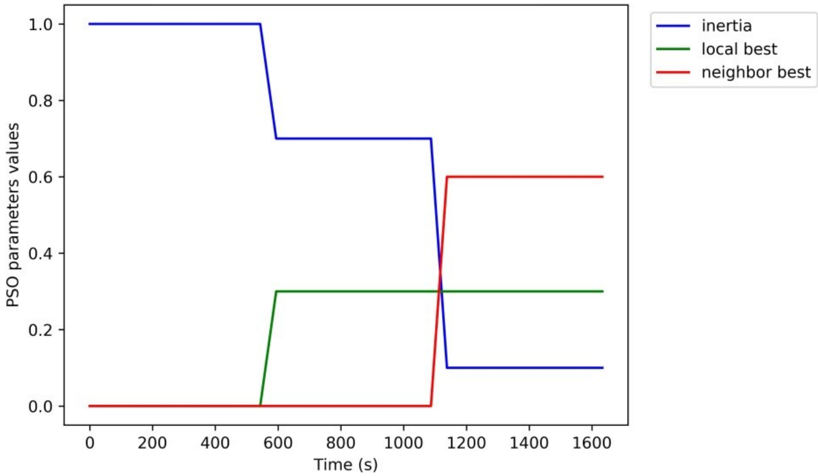


Figure 21. PSO parameters evolution during the simulation time

The dPSO-U characterization carried out in this thesis can be defined as a *coarse-grain* type because it takes discrete values for the final values of the weights. The aim is to have a picture of how the dPSO-U behaves with different values and a coarse-grain characterization serves this purpose. Identifying the best-performing combinations of weight values is useful because it will enable future studies performing a fine-grain characterization centred in small variations of these values. Considering all the possible combinations of the dPSO-U weight values would have consumed extensive simulation time and data processing.

In order to evaluate the effect of different weight final values multiple simulations were run, using the value sets shown in Table 5. These have been organized in different groups, namely: i) *equal*, ii) *only-local-best*, iii) *only-neighbour-best*, iv) *residual-local-best* and v) *residual-neighbour-best*. The reason for having these groups classification is as follows. In the *equal* group, the aim is to analyse the effect of the local and neighbour best weights having the same value. The *only-local-best* case will show the behaviour of the algorithm when there is no neighbour best effect. The analogue situation is the *only-neighbour-best* case, in which there is not a local best effect. The *residual-local-best* analyses the case when the neighbour best weight increases in different simulation executions and the local best keeps a residual value of 0.2. The opposite case is the *residual-neighbour-best* in which the neighbour best weight has a residual value of 0.2 and the local best weight is being increased on different simulation executions.

Table 5. Combinations of the weights final values

		Inertia	Local best	Neighbour best
Equal	Case 1	0.6	0.2	0.2
	Case 2	0.4	0.3	0.3
	Case 3	0.2	0.4	0.4
	Case 4	0.0	0.5	0.5
Only local best	Case 5	1.0	0.0	0.0
	Case 6	0.75	0.25	0.0
	Case 7	0.5	0.5	0.0
	Case 8	0.25	0.75	0.0
	Case 9	0.0	1.0	0.0
Only neighbour best	Case 10	1.0	0.0	0.0
	Case 11	0.75	0.0	0.25
	Case 12	0.5	0.0	0.5
	Case 13	0.25	0.0	0.75
	Case 14	0.0	0.0	1.0
Residual local best	Case 15	0.6	0.2	0.2
	Case 16	0.4	0.2	0.4
	Case 17	0.2	0.2	0.6
	Case 18	0.0	0.2	0.8
Residual neighbour best	Case 19	0.6	0.2	0.2
	Case 20	0.4	0.4	0.2
	Case 21	0.2	0.6	0.2
	Case 22	0.0	0.8	0.2

As a note for clarifying the characterization procedure followed, it is important to highlight that each simulation execution consisted of 80 iterations, having a fixed set of final values of the aforementioned weights. After having a simulation completed with its 80 iterations and a specific set of parameter weights, a new combination of weight values was selected from Table 5 and a new simulation was launched with these new values.

3.4.3.1 Characterization results

In this section, the results that correspond to the characterization of the algorithm with different combinations of the weight values are presented. Figure 22 shows the results according to the metric called *percentage of nodes discovered (NDIS)*.

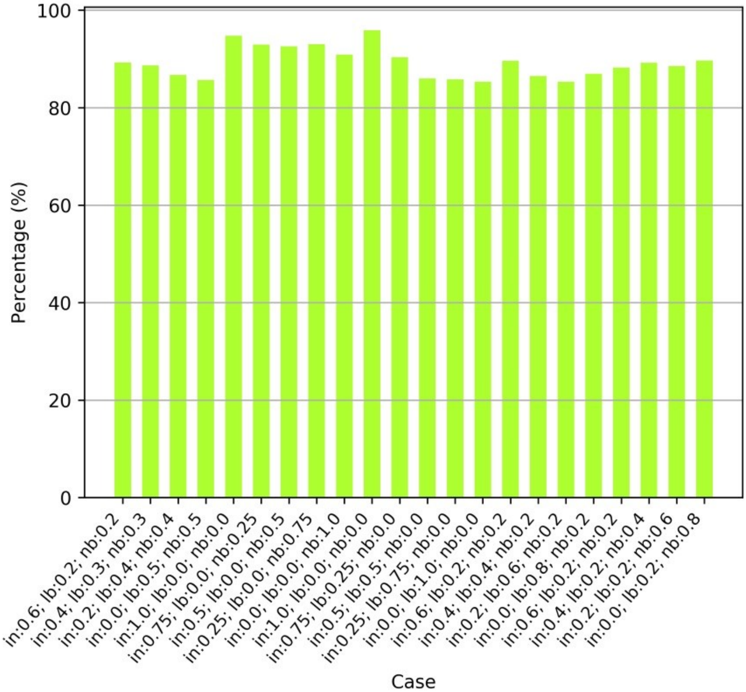


Figure 22. Percentage of ground nodes discovered (NDIS)

As it can be observed in Figure 22, the best result is achieved by the case in which the parameters weights are 1.0, 0.0 and 0.0 for the inertia, local best and neighbour best respectively. In this case, the algorithm spends the entire simulation time with the inertia weight equal to 1, and thus the exploration ability of this set of values is higher than others. It is important to remark that almost all the cases analysed are reaching a discovery percentage of 80% of the victims. The cases from the group only-neighbour-best are even able to discover over 90% of the victims. In order to simplify the results representation, the following acronyms have been used along the charts and text of this section: i) *in* corresponds to inertia, ii) *lb* corresponds to local best, and iii) *nb* corresponds to neighbour best.

Figure 23 shows the time needed by the UAVs to discover the 25%, 50%, 75% and 100% of the victims in the scenario, which corresponds to the metric *TTDIS*. The time needed for discovering the 25% and 50% of the victims is quite similar in the different cases considered. The more noticeable differences, although not big, are in the time needed for discovering the 75% (blue bars). It is important to mention that higher inertia values favour the situation of UAVs covering a bigger scenario area.

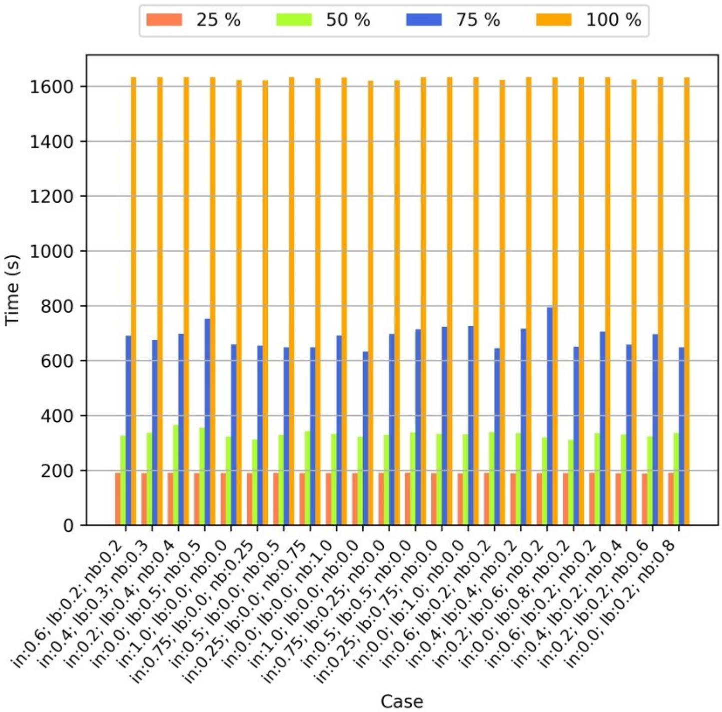


Figure 23. Time up to discovering a percentage of victims (TTDIS)

By looking at the blue bars in Figure 23, it can be observed that the cases in which inertia values are around 0.5 or higher, the time spent on discovering victims is most of the times lower than in other cases. However, higher values in local and neighbour best components favour each UAV to explore the surroundings of the location in which the maximum number of victims were discovered. This could also favour the case of a UAV discovering more victims in the same cluster and therefore reduce the time spent in discovering victims. This is the reason why cases such as the one with values in:0.2, lb:0.6, nb:02 also has a discovery time similar to the ones with values in:1.0, lb: 0.0, nb:0.0 or in:0.75, lb: 0.0, nb:0.25. Besides, the random movements of victims on the ground also affect the discovery time, so one of the good cases from above can perform poorly in a single-time discovery mission. Therefore, the best approach here would be to select cases with good balance among the values of the inertia, local and neighbour best that have optimal or acceptable discovery time, because the balance will allow these cases to yield also good performance in other metrics that are considered in this section, such as the convergence metrics which are shown later in the section.

The number of UAVs that converge to any of the clusters is shown in Figure 24. The results shown in Figure 24 correspond to the *NCONV* metric (*percentage of UAVs converging to a cluster*). It is noticeable that the cases reaching a higher convergence coincide with the neighbour best parameter having the highest values, specifically between 0.4 and 1.0. The two groups sharing this condition are the *only-neighbour-best* and the *residual-local-best*. There are two cases in which the percentage of UAVs converging is under 20%. These cases correspond to cases 5 and 10 of Table 5. In these cases, the local and neighbour best weights are equal to 0, while the inertia weight is equal to 1 for the entire simulation duration. According to these values, the UAVs will move only controlled by the inertia, not being attracted by the local or the neighbour bests at any point. Therefore, the UAV network is not able to converge to a cluster.

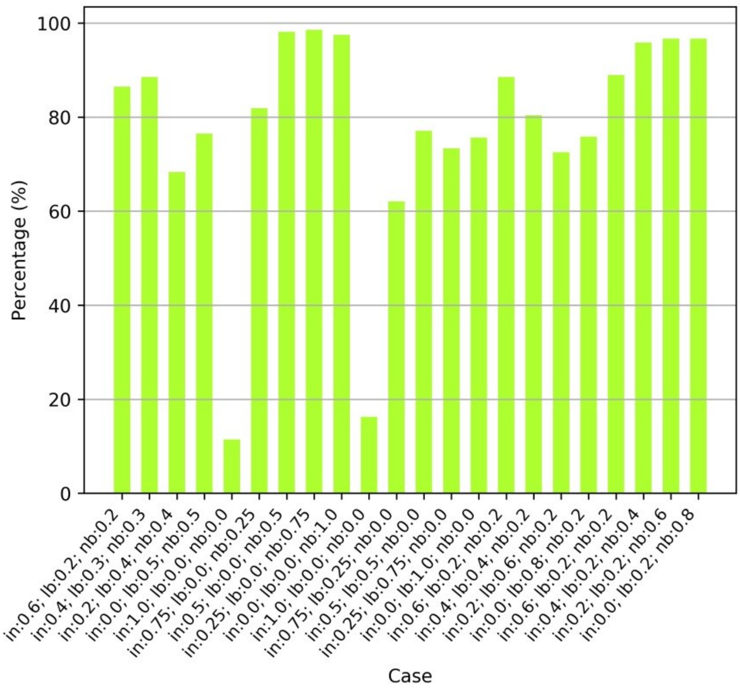


Figure 24. Percentage of UAVs converging to a cluster (NCONV)

Figure 25 shows the *TTCONV* metric (*convergence time of the UAVs to any of the clusters*). The figure shows that the cases that need less time to converge to a cluster are those in which the local best takes higher values. This condition occurs in the groups *equal* (when the local best has the value of 0.5), *only-local-best* and *residual-neighbour-best*. Although the cases of the groups *only-neighbour-best* and *residual-local-best* need more time to converge than those specified before, its performance should not be dismissed as it is around 1200 seconds and these groups showed great results in previous metrics such as those shown in Figure 22 and Figure 24. Figure 25 also shows that the proposed algorithm is able to make the UAVs to explore and converge to a cluster spending between 800 and 1200 seconds, in most of the cases. This means that the mission can be completed in 12 to 20 minutes. This amount of time is a reasonable flight time for most professional multicopters [207]. Besides, fixed-wing UAVs are able to fly during longer time periods [208]. Therefore fixed-wing UAVs can spend around 20 minutes in the exploration and convergence mission and still have enough energy to perform other tasks afterwards.

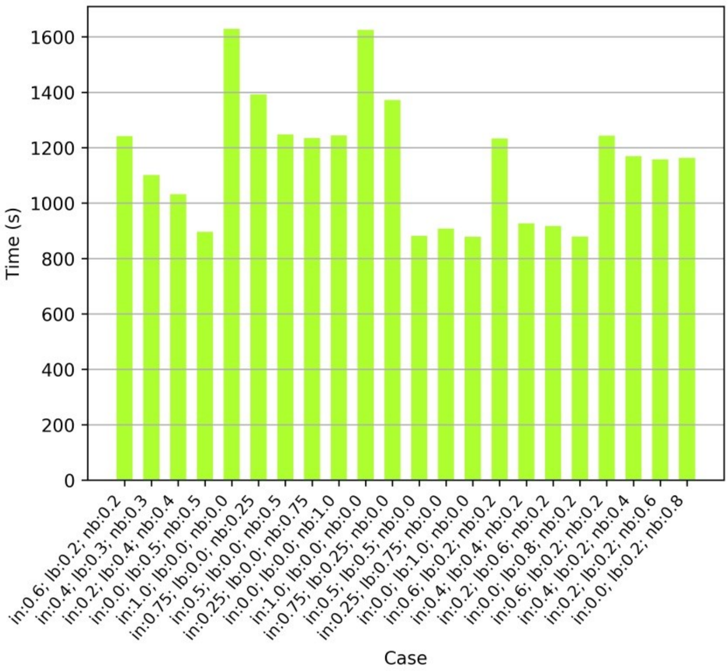


Figure 25. Convergence time of UAVs to a victims cluster (TTCONV)

In Figure 26 the amount of connection events between victims and UAVs is shown. This corresponds to the *NCONN* metric (*number of connections between ground nodes and UAVs).* The left-most bar in each case shows how frequent is occurring the situation in which a node does not have any connection event with a UAV. According to this aspect, the best performing case is the one in which the inertia weight has a value equal to 1.0 and both the local best and the neighbour best have a value of 0.0. However, this case is known to perform not well regarding the convergence metric (NCONV). Also, other cases performing appropriately in Figure 26 are those belonging to the group *only-neighbour-best*. Although it cannot be seen directly in Figure 26, an important aspect that the simulations yield is the most frequent number of connections that one node can have with the UAVs, which is a node having 31 connection events in average. Finally, the green bars in Figure 26 show the maximum number of connection events that one node can have, being all cases performing quite well with the exception of the case of the inertia, local best and neighbour best having values equal to 1.0, 0.0 and 0.0 respectively; and also the cases belonging to the group *only-neighbour-best*.

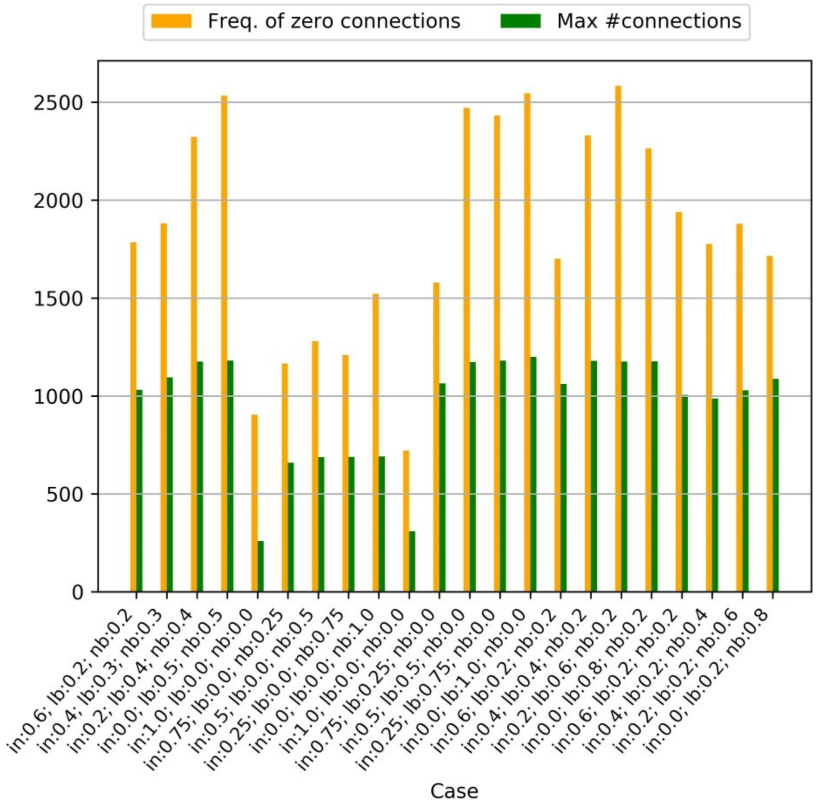


Figure 26. Number of connections between victims and UAVs (NCONN)

Figure 27 shows the time that elapses between two consecutive connection events between one ground node and any of the UAVs. This corresponds to the *TECONN* metric. On the one hand, by analysing the number of nodes having 1 second elapsed between two consecutive connection events, it is clear that all cases are performing well except the ones that have the inertia weight equal to 1.0 and local and neighbour best weights equal to 0.0. This behaviour is related to the fact that these cases are the ones with more exploratory ability but less convergence. For this reason, a communication-related metric like TECONN shows worse results in these cases. On the other hand, the number of nodes having none or only 1 connection is lower in the case of the inertia weight equal to 1.0 and local and neighbour best equal to 0.0, which is also associated with the fact of better exploratory ability. Although is not shown in the figure for clarity reasons, it is important to mention that the most frequent situation is the one in which nodes have only 1 second elapsed between consecutive connections to UAVs.

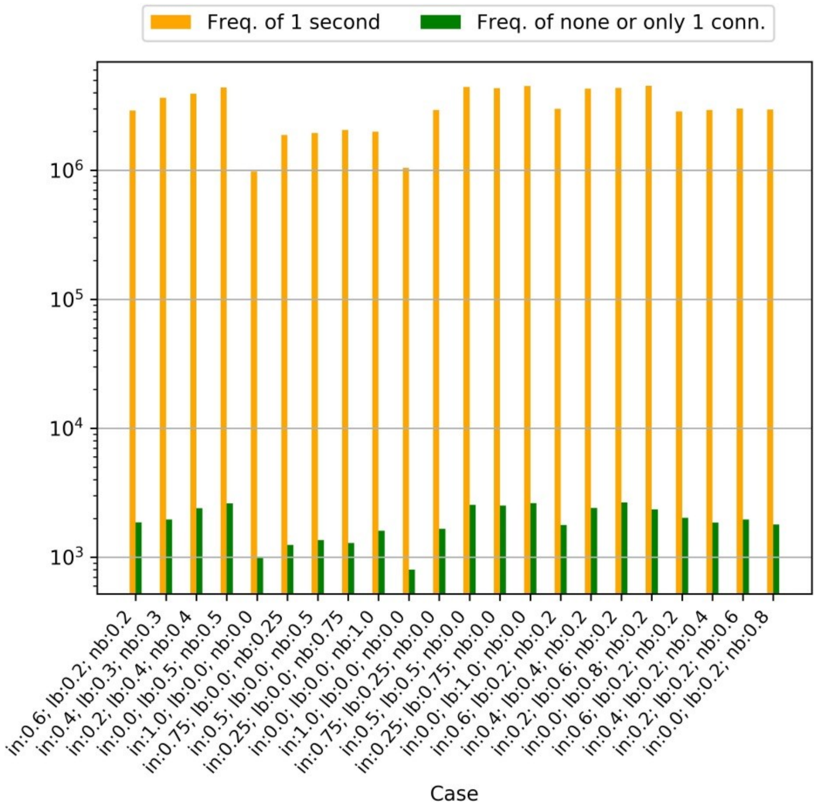


Figure 27. Time between consecutive node-UAV connections (TECONN)

3.4.4 dPSO-U behaviour with a variable number of clusters

In this section, the behaviour of the dPSO-U algorithm when varying the number of clusters in the scenario is described. One of the best cases of the dPSO-U algorithm has been selected among all the characterization cases considered in the previous section. The selected one is *case 17* from the group residual-local-best, which has the values 0.2, 0.2 and 0.6 for the inertia, local best and neighbour best respectively. In order to perform this analysis, one instance of the dPSO-U algorithm has been run using 10 different scenarios, where each scenario has a different number of clusters. The number of ground nodes has been maintained to 200 in all scenarios. This means that in the scenario that has only one cluster, all the victims are included in this cluster. In the cases of the scenarios that have more than one cluster, the 200 victims are distributed over the different clusters. The number of UAVs has been equal to 6 in all the scenarios. These settings have allowed analysing the behaviour of the proposed algorithm when the victims are distributed over a different number of clusters.

The simulations settings used in this section are the same as those shown in Table 5 except for the number of clusters, which have been varied as shown in the first column of Table 6. The results of this analysis are shown in Table 6.

Table 6. dPSO-U performance results with a variable number of clusters

# clusters	Victims discovered (%)	UAVs converging to a victims cluster (%)	Mean of the convergence time of the UAVs to the clusters (s)	Frequency of nodes with zero connections to a UAV	Frequency of nodes connecting to UAVs every 1 second
1	80.98 %	54.79 %	1269.1 s	4705	1923493
2	85.67 %	73.33 %	1160.1 s	2996	2588979
3	85.21 %	91.67 %	1013.0 s	2620	3406488
4	87.58 %	91.46 %	987.7 s	2224	3432252
5	82.78 %	96.46 %	969.5 s	3103	3061198
6	79.37 %	95.62 %	972.0 s	3589	2939748
7	81.19 %	97.92 %	954.9 s	3266	2972984
8	79.51 %	99.38 %	939.6 s	3573	2912765
9	82.33 %	98.54 %	909.9 s	3102	2903312
10	84.43 %	97.29 %	941.9 s	2786	3242748

The metrics considered for assessing this section's results are the percentage of ground nodes discovered (NDIS), shown in the second column; the percentage of UAVs converging to a cluster (NCONV), shown in the third column; the convergence time of the UAVs to any of the clusters (TTCONV), shown in the fourth column; and the time elapsed between consecutive connection events among ground nodes and UAVs (TECONN) which corresponds to the two right-most columns.

As shown in Table 6, and according to the NDIS metric, the dPSO-U algorithm is able to discover an important number of victims in scenarios with a different number of clusters, always with a percentage over the 79%. This is an important result as it is directly related to the first objective described in section 3.1, i.e. the exploration capability of the mobility model. It is important to clarify here that there is not a clear trend that can be identified from the second column of the table. The percentage of victims discovered is around 83% but may decrease or increase in specific cases. The reason for this is that when including a new cluster in the scenario, its position and area are chosen randomly and some clusters may be more likely to be discovered than others.

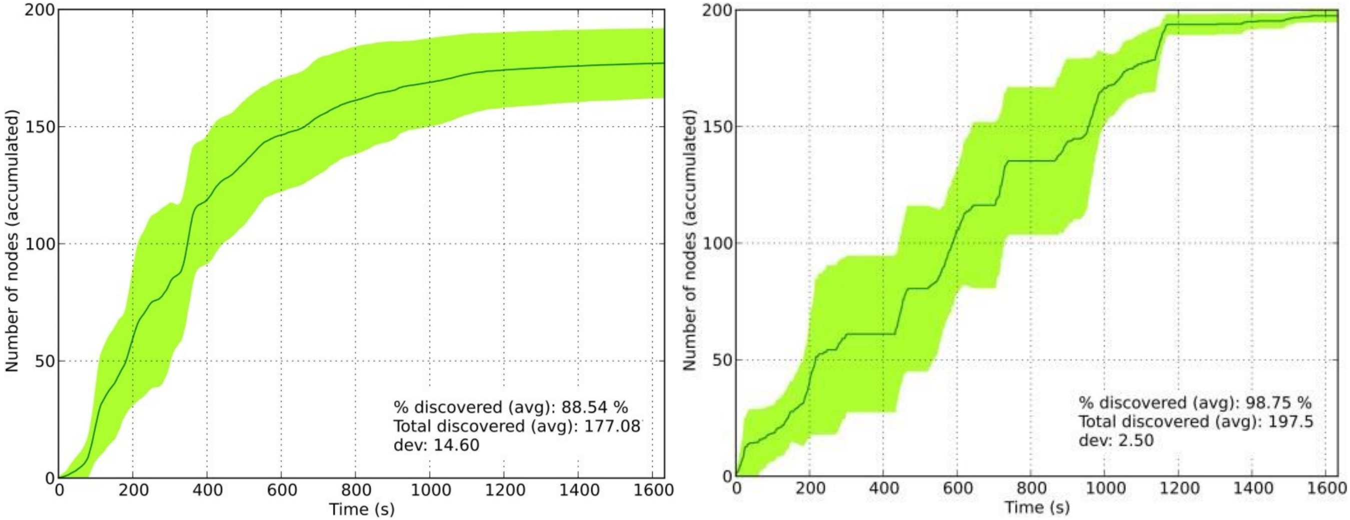
Regarding the convergence to the clusters (NCONV), the results shown in the third column demonstrate that with a higher number of clusters, the majority of UAVs are able to converge to a cluster. In all the cases the convergence is over 90%, except for the scenarios with one and two clusters. This is due to the fact that in a scenario with fewer clusters, there are many areas in the scenario without ground nodes and therefore not all the UAVs would be able to discover a cluster or receive information about a cluster from another UAV. If a UAV is not able to discover a cluster during the simulation time (or receiving information about a cluster from an encounter with another UAV) it will continue exploring and therefore it will not converge to a cluster. Also, according to the TTCONV metric shown in the fourth column, the time that the UAVs require to converge to a cluster has the tendency to decrease when the number of clusters increases. When there are more clusters spread over the scenario it is more likely for a UAV to discover and converge to a cluster faster than in the cases where there are only a few.

Also, regarding the connections between UAVs and ground nodes (TECONN), two aspects have been introduced in Table 6. The first one, shown in the fifth column, shows the frequency of victims not having any connection event with a UAV. According to this aspect, the dPSO-U algorithm shows that with scenarios with more clusters, the frequency of the cases in which nodes are not under UAV wireless coverage decrease. The second aspect, shown in the sixth column, shows the frequency of victims connecting to UAVs every 1 second, i.e. a continuous connection during a specific period of time. As shown in Table 6, it can be observed that while the number of clusters in the scenario increase, there are more ground nodes experiencing a better connection service, i.e. more nodes are granted with connections to the UAVs every 1 second. These results are related to the fact that victims are more spread over the scenario in the case of a higher number of clusters. In this situation it is more likely that UAVs encounter ground nodes, reducing the number of victims with zero connections. Also, as the convergence is higher in the cases with more clusters, the UAVs will provide a better service to the ground nodes after the convergence phase, i.e. there will be more cases of connections every 1 second between ground nodes and UAVs.

As a summary, the two main objectives of the problem described in 3.1 were: i) exploring the scenario in search for victims and, ii) converging to a victims cluster. As shown in Table 6, the dPSO-U algorithm is able to meet these two objectives even when the number of clusters varies.

3.4.5 Comparison: dPSO-U vs lawn mower

In this section, one of the best cases of the dPSO-U algorithm is compared against the Lawnmower algorithm. The selected value set for the weights corresponds to *case 17* from Table 5, within the group *residual-local-best*, and which has the values 0.2, 0.2 and 0.6 for the inertia, local best and neighbour best respectively. Figure 28 shows the number of ground nodes discovered during the simulation.



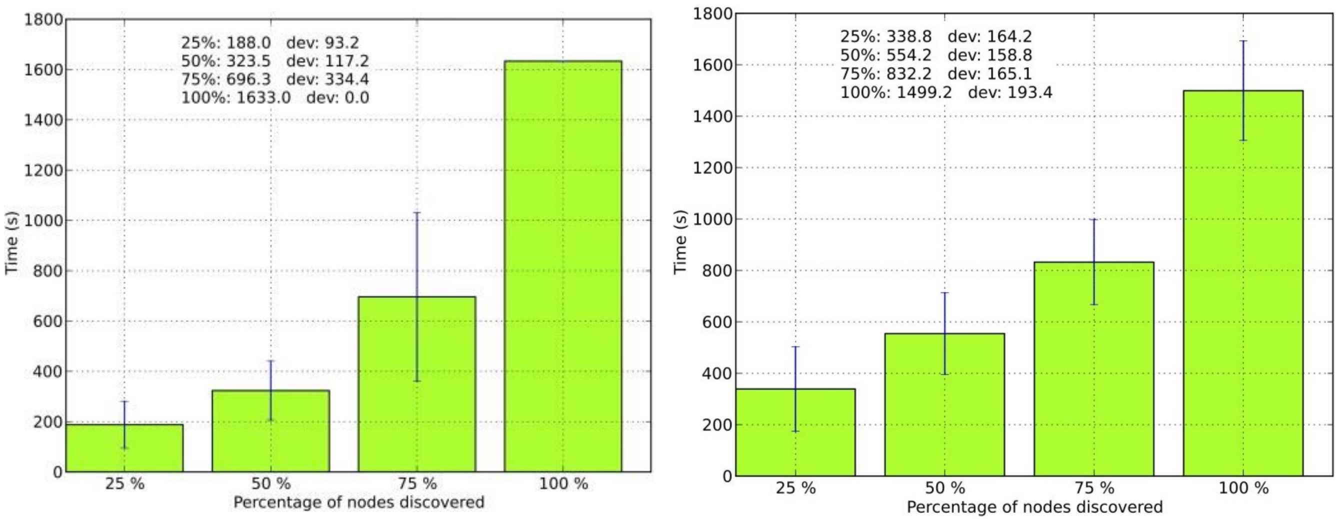
a) dPSO-U algorithm

b) lawn mower

Figure 28. Total number of discovered nodes

The left-hand side of Figure 28 shows that the proposed dPSO-U algorithm is able to discover 88.54% of the victims on average. It is noticeable the continuous increase that the proposed dPSO-U algorithm has, allowing to discover an important number of victims sooner than the Lawnmower algorithm. In addition, by comparing y-axis values in Figure 28, corresponding to the nodes discovered at $t = 200; 400; 600; and\ 800$, it is remarkable how the dPSO-U has always discovered (on average) more ground nodes than the Lawnmower. The right-hand side of the figure shows that the final number of nodes discovered by the Lawnmower algorithm is, on average, a 10% bigger than in the proposed dPSO-U algorithm. This result is expected taking into account that the Lawnmower has planned trajectories that guarantee sweeping the entire scenario area. Besides, the discovery slope is more irregular in the Lawnmower case.

Figure 29 shows the results for the TTDIS metric, i.e. the time needed for discovering the 25%, 50%, 75% and 100% of the ground nodes. It takes less than 700 seconds for the proposed dPSO-U algorithm to discover the 75% of the nodes. However, due to the fact that not all the nodes are discovered, the 100% bar shows that the entire simulation duration was not enough to discover all the victims in the scenario. The Lawnmower algorithm is able to discover (in most of the cases) all the nodes in less time than the simulation duration. However, the proposed dPSO-U algorithm is able to discover the 25%, 50% and 75% of the nodes in less time than the Lawnmower. This is related to the curve slope shown in Figure 28, which has a homogeneous increase trend in the case of the dPSO-U algorithm.



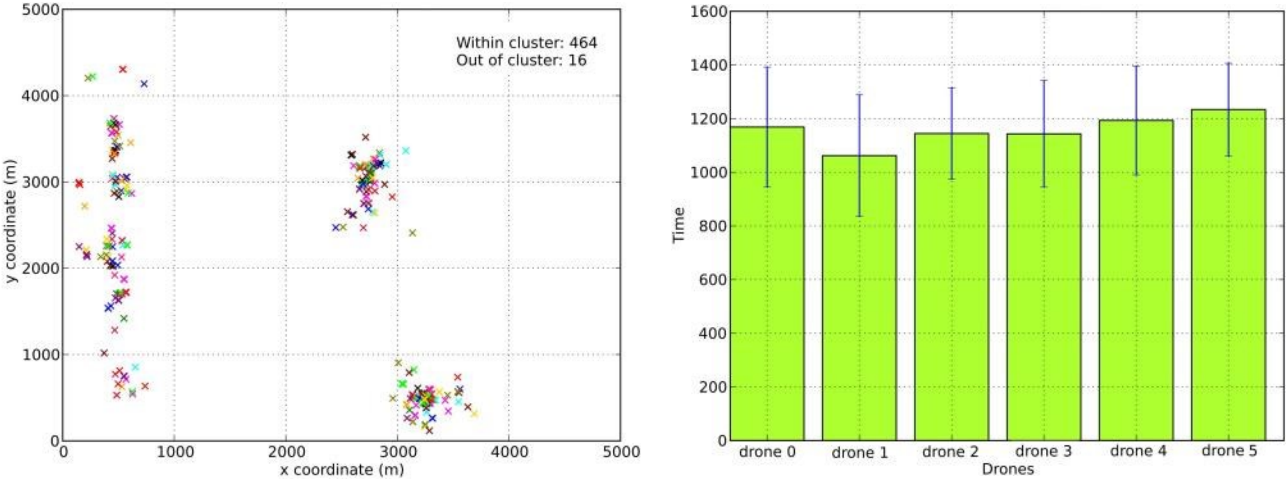
a) dPSO-U algorithm

b) lawn mower

Figure 29. Time up to the discovery of a percentage of nodes (TTDIS)

Figure 30 shows two metrics of the proposed dPSO-U algorithm. The left part of the figure shows the final positions of the UAVs, which clearly demonstrates that the proposed dPSO-U algorithm is able to make them converge to the three clusters that are shown in Figure 12. Each colour of the figure represents the UAVs final positions for each one of the algorithm iterations.

The right part of the figure shows the time that each UAV needs to converge to a cluster, which corresponds to the TTCONV metric but showing separate results per each UAV in the network. It is noticeable that the average of the convergence time of all UAVs is less than 1200 seconds. In the simulations, the Lawnmower algorithm has been simulated until the UAV network finishes an entire sweep of the scenario area. Thus, the final positions of UAVs in the Lawnmower algorithm always coincide with a corner. This is why there is not included an analogous figure to Figure 30 for the Lawnmower case. It would be necessary that another algorithm makes the UAVs converge to a cluster after the entire scenario sweep has finished, thus needing more time than the simulation duration for the convergence.



a) UAVs final positions

b) Convergence time of UAVs to a cluster (TTCONV)

Figure 30. UAVs final positions and convergence time to a cluster (dPSO-U)

Figure 31 and Figure 32 show the *histograms* of the node connection events with any UAV of the network, corresponding to the NCONN metric. Figure 31 corresponds to the proposed dPSO-U algorithm case and Figure 32 to the Lawnmower case. The number of nodes having zero connections is considerably bigger in the proposed dPSO-U algorithm case in comparison to the Lawnmower case. However, by analysing the x-axis, the dPSO-U algorithm presents a wide range of cases, i.e. there are nodes that only had 1 connection event up to nodes with more than 1000 events. In the case of the Lawnmower, the x-axis has almost all the values centred between 0 and 100 connection events. The top value is 130, which means that the maximum number of events that a node may have is 130. Therefore, the proposed dPSO-U algorithm is a better candidate for providing communication services to victims due to the ability to move towards the clusters. By doing this the victims may exchange more information with the UAV network. However, in order to be able to provide a better communication service to the majority of ground nodes, the 12% of the nodes are not discovered by the dPSO-U algorithm, as it has been shown in Figure 28.

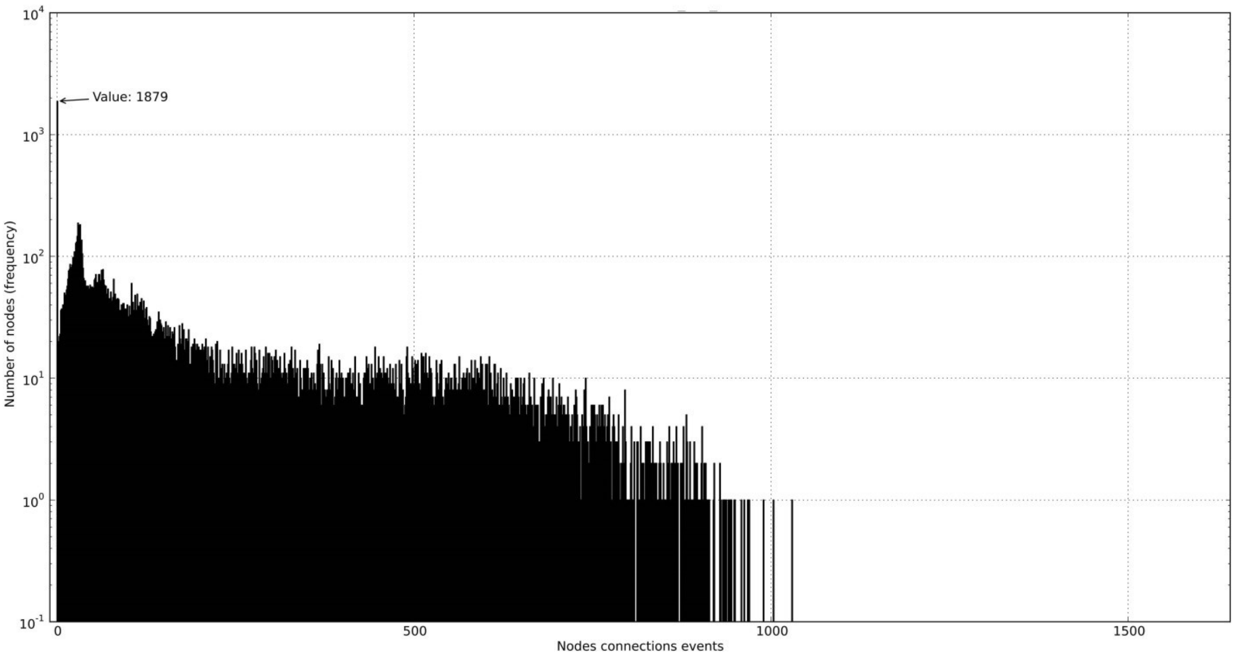


Figure 31. Histogram of node-UAV connection events (dPSO-U)

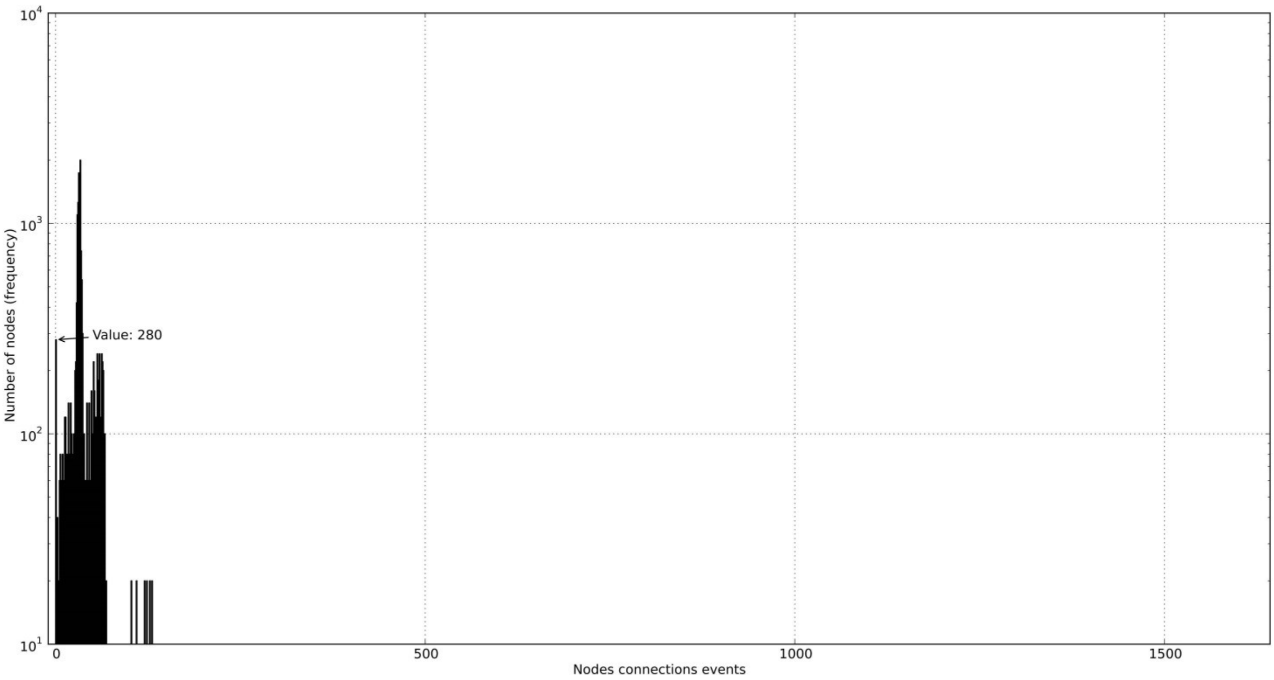


Figure 32. Histogram of node-UAV connection events (Lawnmower)

Figure 33 and Figure 34 show the time elapsed between consecutive connection events of a node, which corresponds to the TECONN metric. In both algorithms, the most frequent case is the one in which the nodes have events separated by 1 second. The right-most bar in both algorithms represents the nodes that did not have any connection events or only had one during the entire simulation. This number is higher in the case of the dPSO-U algorithm (Figure 33), due to the fact that the Lawnmower algorithm (Figure 34) is able to discover almost all nodes in the scenario. However, the left-most bar, which shows the number of nodes that had only 1 second elapsed between consecutive connection events is considerably higher in the dPSO-U algorithm in comparison to the Lawnmower algorithm. By analysing the entire left part of the x-axis, which represents the cases with smaller time elapsed between two consecutive events, the dPSO-U algorithm shows higher frequencies than the Lawnmower algorithm. This is related to providing a better communication service to victims as the time between connection events is shorter. Finally, the number of values shown along the x-axis is bigger in the dPSO-U algorithm, demonstrating that the elapsed time between consecutive connections can take a wide variety of values. The left-most part of the Lawnmower case has smaller values and also there is not a continuous set of values along the x-axis, only small regions around the values of 500 and 700 seconds. This also demonstrates that the dPSO-U algorithm has better behaviour for providing better communication service to ground nodes.

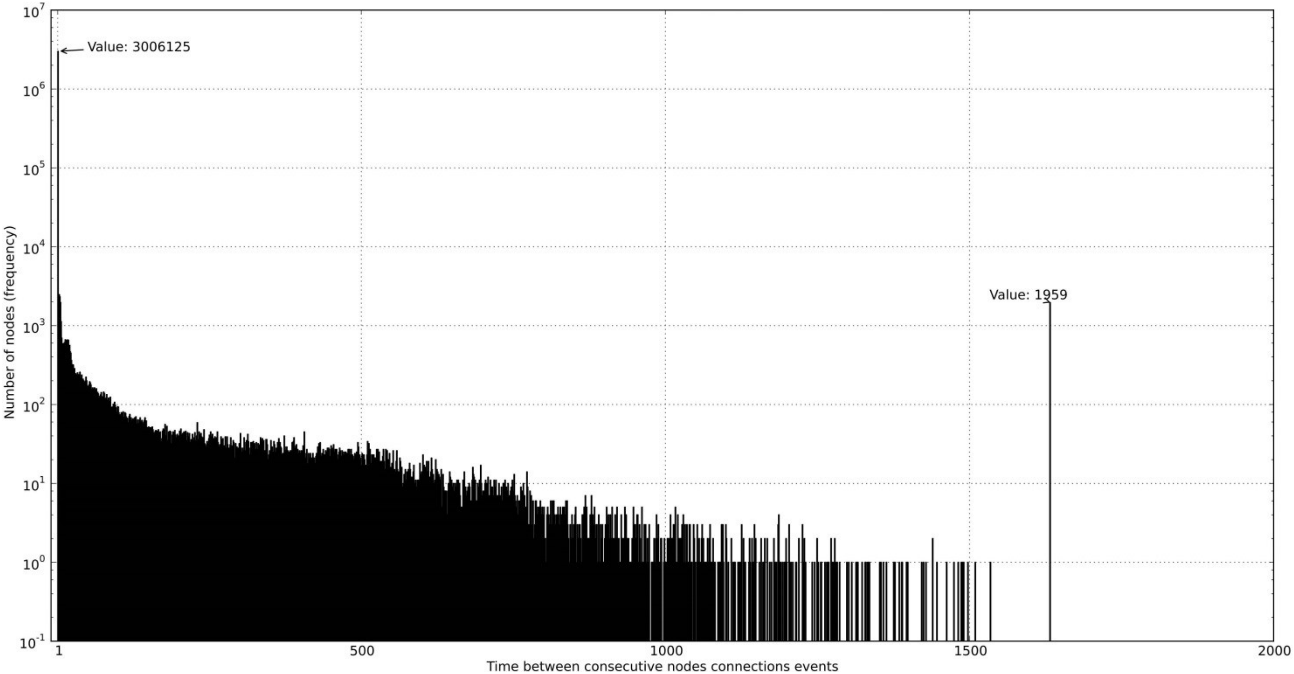


Figure 33. Histogram of the time elapsed between consecutive node-UAV connection events (dPSO-U)

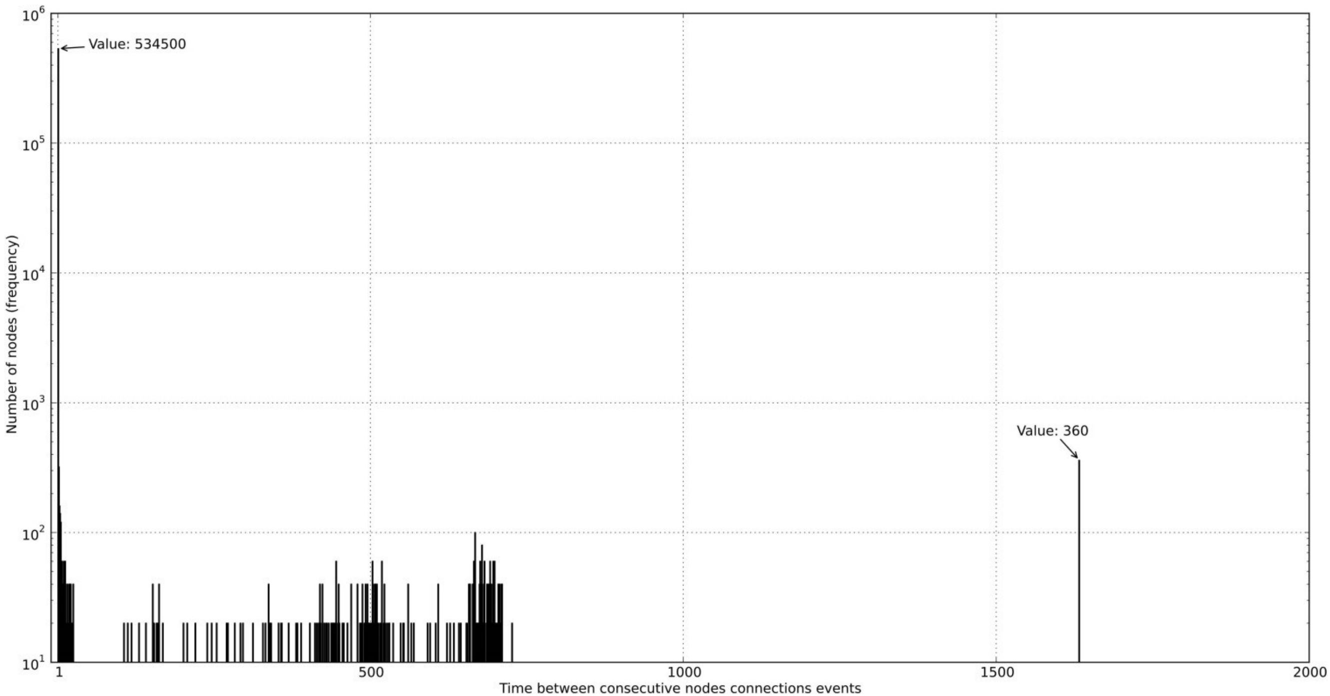


Figure 34. Histogram of the time elapsed between consecutive node-UAV connection events (Lawnmower)

3.5 Discussion of results

This section gathers the main details of the work described in this chapter and the results shown in previous sections. The only purpose of this section is not to introduce new data but only to summarize the information described in this chapter.

This chapter has proposed a mission-based mobility model for a UAV network. The mission context corresponds to an emergency relief operation in a disaster scenario. The scenario context corresponds to a large scale area where several groups of ground nodes (i.e. victims) are waiting for an emergency response team. These groups are called clusters and occupy different locations and have different size and shapes. The UAV network mobility model aims at meeting two main objectives: i) exploring the scenario gathering information about the victims' locations, and ii) making the UAVs converge to the various clusters discovered during the exploration phase. The main contributions of this chapter are listed below:

- A new distributed algorithm called dPSO-U based has been proposed as a mission-based mobility model for a UAV network meeting the objectives described above. The proposed dPSO-U mobility model is based on the well-known PSO algorithm, considering the UAVs as the particles of the algorithm which exchange information with each other according to the typical wireless communication constraints of UAVs.
- The dPSO-U mobility model has been characterized for several sets of final values of the inertia, local best and neighbour best weights. The proposed dPSO-U mobility model uses dynamic weights for the inertia, local best and neighbour best terms. These dynamic weights provide the UAV network with the ability to explore the scenario area and then make the UAVs converge to the different clusters. Sets of values of the aforementioned weights have been identified for meeting the mission objectives.
- Several metrics that assess the exploration, convergence and communication provision has been used. These metrics are the percentage of ground nodes discovered (NDIS), the percentage of UAVs converging

to a cluster (NCONV), the time to discover a percentage of ground nodes (TTDIS), the convergence time of the UAVs to a cluster (TTCONV), the number of connections between ground nodes and UAVs (NCONN), and the time elapsed between consecutive connection events between a ground node and a UAV (TECONN). These metrics have allowed analysing the capabilities of the several sets of final values of the inertia, local best and neighbour best weights. For instance, the case with values 0.2, 0.2 and 0.6 for the inertia, local best and neighbour best respectively has been identified as one of the best value combinations for meeting the mission objectives. Almost all value sets can be organized in three groups: i) those with better exploration capability but less convergence, ii) those with good convergence but with less exploration capability, and iii) those that meet an equilibrium between the exploration and the convergence capabilities.

- Also, the dPSO-U mobility model has been validated in different scenarios, having the number of clusters varying from 1 to 10. The specific set of values for the inertia, local best and neighbour best have been 0.2, 0.2 and 0.6 respectively. The metrics used to assess the behaviour of the mobility model in this situation have been the percentage of ground nodes discovered (NDIS), the percentage of UAVs converging to a cluster (NCONV), the convergence time of the UAVs to a cluster (TTCONV) and two other metrics related to the number of connection events between ground nodes and UAVs (NCONN), specifically the frequency of nodes with zero connection events and the frequency of nodes connecting to UAVs every 1 second. The dPSO-U mobility model has been able to meet the mission objectives, i.e. the exploration capability has been demonstrated as the total number of victims discovered has been over 79% in all cases, and also, in all the cases, the convergence is over 90%, except for the scenarios with one and two clusters.
- Finally, the last goal was to compare the proposed dPSO-U mobility model against another algorithm with good performance in exploring scenario area like the one used in this chapter. The Lawnmower algorithm has been selected as the algorithm used for this comparison. The dPSO-U mobility model has demonstrated its ability to overcome the Lawnmower in terms of reducing the exploration and convergence time while maintaining a high percentage of victims discovered. The dPSO-U algorithm explores a

considerable size of the scenario area and makes the UAVs to converge to the clusters even before that the Lawnmower has finished the scenario area exploration. Moreover, the dPSO-U algorithm has shown better results in terms of communication service aspects since the first stages of the mission.

In conclusion, the mission-based mobility model proposed, called the dPSO-U mobility model, can be considered one of the few mission-based mobility models for UAV networks found today in the literature which complies with the requirements of an exploration and convergence mission, and also showing good performance according to the several metrics used.

4. MOBILITY MODELS FOR ADAPTIVE COVERAGE

"Si tu mal no tiene cura ¿para qué te apuras?, y si tiene cura, entonces… ¿para qué te apuras?"

Jaime Sánchez Vázquez

The previous chapter proposed a mobility model able to make a UAV network to explore a disaster scenario and its UAVs to converge to several areas where ground nodes (i.e. victims) were grouped. This chapter focuses on a smaller group of ground nodes that are moving within an area with smaller dimensions than the scenario considered in section 3.2.1. In this situation, a UAV network is given the mission to provide wireless coverage and therefore communication services to these ground nodes. For this purpose, a mobility model is proposed with two main objectives: i) generating trajectories for the UAVs such that the number of victims under the UAV network wireless coverage area is maximized, and ii) maintaining the UAVs as a connected network, thus avoiding UAVs disconnections. This chapter is organized in the following sections: problem description, problem model, proposed solution, simulation results and discussion of results.

4.1 Problem description

The previous chapter considered that the exploration mission was accomplished once the UAV network has explored the scenario, detected as many ground nodes as possible and the UAVs have converged to the different groups of victims, i.e. clusters. Although not necessarily, the problem described in this section could be considered as the *continuation* of the one described in section 3.1. Specifically, once the UAV network has gathered information about the locations of the victims and the UAVs are located within the region of a cluster, these UAVs can be very helpful assisting the ground nodes (i.e. victims and first responders) *in the cluster*, providing *communication services* to them. The communication services that the UAV network can provide to the ground nodes may range from important informative messages (such as first aid advice, or organizational instructions for keeping the victims safe until the emergency responders arrive) to establishing direct communication among first responders and victims. Therefore, a new problem arises, which is organizing the UAV network in order to provide communication services to as many ground nodes as possible.

Based on the aforementioned problem statement, the goal is to propose a mobility model able to emulate the behaviour of a UAV network participating in a mission with two main objectives. The first objective is to generate trajectories for the UAVs so the number of ground *nodes under the wireless coverage area* of the UAVs is *maximized* during the mission (thus adapting on the fly to the mobility of the nodes). The second objective is to maintain the UAVs as a *connected network*, avoiding UAVs disconnecting from the network.

Although both problems, the one described in section 3.1 and the one described in this section, could be considered to be consecutive in time, these have been addressed separately during the research developed for this thesis and therefore both proposed solutions have some aspects in which differences appear. Examples of these differences are the size of the scenarios considered, the level of details in the scenarios, the number of ground nodes, among others. Having addressed both problems separately allows using each mobility model for separate missions as well, e.g. using the mobility model from section 3.3 only for an exploration mission without requiring providing wireless coverage to a cluster later, and vice versa.

4.2 Problem model

With the aim of addressing the problem described in the previous section a mission-based mobility model for a UAV network is proposed. The problem is modelled as follows. The scenario considered is two dimensional and smaller than the one considered in section 3.3. Specifically, the scenario has a size of 1000 meters per side. In this case, this scenario could be considered as the region corresponding to a cluster of section 3.3. Also, the ground nodes considered are those that would belong to a cluster, i.e. a subset of the ground nodes from the entire nodes set considered in section 3.3. These ground nodes are supposed to be victims moving in unpredictable ways and first responders.

The UAV network is assumed to start the mission located in the *centre* of the disaster scenario area. As one of the mission objectives is to maintain a connected network, the DTN paradigm no longer applies here. Therefore, the UAV network is considered to adhere to an appropriate paradigm like the *Wireless Mesh Network (WMN)*. During the entire mission, the UAVs exchange messages with each other whenever they are separated a distance smaller than the wireless maximum communication range. The idea behind the *information sharing* mechanism is that all UAVs in the network have the same data related to the ground nodes and other UAVs, e.g. their locations. This will allow the UAV network to make specific actions based on this information, e.g. calculating the Jaccard distance between the network neighbours (this concept will be explained later on). This is also the reason for the second objective of the mission, i.e. keeping a connected UAV network at any time.

Based on the previous information exchange mechanism, the proposed mobility model algorithm will be providing each UAV with new positions to occupy in the scenario, as part of each UAV's trajectory. The trajectories generated by the mobility model have to meet the two mission objectives, namely: i) provide wireless coverage to the maximum number of ground nodes as it is possible (and adapt to the movements of the nodes), and ii) maintain the UAV network as a connected network. A depiction of an example of the mobility model and the UAV network organization is shown in Figure 35, where red dots represent ground nodes under the UAV network wireless coverage area and black dots represent those out of the coverage area. A possible initial configuration is shown on the left side of Figure 35 where UAVs are close to the scenario centre. On the right-hand side of the figure, the mobility model has provided new locations to the UAVs which maximize the number of ground nodes under the wireless coverage area. Please note that Figure 35 is only an example of the mobility of the UAV network and not the real mobility model, which will be later explained with more detail.

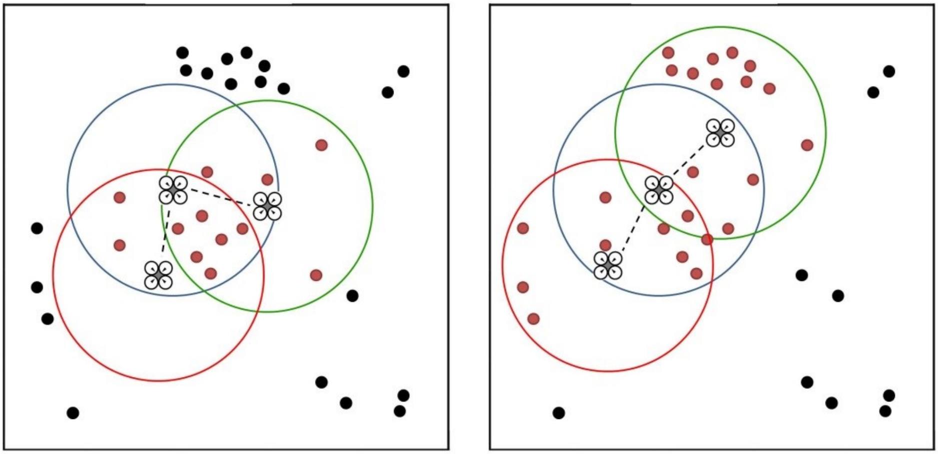


Figure 35. UAVs maximizing ground nodes coverage (right) with respect to a previous configuration (left)

Further details on the considerations and assumptions made for modelling the problem are provided in this section. The first subsection describes the environment model regarding the disaster scenario and the second one provides details about the UAV network models.

4.2.1 Scenario model

This chapter considers an urban disaster scenario and focuses on the *incident site*, i.e. the area where the victims are located before the emergency response team arrives [47]. This scenario is smaller in comparison to the one considered in section 3.2.1. Specifically, in chapter 3, the scenario size is of 5000 square meters while this chapter considers a scenario of 1000 square meters. At the same time, the scenario considered in this section corresponds to an urban area, such as a portion of a small town or village which is affected by a disaster. As mentioned in previous sections, this scenario considered in this chapter could be considered as one of the clusters that were described in section 3.2.1, but presenting now more details and therefore being a more detailed model.

The movements of the victims within an incident site can be very heterogeneous and difficult to categorize. Random movements are very likely to be found on victims. Also, because of considering an urban area, the scenario has been modelled with more details, having *buildings*, *streets* and *open areas*. *Architectural features* of the disaster area such as buildings and streets may affect the movements of the victims. As an example, victims could move along a road trying to escape from the danger but they cannot jump over a building, or they might find a blocked street due to building wreckage.

There is not much information in the literature about movement traces of victims within an incident site. Previous works on disaster mobility models are mainly focusing on rescue workers mobility [47] [179] [45] [209]. Among the few of them modelling the mobility of the victims, an example is [47], which describes the incident site as a squared scenario in which victims move all over the space following the random waypoint (RWP) mobility model. This section proposes a more detailed and complete urban disaster scenario model.

4.2.1.1 Scenario assumptions

The main features of the scenario model proposed in this chapter are as follows:

- The scenario modelled has two dimensions (2D) and is composed of different regions. Similar flat and squared scenarios have been proposed in other works [154].
- Several regions types are defined, each of these representing typical elements that are found in urban scenarios, such as roads and building blocks. Each region type is characterized by specific constraints associated with its shape and the movement that the victims are allowed to perform within the region. The main region types are: i) streets, ii) building blocks iii) open areas such as parks, and iv) prohibited areas, in which the victims are not allowed due to structural features (e.g. fences, walls…) or dangers (e.g. fires, wreckage…).
- There are other regions which are typical of disaster scenarios. Building wreckage or debris usually appears in disaster scenarios. Thus, other

regions are considered, such as i) *blocked roads* and ii) *buildings traps*. *Blocked roads* are roads with specific points in which victims only have two possible movements, to stop at that point or to move in the opposite direction. *Buildings traps* are buildings or other architectural structures that keep some victims trapped inside. Those trapped victims cannot escape without the help of a rescue team.

4.2.1.2 Ground nodes mobility model assumptions

In the proposed model, ground nodes (i.e. victims) are moving within the aforementioned scenario according to the following considerations:

- Victims may move randomly, changing their speed and direction at any time, but only within a region. To model the movements of the victims, the RWP mobility model is used but improved with specific movement constraints associated with each region defined (e.g. victims move in a street region using only a linear movement).
- Victims' speed varies between 0.5 ms^{-1} up to 3 ms^{-1}. Also, victims may be static during a specific time frame i.e. not moving at all. The highest speed represents victims running around, looking for help, escaping from potential danger or acting under the influence of a nervous breakdown. Static victims and those moving at the lowest speeds represent victims that might have difficulties to move, probably because of the injuries suffered during the disaster.
- *Sudden changes* are also likely to occur in disaster scenarios, such as a building collapse or an explosion. These situations have been modelled by making some victims groups disappear from the disaster area at a few specific times.

An example of the disaster scenario proposed with the different regions (marked with the coloured rectangles), is depicted in Figure 36. The different regions features are described in the legend of the figure. This is the urban disaster scenario model that has been used for the simulations carried out for this chapter.

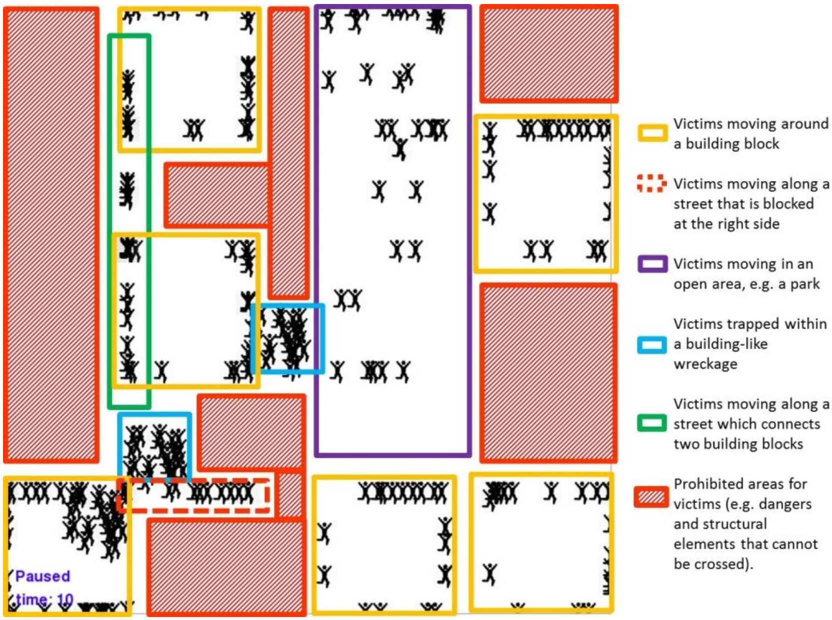
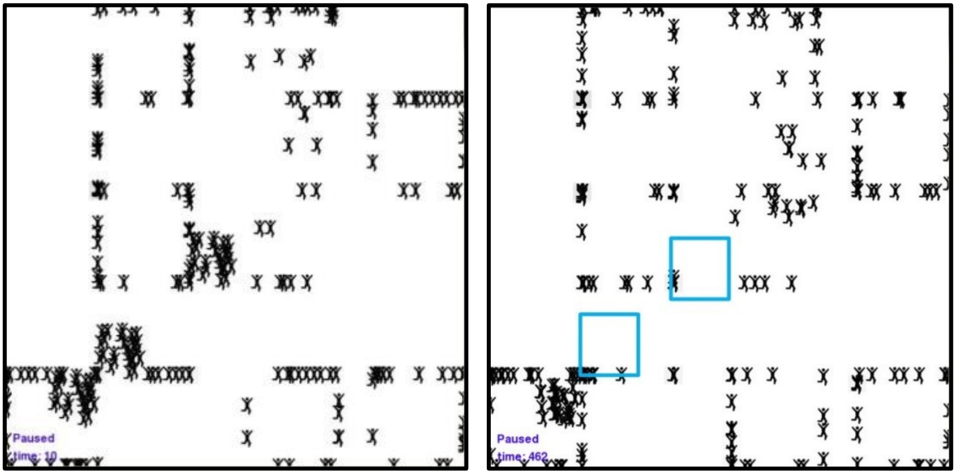


Figure 36. Proposed disaster scenario model with regions and victims

The situation of several victims groups disappearing from the disaster scenario is shown in Figure 37. Specifically, the two blue squares mark the places where there was a concentration of victims (Figure 37a) that disappeared all of a sudden at specific times (Figure 37b).

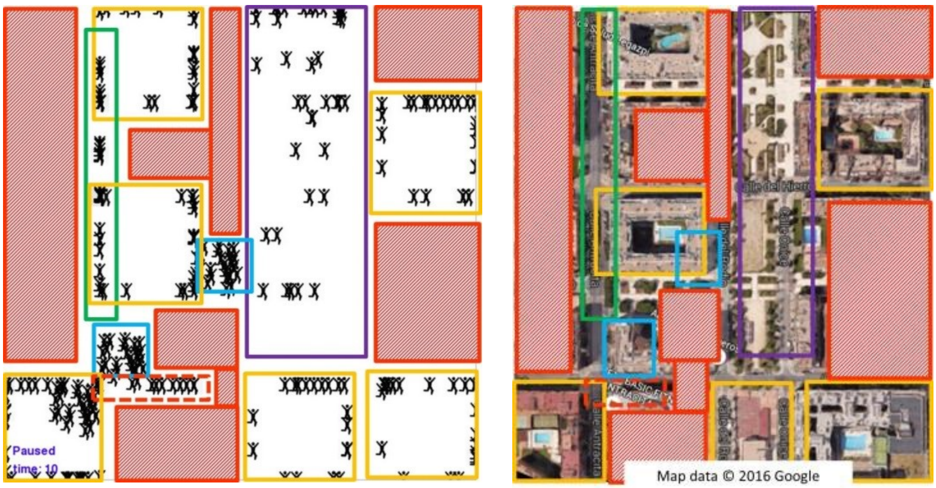
The urban disaster scenario proposed in this section is shown in Figure 38 in comparison to a digital map picture of a real city (Madrid, Spain; coordinates: 40.39, -3.69). It can be appreciated in Figure 38 that, despite both the model and the satellite image are not exactly equal, there are important similarities between them.



a) Disaster scenario with all victims

b) Two groups of victims disappeared (blue squares)

Figure 37. Scenario before (a) and after (b) the disappearance of victims



a) Disaster scenario proposed

b) Real city scenario

Figure 38. Disaster scenario model versus a real urban scenario

4.2.2 UAV network model

Several assumptions have been made regarding the UAV network model. These assumptions have been classified into three groups: i) the ones related to the UAV navigation, ii) those related to the communications aspects and iii) those related to the mission aspects.

4.2.2.1 UAV navigation assumptions

In the proposed approach the following assumptions have been done regarding the UAV navigation aspects:

- The UAVs considered are helicopter-like. This type of UAVs has the ability to hover over a specific location, which is an advantage for providing communication services to ground nodes.
- The UAV trajectories are generated with the mobility model algorithm proposed in section 4.3.1. These are high-level trajectories which consist of a sequence of waypoints.
- The UAVs movement is assumed to take place in a two-dimensional space, which simplifies the UAV dynamics and avoids overloading the simulations. This assumption has also been made in other works such as [187] [156] [188].
- Collision avoidance mechanisms have been not considered [137], or are simplified [160] [154] [166] in similar research works. In this chapter, a simplified collision avoidance mechanism is considered, which is based in the change of the flight altitudes of UAVs in case of a potential collision, as proposed in [12] [160] [166]. As the UAVs movements have been modelled in a two-dimensional space, the collision avoidance mechanism is unnoticed from the point of view of the simulations.
- The UAVs maximum speed is 10 ms^{-1}. This is a value which highly depends on the type of the UAV and its equipment and for this reason, has been set to the average speed of a standard UAV.
- The UAVs know the scenario dimensions and its boundaries coordinates in advance. Also, the UAVs have knowledge of the victims' locations from a previous exploration mission such as the one described in section 3.3.

Another option here is to consider that victims may use their smartphones and an emergency application to form a mesh network. This can be used to feed all connected victims locations to the UAV network. Similar mechanisms using *hello* messages have been previously proposed to be used by rescuers and emergency response teams so they can be detected by a UAV network [194] [23].

- The UAVs start the mission from a squared space centred in the disaster scenario area. This position is calculated from a previous exploration task such as the one described in section 3.3.

4.2.2.2 UAV communication assumptions

The proposed approach the following assumptions have been done regarding the UAV communication aspects:

- Each UAV is equipped with short-range wireless communication devices that allow the communication with other UAVs and with ground nodes (victims or first responders).
- Some UAVs may also have long-range wireless communication devices with the ability to communicate with a ground control station and/or a satellite.
- The mechanism used by UAVs for detecting nodes on the ground (updating their locations) may be by using wireless communication technologies. Potential candidates for these technologies are the IEEE 802.11 standards [39] [23] [189] [190] [191] [172] [192] due to the numerous handheld devices that offer this communication technologies [193]. Several works present potential solutions that could be used to know the ground nodes that are within the wireless coverage area [39] [194]. Also, MANET approaches like the ones proposed in [195] [196] [197] could be used so the UAVs could "sense" the ground nodes' smartphones. However, the proposed approach is not limited to these technologies and other discovery mechanisms could be used such as cameras and artificial vision techniques. Also, the active behaviour of victims for facilitating their discovery with SOS signals emitted via their smartphones can be used. This could allow forming a mesh emergency network among the ground

nodes smartphones and at the same time connect it to the UAV network. This is considered as a viable way of getting updated information about the victims' locations. As aforementioned, similar mechanisms that use *hello* messages have been previously proposed to be used by rescuers so they can be detected by a UAV network [194] [23].

- The communication is based on the disk model assuming a 250 meters radius [163] [156]. Any pair of UAVs separated a distance smaller than 250 meters will be able to establish a communication link [198] [199]. Other works have considered longer communication ranges such as 500 m [23] [81] but this heavily depends on the communication equipment of the UAV [200] [201]. There can be considerable variability between the wireless communication equipment of different UAV models. Besides, UAVs are resource-constrained systems in terms of payload and batteries. A conservative transmission range is assumed in this section for validating the proposed mobility model in the case of UAVs with modest wireless capabilities.
- The UAVs form a connected network where any UAV is always connected to at least one UAV.
- The routing mechanism considered can be any routing algorithm appropriate UAV network. UAVs require sharing specific information with each other periodically, such as the victims' locations that each UAV is aware of, the victims under each UAV wireless coverage range, and each UAV position. This amount of information is considered lightweight as the number of UAVs is not high (six in this chapter's simulations).

4.2.2.3 UAV mission assumptions

The following assumptions have been considered regarding the mission aspects:

- The aim of the UAV network is to periodically recalculate the UAVs optimal positions for providing communication services to as many ground nodes as possible. The initial approach assumes that *servicing* a ground node is the situation in which a UAV is in a location from which is able to establish a wireless communication link with a ground node. Therefore, the aim of the UAVs is to have as many ground nodes as possible under the UAV network wireless coverage area.

- The expected behaviour of the UAV network is to adapt to scenario variable conditions i.e. the movement of ground nodes.
- The assistance that the UAVs provide to the victims may be either providing emergency information (e.g. informing victims about a safe path outwards the disaster scenario) or by enabling communications (e.g. allowing the victims to communicate among themselves or with first responders in the area).

4.3 Proposed solution

The mobility model proposed in this section is based on several aspects, namely: i) the *Jaccard distance* between the UAVs, ii) a *virtual forces algorithm (VFA)* based on the Jaccard distance, and iii) several *metaheuristics* used as *optimization* algorithms for calculating the optimal Jaccard distance between UAVs. The fundamentals regarding the Jaccard distance concept are described in Appendix A. The Jaccard-based mobility model algorithm proposed for a UAV network is described in the next subsections. This mobility model aims at generating mission-based trajectories for the UAV network with two main goals, namely: i) maintaining the maximum number of ground nodes under the UAV network wireless coverage area (while adapting to the movements of the nodes), and ii) maintaining the UAVs as a connected network.

4.3.1 Jaccard-based mobility model for adaptive coverage

4.3.1.1 Jaccard distance in a UAV network

The Jaccard-based mobility model is an innovative approach for generating high-level trajectories for a UAV network that needs to adapt to the scenario context, i.e. the mobility of ground nodes. This approach is based on the dissimilarity metric known as Jaccard distance (Appendix A). The Jaccard distance is a metric that is used in this section for measuring the *dissimilarity* between UAV pairs, based on the ground nodes (i.e. victims) that each UAV has under its wireless coverage area.

The Jaccard distance and the *Euclidean distance* are *different* concepts; however, it has been shown that there exists a correlation between the two of them [210]. The reasons for selecting the Jaccard distance as a parameter for the mobility model proposed instead of the Euclidean distance is as follows. The Euclidean distance provides information about the physical proximity of a pair of UAVs. However, it does not provide information about whether a pair of UAVs is sharing ground nodes or not, i.e. if there are ground nodes under the region where both UAVs wireless coverage areas overlap. The Jaccard distance, however, takes this into account as it uses the total number of ground nodes under the wireless coverage area and also the shared ones (those within the overlapping region) in order to measure the dissimilarity of two UAVs.

As an example, let's consider a pair of UAVs *sharing* many ground nodes (i.e. victims). This situation is depicted in Figure 39 in which two UAVs have many victims located in the region where their wireless coverage areas overlap (red dots). However, these two UAVs can be considered dissimilar with respect to their Euclidean distance as both are located at the edge of the wireless coverage area of each other. But it is noticeable the fact that there is a group of victims (black dots) out of the wireless coverage area of both UAVs, not receiving communication services at all. By only considering the Euclidean distance, it is not possible to be aware of the black dots in Figure 39. This is not the desired solution and there might be other UAV locations that could increase the number of serviced victims if other aspects, apart from the Euclidean distance, are considered.

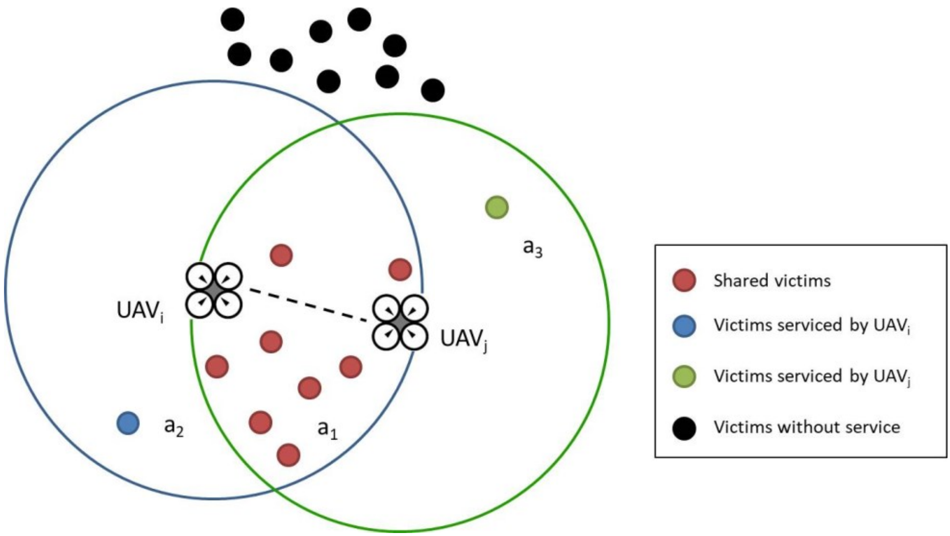


Figure 39. UAVs relation: dissimilar (Euclidean) and similar (Jaccard)

On the contrary, by using the Jaccard distance, the UAVs in Figure 39 will be similar, and therefore a decision may be taken in order to look for other configuration, i.e. other UAVs positions to increase the dissimilarity. Other possible UAVs locations that maximize the number of victims under the wireless coverage area are shown in Figure 40. In the new UAVs configuration shown in Figure 40, UAV_j has simply moved upwards covering the victims that were not serviced in Figure 39. Now, UAV_j will have these victims under its wireless coverage range (green dots). Also, most of the victims that were previously considered as shared victims are now under UAV_i wireless coverage range exclusively. This configuration has the advantage that the number of serviced victims has increased, while the shared victims have decreased.

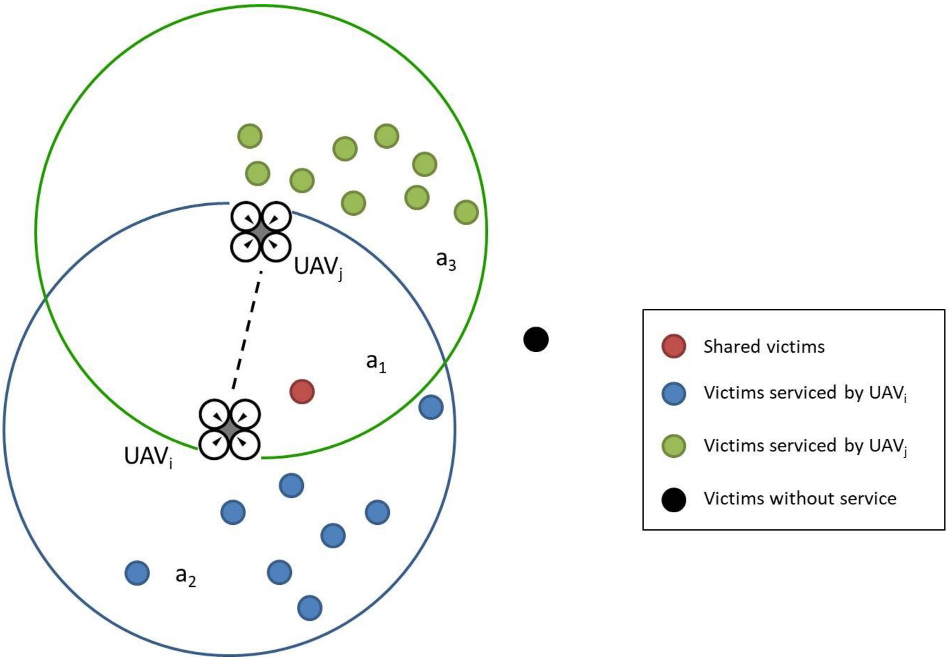


Figure 40. UAVs relation: dissimilar (Euclidean and Jaccard)

Formally, the Jaccard distance is a metric which measures the dissimilarity between sample sets as it has been described in Appendix A. The Jaccard distance is closely related to the *Jaccard coefficient* but these two represent the opposite metric. This means that the Jaccard distance measures the dissimilarity while the Jaccard coefficient measures the similarity of sample sets. The Jaccard coefficient is used in this section only with the purpose of defining the Jaccard distance for a UAV network.

In the Jaccard-based mobility model proposed, the Jaccard coefficient for any pair of UAVs is defined as the number of ground nodes located within the region where the two UAVs wireless coverage areas overlap, divided by the total number of ground nodes under the wireless coverage area of both UAVs. Based on the situation depicted in Figure 39 and Figure 40, the Jaccard coefficient (represented by the symbol J_{ij}) may be calculated with the expression (6).

$$J_{ij} = \frac{a_1}{a_1 + a_2 + a_3} \qquad (6)$$

where $J_{ij} \in [0,1]$ and the terms a_1, a_2, and a_3 are defined as follows:

- a_1: The number of ground nodes shared by UAV$_i$ and UAV$_j$. This is represented by the red dots in Figure 39 and Figure 40.
- a_2: The number of ground nodes exclusively under UAV$_i$ wireless coverage area. This is represented by the blue dots in Figure 39 and Figure 40.
- a_3: The number of ground nodes exclusively under UAV$_j$ wireless coverage area. This is represented by the green dots in Figure 39 and Figure 40.

Based on the previous definition of the Jaccard coefficient (6), the Jaccard distance (represented by Jd) can be calculated with the expression shown in (7). Please note that although (39) and (7) both represent the same concept of the Jaccard distance, (7) uses a different notation. From now on, the term Jd_{ij} will be used to refer to the Jaccard distance between UAV$_i$ and UAV$_j$.

$$Jd_{ij} = 1 - J_{ij} \tag{7}$$

The maximum values that the Jaccard distance may take belong to the range (0,1). Taking into account the Jaccard distance Jd_{ij} and the Jaccard coefficients, Table 7 and Table 8 show the relation between the values taken by these metrics and their translation to the UAV network configuration. Following this example, two UAVs are similar if they share many ground nodes. In this case, these UAVs will have a Jaccard distance close to the value 0. On the contrary, if these two UAVs share very few nodes or none they will be considered dissimilar and the Jaccard distance between them will be close to value 1.

Table 7. Jaccard coefficient and Jaccard distance relation (I)

Name	Value range	Description
Jaccard coefficient	Min: 0	Dissimilar
	Max: 1	Similar
Jaccard distance	Min: 0	Similar ⇒ Small distance ⇒ Close
	Max: 1	Dissimilar ⇒ Big distance ⇒ Far

Table 8. Jaccard coefficient and Jaccard distance relation (II)

Jaccard coefficient		**Jaccard distance**	
Dissimilar	Min: 0	Max: 1	Dissimilar ⇒ Big distance ⇒ Far
Similar	Max: 1	Min: 0	Similar ⇒ Small distance ⇒ Close

4.3.1.2 Network neighbour and Jaccard neighbour

At this point, it is important to introduce a new concept for the UAV network, the *Jaccard neighbours*. There is a difference between *network neighbours* and Jaccard neighbours. A network neighbour is a generic concept of any network. Two UAVs are defined as network neighbours if they can establish a direct communication link with each other. An example is shown in Figure 41 and Figure 42. In Figure 41, at time $t = t_1$, UAV_i is separated from UAV_j a distance d smaller than the wireless communication range distance (d_{rc}), therefore, UAV_i and UAV_j are network neighbours. On the contrary, UAV_i is separated from UAV_k a distance d greater than the wireless communication range distance (d_{rc}), therefore these UAVs are not able to establish a direct communication link and are not considered network neighbours.

Figure 42 shows a time $t = t_2$ after the previous situation, in which the UAVs have moved, and the distances existing between them have changed, leading to a new topology. In this case, UAV_i is separated from UAV_k a distance d smaller than d_{rc} and UAV_i is able to establish direct communication links with both UAV_j and UAV_k. It is important to remark that, UAV_j and UAV_k cannot establish a direct communication link; these UAVs will be able to exchange information through UAV_i as the networking paradigm considered is a multihop ad hoc network. The UAVs in the network are considered to exchange information with each other when they are able to establish a direct or indirect communication link.

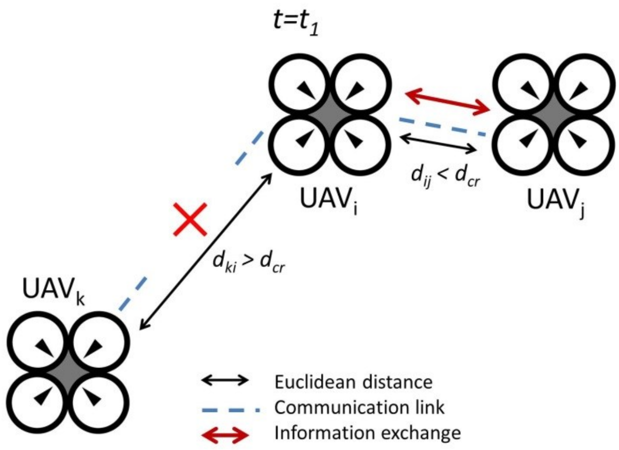


Figure 41. Network neighbours and information exchange (I)

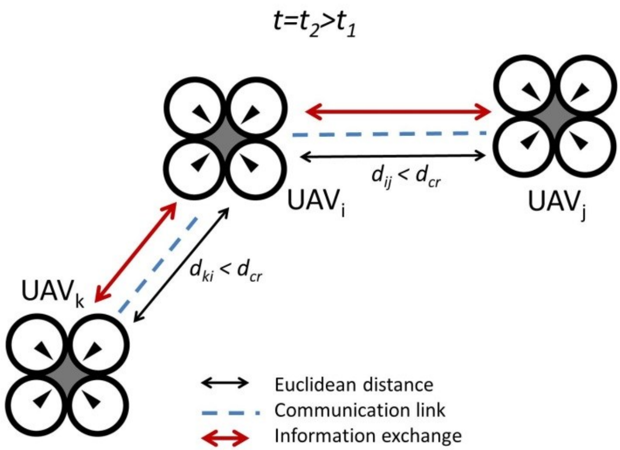


Figure 42. Network neighbours and information exchange (II)

The concept of Jaccard neighbour refers to a subset of the network neighbours. Two UAVs that are Jaccard neighbours are required to be network neighbours but two UAVs that are network neighbours are not necessarily Jaccard neighbours. Two UAVs are considered Jaccard neighbours if they comply with the following conditions:

- The two UAVs are network neighbours.
- The two UAVs calculate the Jaccard distance Jd_{ij} with each other periodically and take Jd_{ij} into account for calculating the next movement.

Therefore, a pair of Jaccard neighbours will monitor its Jaccard distance Jd_{ij} periodically. Also, they will calculate the next positions to occupy in order to keep Jd_{ij} close to a specific value. In a first approximation, the ideal value to maintain would be $Jd_{ij} = 1$, which corresponds to maximizing the number of ground nodes under the UAVs wireless coverage area. However, different aspects can be considered and, later on in this chapter, the specific Jaccard distance value that two Jaccard neighbours aim to maintain will be discussed. It is important to mention that two UAVs that are network neighbours but are not Jaccard neighbours do not have such requirement of moving depending on the Jaccard distance existing between them. Figure 43 and Figure 44 represent the concept of Jaccard neighbour.

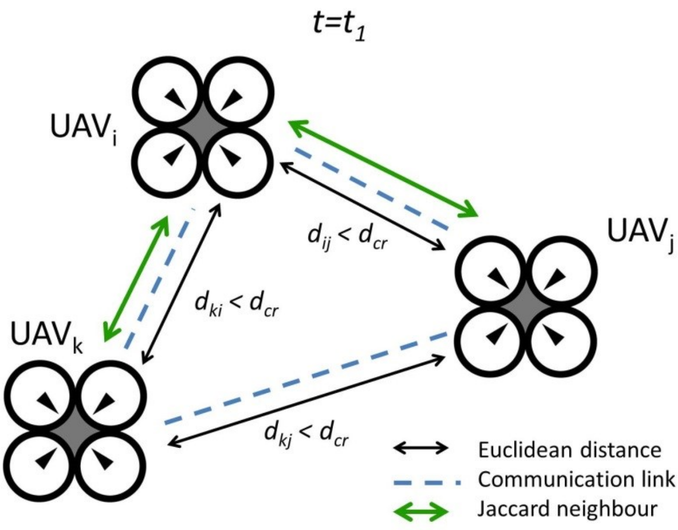


Figure 43. Jaccard neighbours vs network neighbours (I)

Two different situations are shown in Figure 43 and Figure 44. In Figure 43 there are three UAVs which are all network neighbours to each other. However, only UAV_i-UAV_k and UAV_i-UAV_j are Jaccard neighbours to each other, but not UAV_k-UAV_j.

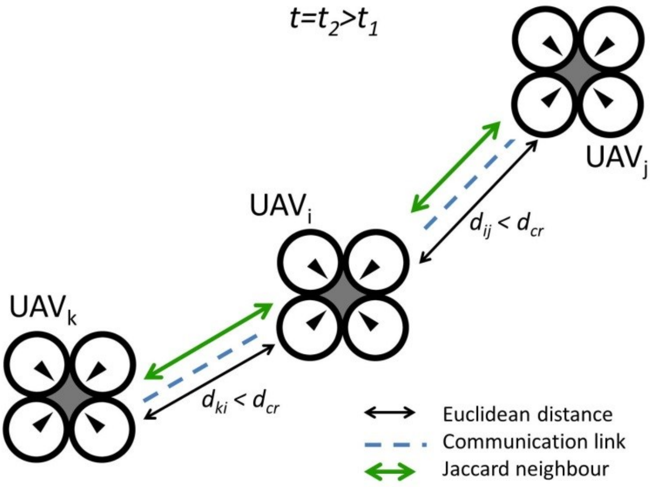


Figure 44. Jaccard neighbours vs network neighbours (II)

By looking at Figure 43, the reader may think of the benefits of having UAV_k and UAV_j being Jaccard neighbours to each other as well. However, that situation will prevent the UAV network to have the ability to stretch as shown in Figure 44. This ability may be useful in certain situations for adapting to the locations of the ground nodes and covering as many as possible. In the case that UAV_k and UAV_j would have been Jaccard neighbours the network topology shown in Figure 44 would not be possible. If these two UAVs were Jaccard neighbours they would not be able to separate from each other a distance greater than the wireless communication range distance, so they would not break the communication link.

A more formal definition of Jaccard neighbours is provided below. Let G be a graph representing the UAV network that is providing communication services to ground nodes. Each node of the network represented by graph G is a UAV (the ground nodes are not represented by G). The edges of the network exist in the case that the distance d between two nodes is smaller than the wireless communication range of the UAVs. The maximum communication range of the wireless technology is defined as d_{cr}, or $distance_{communication\ range}$. The edges of graph G represent the network neighbours of the UAV network. This is defined in the expressions (8), (9), (10), (11) and (12).

$$\mathrm{G(V,E)} \quad (8)$$

$$V = \{0,1, \dots, i, j, k, \dots\} \tag{9}$$

$$E = \{\{0,1\}, \dots, \{i, j\}, \{i, k\}, \dots\} \tag{10}$$

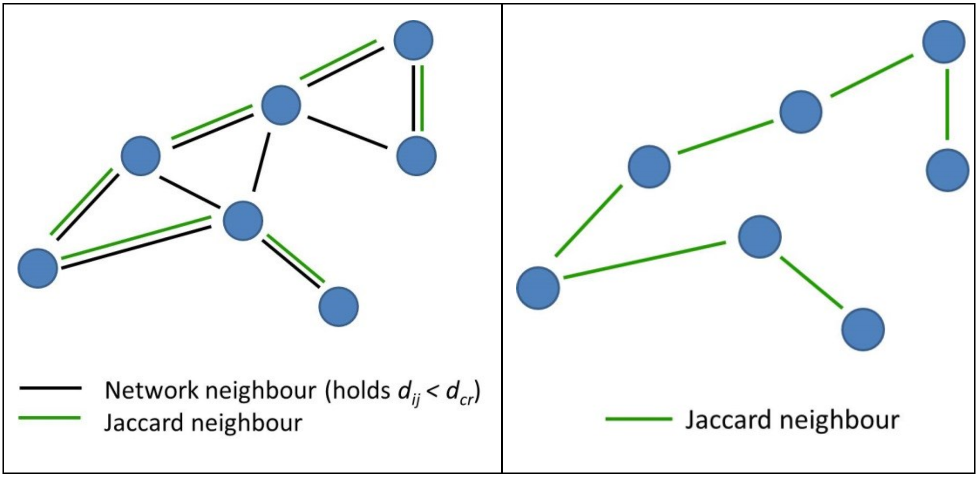
$$i \in V \; \forall \; i \tag{11}$$

$$\{i, j\} \in E \text{ if } d_{ij} < d_{cr} \tag{12}$$

Where:

- V: Nodes of the network. In this case, each node corresponds to a UAV.
- E: Edges of the network. In this case, these represent the communication links established between each pair of nodes. An edge exists for those UAVs which have an Euclidean distance smaller than the maximum wireless communication range (d_{cr}).
- d_{ij}: Euclidean distance between nodes i and j.
- d_{cr}: Maximum wireless communication range of the UAVs.

An example of graph G is shown on the left side of Figure 45 where black colour lines represent the network neighbours, i.e. the edges of graph G.



a) Network and Jaccard neighbours b) Jaccard neighbours only

Figure 45. Graph representation of network and Jaccard neighbours

On top of the graph shown on the left side of Figure 45, a different set of edges are shown in green colour. The green edges define a subgraph $\mathrm{JG} = G'(V', E')$ consisting of pairs of nodes that are Jaccard neighbours. The JG graph is shown on the right side of Figure 45. By selecting the Jaccard neighbours as it has been shown in Figure 45, the UAV network will be able to stretch in the case that this is needed for adapting to ground nodes locations and thus providing communication services to more victims. This is defined in the expressions (13), (14) and (15). An example of this situation is shown in Figure 46.

$$\mathrm{JG} = G'(V', E') \tag{13}$$

$$V' = \mathrm{V} \tag{14}$$

$$E' = \{\mathrm{i}, \mathrm{j}\} \in Jaccard\ neighbour \tag{15}$$

Where:

- V': Nodes of the network that belong to the Jaccard neighbours group. Each UAV is supposed to be Jaccard neighbour of at least another UAV. Therefore all nodes from graph G are included.
- E': Edges of the graph. These edges is a subset of the edges of graph G with the requirement that each node is a Jaccard neighbour of one or more nodes of the graph JG.

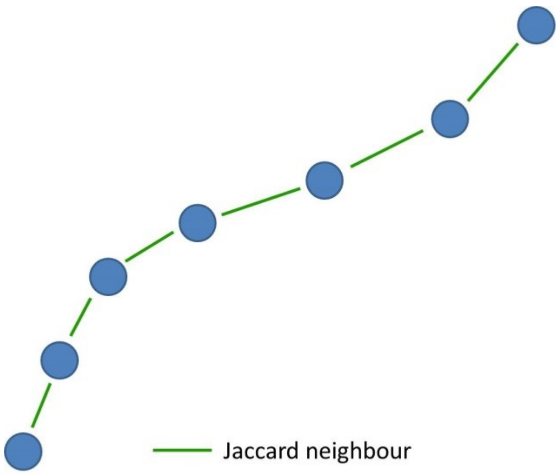


Figure 46. Jaccard neighbours selection able to stretch the network

It is important to remark that as the UAVs move with time, the graphs JG and G evolve while new network neighbours appear and others disappear. This means that black colour edges may appear and disappear over time, and consequently the topology of the network as well. However, regarding the Jaccard neighbours subgraph, despite it can evolve as well over time, is not meant to evolve rapidly. This means that the green edges in JG may suffer some slight changes, but each UAV will always have a green edge connecting it to the UAV network during the entire mission.

4.3.1.3 Target Jaccard distance

Based on the concept of the Jaccard distance and Jaccard neighbours described in previous sections, the Jaccard-based mobility model aims at maintaining the Jaccard distance close to an optimal value for each pair of UAVs that are Jaccard neighbours. At this point, the reader may wonder, what is the optimal value for the Jaccard distance? The idea is to select a value that makes any UAV pair to maximize the number of ground nodes under the wireless coverage area. Ideally, considering only two UAVs, this value would be equal to 1. According to Table 7 and Table 8, having a Jaccard distance equal to 1 correspond to UAVs that have more ground nodes under the wireless coverage area and also fewer under the overlapping region (shared ground nodes). However, there may be mission requirements for a UAV network in which the optimal value for the Jaccard distance would not be equal to 1. Examples of some of these cases are: i) optimizing the UAV network for adapting to traffic requirements (e.g. having a pair of UAVs sharing ground nodes on purpose due to one of the UAVs suffering from traffic overload), and ii) providing a robust service to specific ground nodes (e.g. guaranteeing that these ground nodes will have communication services even in the case of one failing UAV), among others.

According to the previous aspects, the idea is to find an optimal Jaccard distance value that makes the UAVs to occupy the positions that maximize the number of ground nodes serviced by the UAV network. This optimal Jaccard distance value is called the *Target Jaccard distance*, also known as TJd or simply the *Target Jaccard*. The Target Jaccard TJd is defined as the Jaccard distance that any pair of UAVs, considered Jaccard neighbours, should maintain so the communication service provided by the UAV network is optimal. From now on, the term TJd will be used to refer to the Target Jaccard distance that any pair of Jaccard neighbours aims to reach to, as it is shown in (16). Also, as a first approximation to the optimization problem, the aspect considered for optimization will be the number of ground nodes (i.e. victims) under the UAV network wireless coverage area.

$$TJd: Target\ Jaccard\ distance \quad (16)$$

$$\Delta Jd_{ij} = |TJd - Jd_{ij}| \quad (17)$$

In order to dynamically calculate the Target Jaccard distance TJd, several metaheuristics are used as optimization algorithms. The metaheuristics used are the *simulated annealing*, *hill climbing* and a *random walk-based algorithm* (used as a *benchmark*). All these metaheuristics are described in this section later on. After the TJd value is calculated, other mechanisms will be put in place in order to reduce the difference between the current Jaccard distance between Jaccard neighbors and the optimal value TJd (17).

4.3.1.3.1 Jaccard-based mobility model cycle

The calculation of the Target Jaccard distance TJd is repeated periodically during the mission. The Jaccard-based mobility model can be divided into *cycles*, each cycle duration corresponds to the *period* of this mobility model, which is considered a parameter design. Calculating the optimal value for the TJd periodically allows the UAV network to adapt to the movements of the ground nodes. The period of the Jaccard-based mobility model is defined as the time that elapses between two consecutive executions of a metaheuristic (which calculates the value for the TJd). An entire execution of the specific metaheuristic used is carried out at the beginning of each cycle. After the metaheuristic execution finishes, it provides the value for the TJd and the optimal positions that each UAV should occupy in order to maximize the number of ground nodes under the wireless coverage area.

With a greater level of detail, the workflow behind the Jaccard-based mobility model is as follows. A cycle starts with the metaheuristic execution. This metaheuristic (which consists of multiple iterations) calculates potential candidate solutions for the TJd. For each TJd candidate value, the current Jaccard distances of each UAV with respect to its Jaccard neighbours are calculated. Then, the virtual forces algorithm (VFA) generates new *virtual positions* for the UAVs, based on ΔJd_{ij} (17), which is the difference between the candidate value of TJd and the current Jaccard distances. The VFA algorithm is later explained in section 4.3.1.3.3. The *fitness function* (described later in section 4.3.1.3.2) is evaluated for each candidate solution and the associated virtual positions. One candidate solution will be selected as the best, among the candidate solutions available and the best candidate so far. The decision on which candidate solutions are kept depend on the specific metaheuristic used and it is explained later. This process is repeated multiple times, once for each iteration of the metaheuristic. Once the metaheuristic execution is finished, an optimal value for TJd and optimal positions for the UAVs are yielded. Before the next cycle beginning, the UAVs move towards the optimal positions. The UAVs auto-generate their trajectories by taking into account the positions assigned but also avoiding network disconnections. As a summary, a cycle consists on a complete execution of the selected metaheuristic and the UAVs trajectories self-generation towards the optimal positions.

In Figure 47, the block called *metaheuristic algorithm* represents that the metaheuristic algorithm is run completely with all its iterations included. The name *metaheuristic algorithm* is used here as a generic way to refer to the different metaheuristics that have been used for simulating the Jaccard-based mobility model, namely: simulated annealing and hill climbing. The implementation of these metaheuristics is described on section 4.3.1.3.2.

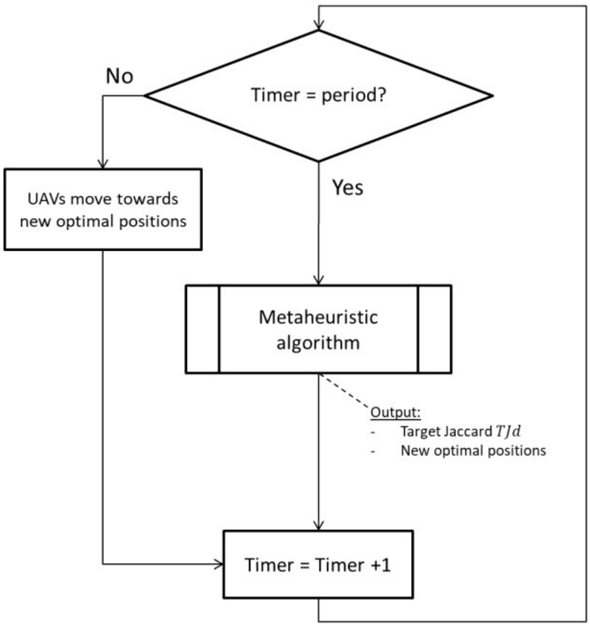


Figure 47. Jaccard-based mobility model cycle

4.3.1.3.2 Metaheuristics

As it has been already mentioned, several metaheuristics have been used for calculating the Target Jaccard distance TJd. The point of using several metaheuristics has been to compare their advantages and disadvantages when used with the Jaccard-based mobility model. The reason for selecting simulated annealing and hill climbing has been due to the fact that these are considerably simple and yet issue good solutions. The aim of the problem proposed requires adapting periodically to the movements of the ground nodes and other metaheuristics may consume more time and resources, not being appropriate for the cycle-based approach described in the previous section. Using a random-walk based algorithm has been for benchmarking, i.e. having a reference of purely random movements and confirm whether simulated annealing and hill climbing bring some benefits. Both, the simulated annealing and the hill climbing algorithms share the same fitness function. The fitness function $f(TJd)$ used is shown in (18) and it has several terms corresponding to the goals of the UAV network as it is described below.

$$f(Jd) = \begin{cases} 0.8 \cdot sn_{total} - 0.2 \cdot jnnn_{max}, & if\ not\ disconnections \\ -1, & if\ disconnections \end{cases} \tag{18}$$

The terms that appear in the expression (18) are defined as follows:

- sn_{total} (*serviced nodes*): It represents the total number of ground nodes that are under the wireless coverage area of the UAV network (each ground node is counted only once). This term has a weight assigned of 80%.
- $jnnn_{max}$ (*Jaccard neighbours and network neighbours difference*): This term measures the difference between the number of Jaccard neighbours that a UAV should have and the number of its network neighbours. The ideal situation is having each UAV connected (i.e. with a direct communication link) only to its Jaccard neighbours. This would imply that the Jaccard neighbours of an UAV coincide with its network neighbours and that this UAV does not have more network neighbours. When a UAV has more network neighbours than Jaccard neighbours, this term penalizes the corresponding candidate solution. As a consequence, candidate solutions where the Jaccard neighbours and network neighbours sets of a UAV coincide will produce higher fitness values. The weight of this term

corresponds to the 20%.

- $disconnections$: It represents the situation in which a UAV disconnects from the UAV network, i.e. when it is not within wireless communication range of any of the other UAVs in the network. A generic connected components algorithm has been implemented to monitor UAV disconnections from the network. A topology that does not comply with the connected network constraint is penalized by this term.

The fitness function defined in (18) does not have the Target Jaccard distance TJd directly represented in any of its terms. This is because of the terms sn_{total}, $jnnn_{max}$ and $disconnections$, which are the ones that depend on TJd. These terms are related to the Target Jaccard distance TJd through the Jaccard-based virtual forces movements which are explained in section 4.3.1.3.3.

Let's recall that the mobility model consists of several cycles, each cycle consisting of a complete execution of the selected metaheuristic and the UAVs trajectories self-generation towards the optimal positions.

4.3.1.3.2.1 Hill climbing

The hill climbing algorithm is a simple yet effective metaheuristic able to provide good results in optimization problems. An introduction to the hill climbing algorithm is provided in Appendix A. The hill climbing algorithm has been the first approach considered for searching the optimal Target Jaccard TJd using the fitness function described in (18).

The hill climbing implementation for the proposed mobility model is as follows. For each cycle of the Jaccard-based mobility model, the hill climbing algorithm is executed once. The execution of the hill climbing algorithm corresponds to several iterations, being the number of iterations of the algorithm a parameter design. At the beginning of the execution, the algorithm randomly generates an initial value for the Target Jaccard distance TJd. In the first iteration, this value is used for calculating the first candidate solutions that are evaluated with the fitness function $f(Jd)$ (18). The procedure for generating the Target Jaccard distance TJd for the next iterations is described below. Let TJd^k be the Target Jaccard distance TJd for the k^{th} iteration as shown in (19). As a consequence, TJd^{k+1} would be the TJd for the $k+1^{th}$ iteration. In order to calculate the TJd for the next iteration i.e. TJd^{k+1}, two possible values for the Target Jaccard distance TJd are generated: TJd_+^k and TJd_-^k. These two values are equal to the previous TJd^k plus 0.1 (TJd_+^k), and minus 0.1

(TJd_{-}^{k}) as shown in equations (20) and (21).

$$TJd^{k}: Target\ Jaccard\ distance\ at\ k^{th}\ iteration \tag{19}$$

$$TJd_{+}^{k} = TJd^{k} + 0.1 \tag{20}$$

$$TJd_{-}^{k} = TJd^{k} - 0.1 \tag{21}$$

$$TJd^{k+1} = \begin{cases} TJd_{+}^{k}, & if\ f(TJd_{+}^{k}) > f(TJd_{-}^{k}) \\ TJd_{-}^{k}, & if\ f(TJd_{+}^{k}) < f(TJd_{-}^{k}) \end{cases} \tag{22}$$

Both TJd_{+}^{k} and TJd_{-}^{k} are used to generate virtual positions of the UAVs, based on the virtual forces algorithm (VFA), which is later explained in section 4.3.1.3.3, and the difference with the current Jaccard distances existing between Jaccard neighbours, i.e. the ΔJd_{ij} (17). Then, the UAVs virtually moved to newly calculated positions and both $f(TJd_{+}^{k})$ and $f(TJd_{-}^{k})$ are evaluated and compared. The value TJd_{+}^{k} or TJd_{-}^{k} that produces the bigger fitness value is selected as the accepted solution, i.e. TJd^{k+1}, as it is shown in (22). Then, the next iteration starts. It is important to mention that the positions generated during the algorithm iterations are virtual positions, i.e. these are only used for assessing the fitness function. Only the positions generated when the metaheuristic finishes are actually included in the UAVs trajectories. This process is depicted in Figure 48.

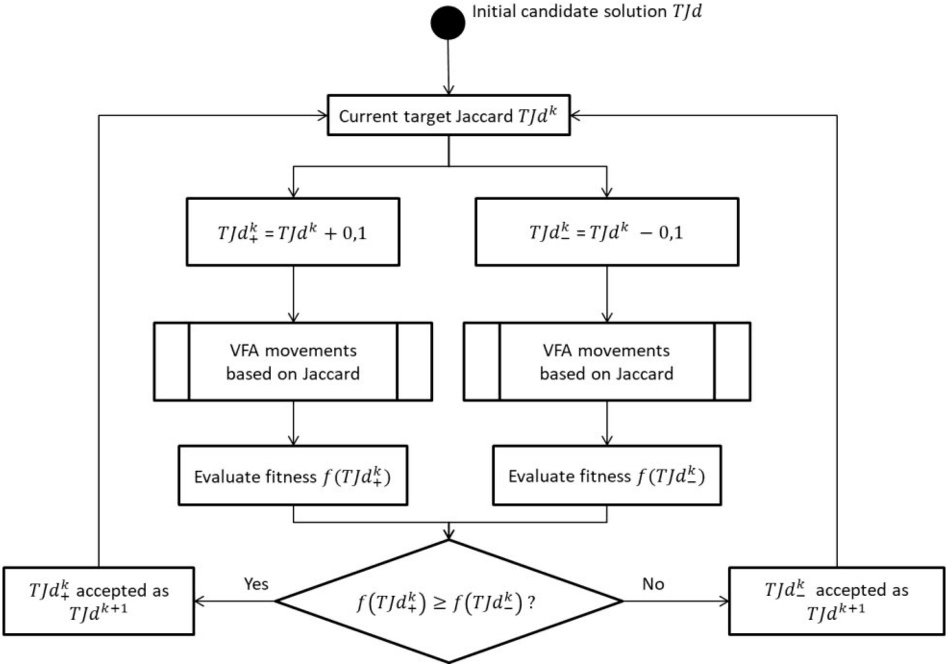


Figure 48. Hill climbing loop for the Jaccard-based mobility model

4.3.1.3.2.2 Simulated annealing

The simulated annealing algorithm presents the benefits of hill climbing for finding good solutions in optimization problems while having a simple implementation. However, it provides a clear benefit over hill climbing; the original hill climbing algorithm does not have the ability to escape from local optima while the simulated annealing does. This algorithm emulates the annealing of solids in the metallurgy industry. The annealing process decreases the temperature of a metallic material gradually, keeping the material on each temperature value for a specific amount of time to allow the material's atoms to reach the lowest energy states possible. An introduction to the simulated annealing algorithm is provided in Appendix A.

The simulated annealing implementation for the proposed mobility model uses the parameters shown in Table 9. These parameters correspond to those described in the simulated annealing section in Appendix A. The reason for selecting these values is later explained in this section.

Table 9. Simulated annealing algorithm parameters

Parameter	Symbol	Value
Initial probability	P_s	0.5
Final probability	P_f	0.0001
Initial temperature	T_s	1.44
Final temperature	T_f	0.10
Temperature factor	F	0.75
Number of sa-cycles	N	10
Number of trials	M	10

The same as it occurred with the hill climbing algorithm, for each cycle of the mobility model, the simulated annealing algorithm is executed once. The execution of the simulated annealing algorithm consists of several iterations. The number of iterations of the algorithm is a parameter design. As described in Appendix A, an entire execution of the algorithm consists of *two loops*. The *outer loop* represents the simulated annealing cycles or *sa-cycles*. Please note that simulated annealing cycles are a different concept from the Jaccard-based mobility model cycle and, for this reason, the term sa-cycle is used in this text so the reader can distinguish between them. Each outer loop iteration, i.e. each sa-cycle, has the same value for the temperature. The temperature for one sa-cycle is calculated by multiplying the temperature of the previous sa-cycle by the temperature factor (F) shown in Table 9. Therefore, the value of the temperature is decreasing with each sa-cycle.

Each sa-cycle contains another loop, i.e. the *inner loop*. The inner loop represents the behaviour of the solid's atoms when moving towards the lowest energy state for a specific temperature value. In this specific implementation, this is analogous to the search for the optimal Target Jaccard distance TJd. The inner loop follows the procedure shown in Figure 49 for a specific fixed temperature value of the outer loop (sa-cycle). The inner loop process is as follows, let TJd^k be the Target Jaccard distance TJd for the k^{th} iteration as shown in (19). As a consequence, TJd^{k+1} would be the TJd for the $k+1^{th}$ iteration. In order to calculate the TJd for the next iteration i.e. TJd^{k+1}, a new candidate solution is randomly generated, i.e. TJd_r^k.

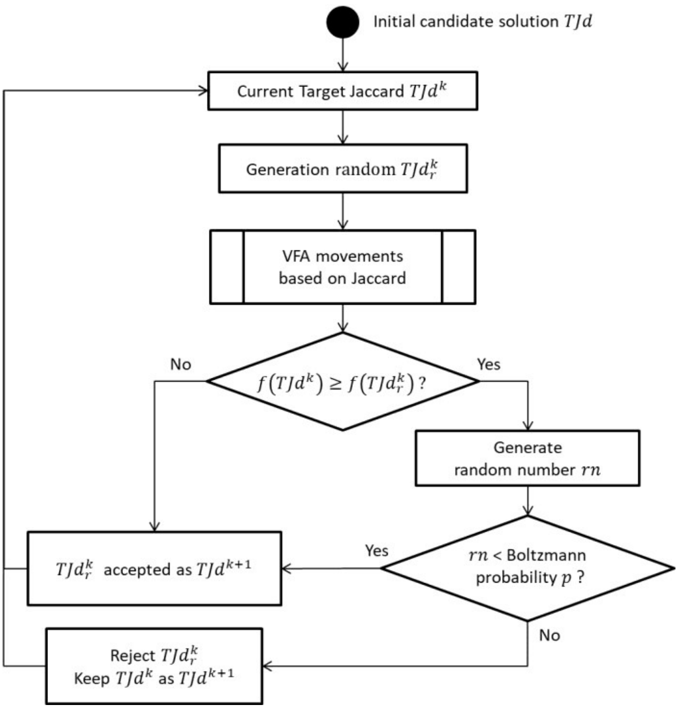


Figure 49. Simulated annealing inner loop for the Jaccard-based mobility model

Then, the virtual forces algorithm (VFA) is used to generate virtual positions for the UAVs, based on the value TJd_r^k and the difference with the current Jaccard distances existing between Jaccard neighbours, i.e. the ΔJd_{ij} (17). The generation of the virtual positions is later explained in section 4.3.1.3.3 with more detail. Then, assuming that the UAVs are virtually located on the newly generated positions, the fitness function is evaluated for both the current Target Jaccard value TJd^k and the newly generated candidate solution TJd_r^k. In the case of $f(TJd^k) \geq f(TJd_r^k)$, i.e. when TJd_r^k is a *worse candidate solution*, a random number rn is generated and in the case that rn is smaller than the Boltzmann probability p shown in (40), TJd_r^k is accepted as TJd^{k+1}. If rn is bigger than the Boltzmann probability p, TJd^k is kept as TJd^{k+1}. On the contrary, if $f(TJd^k) < f(TJd_r^k)$, i.e. when TJd_r^k is a better candidate solution, TJd_r^k is accepted as TJd^{k+1}. This is shown in equation (23). After TJd^{k+1} value is updated, either with TJd_r^k or with TJd^k, the next iteration of the inner loop starts. It is important to mention that the positions generated during the algorithm iterations are virtual positions, i.e. these are only used for assessing the fitness function. Only the positions generated when the metaheuristic finishes are actually included in the UAVs trajectories.

$$TJd^{k+1} = \begin{cases} TJd^{k}, & if\ f(TJd^{k}) \geq f(TJd_{r}^{k})\ and\ rn > p \\ TJd_{r}^{k}, & \begin{matrix} if\ f(TJd^{k}) \geq f(TJd_{r}^{k})\ and\ rn < p \\ or \\ if\ f(TJd^{k}) < f(TJd_{-}^{k}) \end{matrix} \end{cases} \quad (23)$$

Before running the simulated annealing algorithm, values for the initial probability (P_s), the final probability (P_f) and the number of sa-cycles (N) must be selected. In this specific case, some initial values and considerations proposed in [211] are assumed, however different values were tested for these parameters. The values presented in the Table 9 showed the expected behaviour of the algorithm convergence and also the expected overall behaviour of maximizing the serviced victims. These values have been used as a result of an empirical fine tuning of the algorithm. However, there might be other combinations of values that could also provide overall good results. These values are used for the calculation of the temperature parameters by using the expressions (41), (42), (43) and (44).

4.3.1.3.2.3 *Stopping criterion*

The stopping criterion defined in this subsection refers to the conditions needed for making both metaheuristics, the hill climbing and the simulated annealing, stop the execution and yield an optimal value of the Target Jaccard TJd and optimal positions for the UAVs. As it was previously mentioned, the Jaccard-based mobility model consists of several cycles, and the execution of the selected metaheuristic should finish before the next cycle starts. The stopping criterion selected is based on stopping the metaheuristic after a *maximum number of iterations*. This avoids excessive computation or time demands. This value has been calculated via experiments with the simulations and the number of 10 iterations was shown to be a valid value for guaranteeing the convergence of the algorithms.

4.3.1.3.3 Random walk

The random walk algorithm is not a metaheuristic per se, as it has not the optimization as a purpose, on the contrary, the random walk can be considered much similar to a mobility model based on a process that selects the next position randomly. Random walk mechanisms can be found on natural processes such as the diffusion of particles in physics or, the swarming of animals in ecology [34]. It can be said that a random walk approach usually has exploration capabilities but its exploitation abilities are very poor.

The random walk approach has been implemented as a benchmark, in order to demonstrate that *guided approaches* such as the metaheuristics implemented i.e. the hill climbing and simulated annealing algorithms are able to meet the objectives set in section 4.1 and also outperform a purely random behaviour governing the UAVs movements. The random walk implementation is shown in Figure 50.

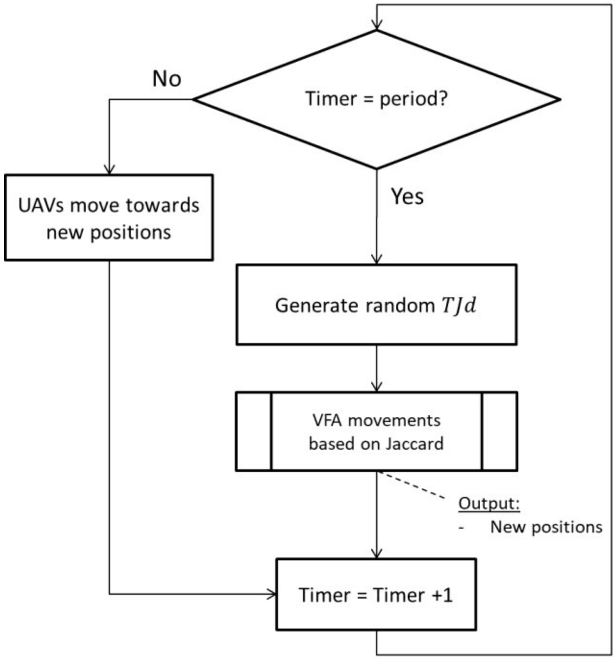


Figure 50. Random walk algorithm for the Jaccard-based mobility model

The random walk randomly selects a value for the Target Jaccard distance TJd. This TJd value is then used by the Jaccard-based virtual forces (VFA) movements described in section 4.3.1.3.3. Basically, the ΔJd_{ij} (17) is calculated, which is the difference between the current Jaccard distances Jd_{ij} (between each pair of Jaccard neighbours) and the Target Jaccard distance TJd. Then the VFA mechanism will generate new positions for the UAVs based on the difference calculated ΔJd_{ij}.

These positions generated by the VFA will make the UAVs Jaccard distances Jd_{ij} to get closer to the desired value TJd. The UAVs will move towards these positions during the time available before the next cycle starts.

4.3.1.4 Jaccard-based virtual forces algorithm (VFA)

The Jaccard-based mobility model uses the virtual forces algorithm (VFA) for calculating the UAVs new positions based on the value of the Target Jaccard distance TJd generated by the metaheuristics. The VFA is a mechanism using the idea of the electromagnetic forces that particles apply to each other in physics. This idea has been used to control the motion of mobile vehicles in different applications [117]. The reader can find a brief introduction to the virtual forces algorithm in Appendix A.

In the specific case considered of the Jaccard-based mobility model, the UAVs in the network are considered as if they were electromagnetic particles and all the forces that each UAV suffers are only due to the presence of the other UAVs. Also, the virtual forces algorithm here does not consider electromagnetic effects but take into consideration the Jaccard distance Jd existing between UAVs. According to (17), the value of ΔJd_{ij} is calculated, which corresponds to the difference between the existing Jaccard distances of each pair of UAVs that are Jaccard neighbours (i.e. Jd_{ij}) and the Target Jaccard distance TJd. Based on this difference ΔJd_{ij}, a pair of UAVs that are Jaccard neighbours will be exposed to a virtual force based on the virtual forces algorithm (VFA). The implementation of the VFA algorithm in this case involves the following statements:

- In the case that UAV_i and UAV_j have $Jd_{ij} > TJd$, these UAVs will experience a virtual attraction force and therefore they will move closer to each other.
- In the case that UAV_i and UAV_j have $Jd_{ij} < TJd$, these UAVs will experience a virtual repulsion force and therefore they will move away from each other.

The terms *virtual attraction* and *virtual repulsion forces* are used to represent the influence of one UAV on others. These virtual forces are equivalent to velocity vectors that will be applied in the next movement to be performed by each UAV. The intensity of the attraction and repulsion virtual forces is given by a relationship between the Jaccard distance Jd_{ij} and the speed at which the UAVs will perform the next move. This relationship is shown in Figure 51, where Jd_{ij} is the Jaccard distance between UAVi and UAVj and TJd represent the different values of the Target Jaccard distance TJd. The term *max_speed* represents the maximum speed at which the UAVs can fly.

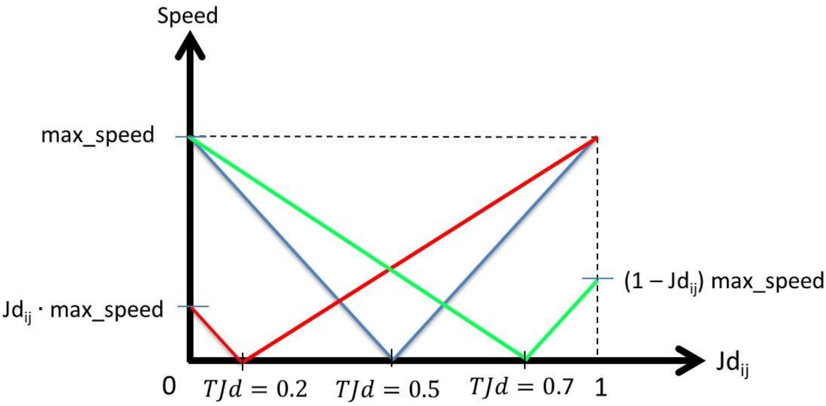


Figure 51. UAV speed vs Jaccard distance Jd_{ij} and Target Jaccard TJd

Figure 51 shows different values for TJd and each value defines a pair of lines that determine the relation between the UAV speed and the Jaccard distance Jd_{ij}. The red and green lines are examples to represent the cases when TJd is close to its minimum or maximum values, i.e. 0 or 1. As it can be seen, for the red and green lines the maximum speed is modulated by a factor in the positions $Jd_{ij} = 0$ and $Jd_{ij} = 1$. This factor coincides with the value of the Jaccard distance Jd_{ij} for the red line, and with the value $1 - Jd_{ij}$ for the green line. In these cases, these factors diminish the speed at which a pair of UAVs could move, when the UAVs are too close to each other (sharing many ground nodes in terms of the Jaccard distance) or too far (sharing very few ground nodes).

As an example, let consider a pair of UAVs, UAVi and UAVj, which has a Jaccard distance of a specific value $Jd_{ij} = 0.9$ at a specific time. Let also consider that at this time, the Jaccard-based mobility model has set the Target Jaccard distance $TJd = 0.7$. In this case, the green line from Figure 51 determines the relation between the UAVs speed and their Jaccard distance. As $Jd_{ij} = 0.9$ and is a value higher than $TJd = 0.7$, it means that UAVi and UAVj are further than expected in terms of the Jaccard distance metric (both UAVs should aim at having a Jaccard distance similar to $TJd = 0.7$). Therefore, UAV_i and UAV_j will experience a virtual attraction force at a speed given by the green line that goes from the point (0.7,0) up to $(1, (1 - Jd_{ij}) \cdot \max\_speed)$. It is clear that the bigger the difference between Jd_{ij} and TJd is, the higher the UAVs speed will be.

The movement direction of a pair of UAVs, e.g. UAV_i and UAV_j, will be determined by the virtual line that goes from the UAV_i position to UAV_j position, connecting both UAVs. Let's consider in the following examples several UAVs, namely UAV_0, UAV_1 and UAV_2. Consider that these UAVs form a UAV network that moves according to the VFA mechanism described in this section. Every UAV creates attraction or repulsion virtual forces on the rest of the UAVs. This is, UAV_0 exercises virtual forces on UAV_1 and UAV_2, UAV_1 on UAV_0 and UAV_2, and UAV_2 on UAV_0 and UAV_1. Consequently, the velocity vector of e.g. UAV_0 will result from the addition of the virtual forces that UAV_1 and UAV_2 exercise on UAV_0. The addition of these forces will determine UAV_0 next movement. This example can be extrapolated to UAV networks with a higher number of UAVs.

An example showing this behaviour is depicted in Figure 52 for a UAV network with 3 UAVs, UAV_0, UAV_1 and UAV_2, and a Target Jaccard distance $TJd = 0.5$. In this example, the UAV_1 and UAV_2 have Jaccard distances with respect to UAV_0 of values $Jd_{01} = 0.2$ and $Jd_{02} = 0.4$ respectively. It is important to note that the values of Jd_{01} and Jd_{02} are smaller than the Target Jaccard distance $TJd = 0.5$. It can be said that in terms of the Jaccard distances, as Jd_{01} and Jd_{02} are smaller, UAV_0 is closer than expected ($TJd = 0.1$) to UAV_1 and UAV_2. Thus, the effect of UAV_1 and UAV_2 over UAV_0 will result in virtual repulsion forces, which are represented by the red vectors v_{01} and v_{02}. The resulting vector of adding v_{01} and v_{02} will be the velocity applied to UAV_0 in its next movement. The current time has been represented by $t = T$ in Figure 52, and therefore the next time (in which the virtual repulsion forces take effect on UAV_0 movement) is represented as $t = T + 1$.

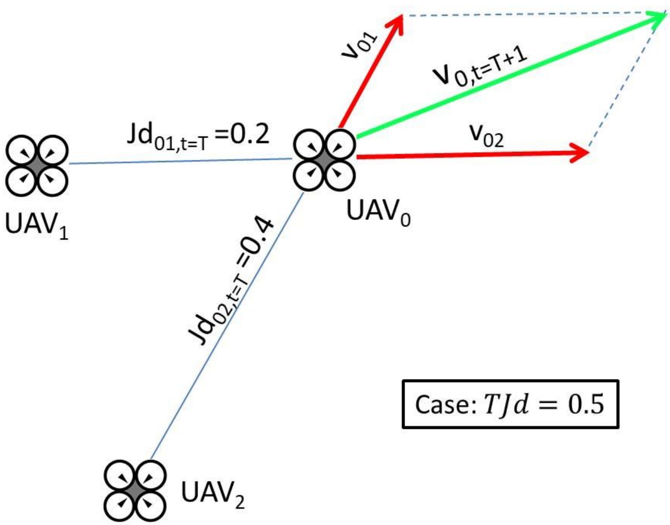


Figure 52. Example of repulsion virtual forces and velocity vectors addition

The VFA mechanism used for the Jaccard-based mobility model, as it has been described so far, would not allow the UAVs to spread enough. Let's recall that the ability to stretch or spreading of the UAV network would allow the UAVs to cover more ground nodes in a specific situation in which the nodes are organized in an extended manner. The reason is that with the VFA mechanism as described up to this point, each UAV would experience an attraction or repulsion force from every UAV of the network (except by itself). Then, any UAV will have lower Jaccard distances Jd_{ij} with closer UAVs and higher ones with UAVs that are further. This will create a set of repulsion forces (from the closer UAVs) and other set of attraction forces (from the UAVs that are further) then resulting on velocity vectors cancelation. This will provoke the UAV network to not to spread enough. This situation is depicted in the example shown in Figure 53. Considering the desired Target Jaccard distance $TJd = 0.5$, the UAV_0 experience virtual repulsion forces from UAV_1 and UAV_2 but also a virtual attraction force from UAV_3. This results in the attraction velocity vector v_{03} that points towards UAV_3 and the repulsion velocity vectors v_{01} and v_{02} that point in the opposite direction of UAV_1 and UAV_2.

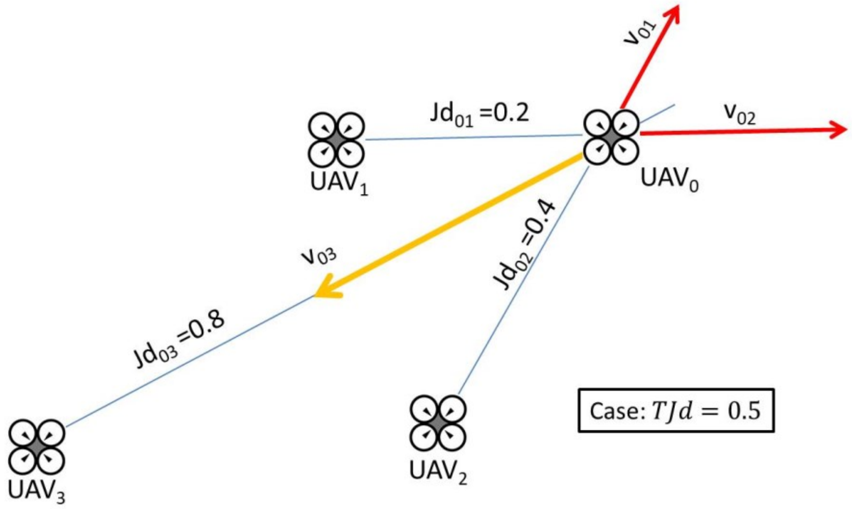


Figure 53. Attraction and repulsion velocity vectors cancellation

Having all network neighbours affecting the calculation of the attraction and repulsion vectors lead to *velocity vectors cancellation*, which is an undesired effect. In order to overcome this limitation, each UAV in the network should select a subset of UAVs, among all the network neighbours, i.e. each UAV in the network should select its Jaccard neighbours. Only the Jaccard neighbours of a UAV will exercise attraction or repulsion forces on it. The Jaccard neighbours selection is later explained in section 4.3.1.4.2.

Considering the example that was shown in Figure 53, it can be said that all UAVs are Jaccard neighbours to each other because all the UAVs exercise virtual forces onto each other. Let's consider now the same example with one difference, UAV_0 will have UAV_1 and UAV_2 as Jaccard neighbours, but UAV_3 will not be a Jaccard neighbour of UAV_0. UAV_3 is a mere network neighbour of UAV_0 in this situation. This situation is shown in Figure 54 and in this case, the only virtual forces that UAV_0 will experience are those from UAV_1 and UAV_2. This will make UAV_0 separate from UAV_1 and UAV_2 in the next movement as it is represented by the repulsion velocity vectors v_{01} and v_{02}. In this case, there is not an attraction force and UAV_0 can move with the aim of spreading the network coverage area.

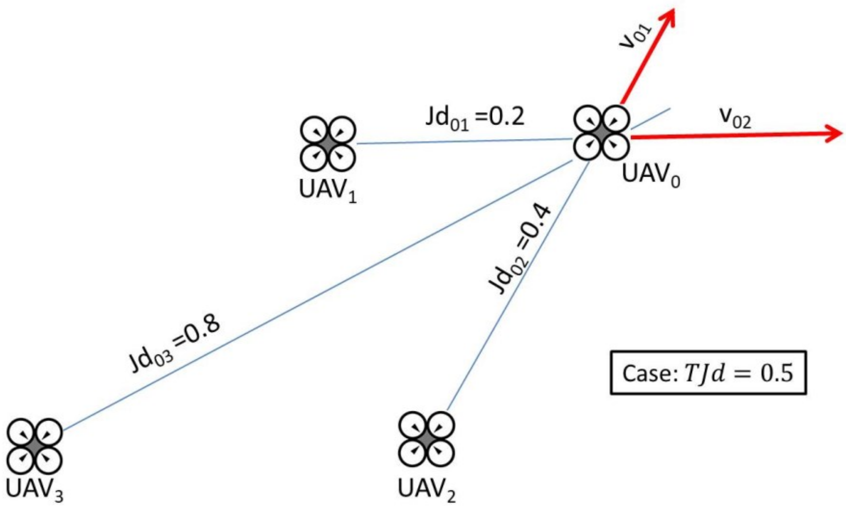
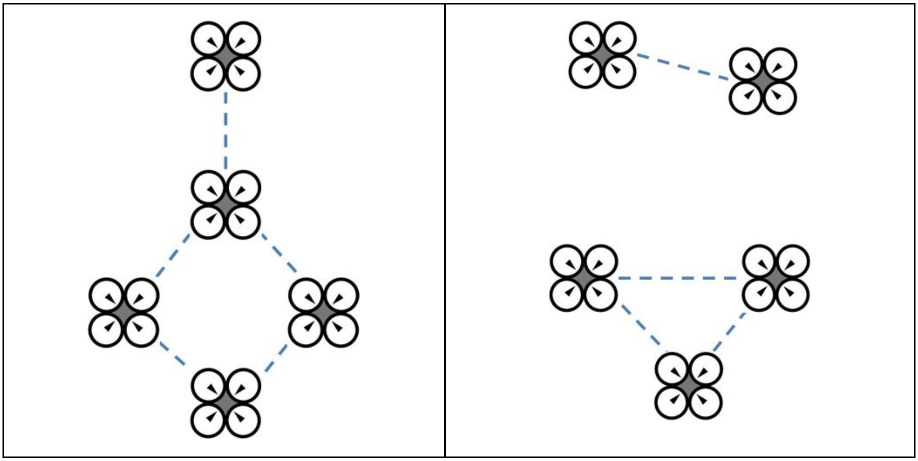


Figure 54. Jaccard neighbours selection avoiding velocity vectors cancellation

4.3.1.4.1 Disconnection avoidance mechanism

As the last addition to the Jaccard-based mobility model, a *disconnection avoidance mechanism* is included. The UAV network is considered to be disconnected when the network is split into two or more groups of UAVs not having wireless connectivity between them. In this context, there can exist groups with only one UAV. Examples of a connected and a disconnected UAV networks are shown in Figure 55, where the blue lines represent the wireless communication links established between each UAV pair.



a) Connected UAVs network b) Disconnected UAVs network

Figure 55. Examples of a connected (a) and a disconnected network (b)

In order to avoid to end up with a disconnected network, a new definition is added to the mobility model, i.e. the *disconnection security distance area* or Sda_i which is defined for each UAV of the network. The disconnection security distance Sda_i corresponds to a specific region on the external zone of a UAV wireless coverage area in the form of an *annulus* or *ring area*. The disconnection security distance Sda_i is shown in Figure 56 for the case of UAV_i. When any of the Jaccard neighbours of UAV_i, e.g. UAV_j, is within the ring area corresponding to Sda_i, UAV_j will be considered in risk of disconnection from UAV_i. In this situation, UAV_j will be affected by additional attraction virtual force towards its Jaccard neighbour UAV_i, which will avoid having them disconnected in the next movements of both UAVs. An example of this is shown in Figure 56 for UAV_2 and UAV_0. It can be noticed that with the absence of the velocity vector v_{d02}, which corresponds to the one generated by the disconnection avoidance procedure, UAV_0 would have been driven away from UAV_2 by the effect of the resulting virtual vector pointing in the opposite direction of UAV_2. With the virtual attraction vector v_{d02}, UAV_0 will be not move away from the coverage area of UAV_2.

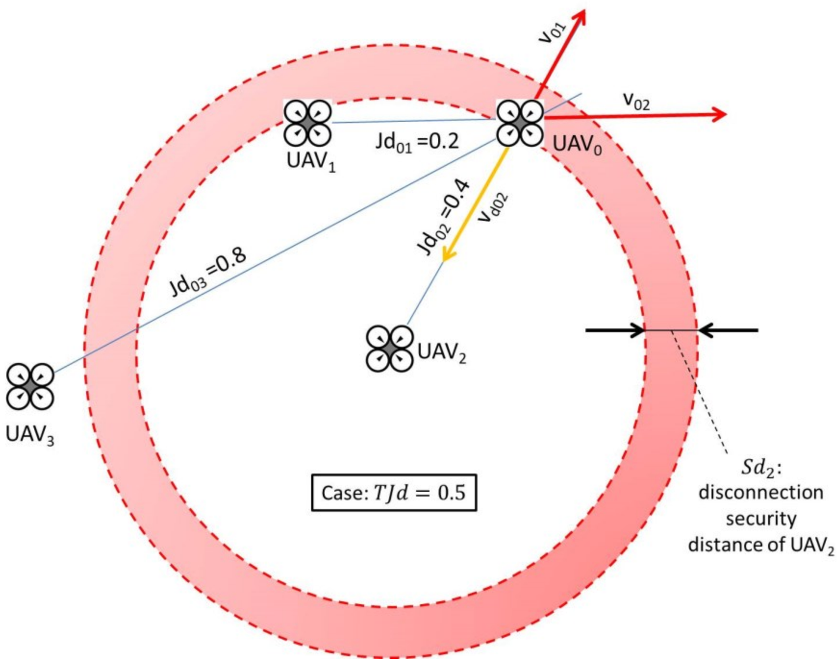


Figure 56. UAV2 disconnection security distance and attraction vector v_{d02}

4.3.1.4.2 Jaccard neighbour selection

In the Jaccard-based mobility model, each UAV can be configured to have a maximum of Jaccard neighbours from 2 up to $D-1$, being D the number of UAVs composing the UAV network. The *maximum number of Jaccard neighbours for each UAV* is represented by the symbol NJn and is defined in (24) and (25).

$$NJn \in [2, D-1] \quad (24)$$

$$D\text{: } total\ number\ of\ UAVs\ in\ the\ network \quad (25)$$

Taking into account the description of the Jaccard neighbour provided in section 4.3.1.2, there are many different ways to select the Jaccard neighbours in the UAV network. Figure 45 and Figure 46 showed that depending on the number of Jaccard neighbours per UAV and the selection of the Jaccard neighbours of each UAV, the network can be able to *stretch* and cover ground nodes organised in *extended regions* in the case of necessity or on the contrary, it can have a more compact and less extended coverage area. The selection of the Jaccard neighbours of each UAV and the maximum number of Jaccard neighbours per UAV NJn are design parameters of the Jaccard-based mobility model. An example is shown in Figure 57 and Figure 58.

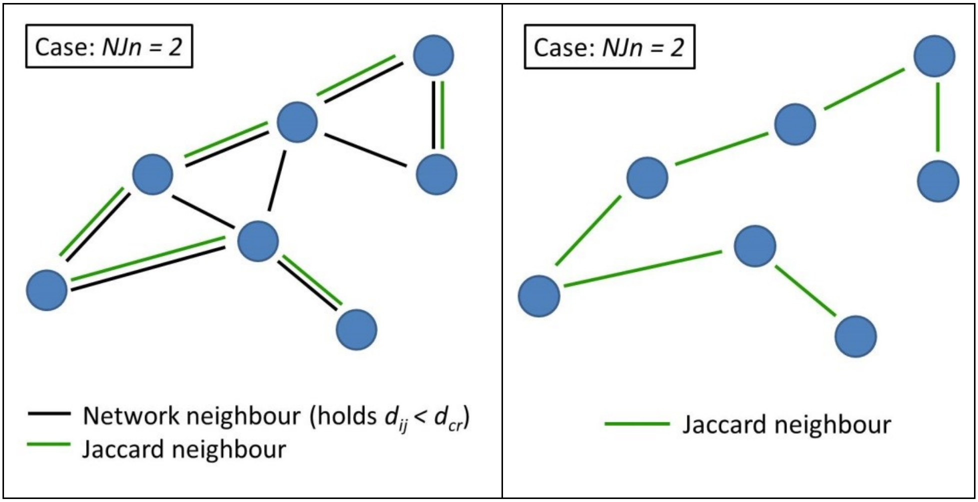


Figure 57. Jaccard neighbours for $NJn = 2$

Specifically, an example in which $NJn = 2$ is shown in Figure 57. On the left hand side, the UAV network neighbours (black edges) and the selection of the Jaccard networks (green edges) are shown. As it can be seen on the right hand side, such selection of Jaccard neighbours will allow the UAV network to stretch and provide coverage to ground nodes with extended distributions. On the contrary, Figure 58 depicts an example in which $NJn = 3$. In this case, it is noticeable that on the right hand side of Figure 58, there are two new green edges, which are marked with the asterisk symbol. The selection of the Jaccard neighbours that produced these two new edges yields a topology with more difficulties to stretch in comparison to the one shown in Figure 57.

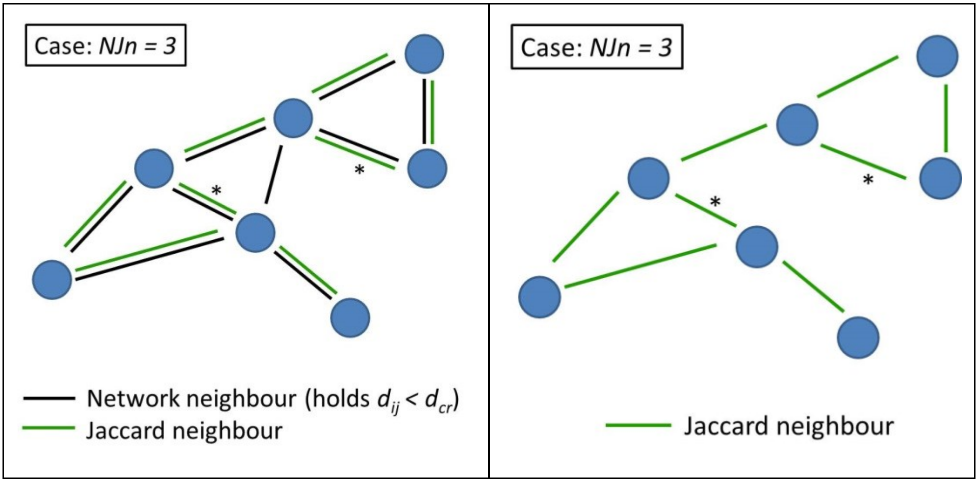


Figure 58. Jaccard neighbours for $NJn = 3$

One possible *selection mechanism* is to choose the Jaccard neighbours for each UAV at the beginning of the mission and to maintain the selection during the entire mission. As an example, the Jaccard neighbours of UAV_i will be always the same.

Another selection mechanism is to define the maximum number of Jaccard neighbours NJn that each UAV can have and then let each UAV select its Jaccard neighbours periodically. In this case, each UAV will measure the Jaccard distance to each network neighbour and will select as Jaccard neighbours those with the lowest Jaccard distance. As the mission evolves and the UAVs move, each UAV can have different Jaccard neighbours. As an example, let's consider that the number of Jaccard neighbours that UAV_0 can have is set to the value 2 and let's look at Figure 56. In the situation depicted the two UAVs that are closer to UAV_0, in terms of the Jaccard distances, are UAV_1 and UAV_2. Therefore, UAV_0 will select UAV_1 and UAV_2 as Jaccard neighbours. On the contrary, UAV_3 will not be selected as a Jaccard neighbour of UAV_0. As a result of this selection mechanism, each UAV will only focus on the most similar UAVs to it in terms of the Jaccard distance (equivalent to the UAVs with the lowest Jaccard distances) to calculate its attraction or repulsion forces.

4.3.1.5 Information exchange between UAVs

In this chapter, several UAVs are located within a medium-sized scenario area (in comparison to the chapter 3 scenario area) and form a connected network. This means that any UAV in the network is continuously connected to at least another UAV. Also, the UAV network considered in this chapter usually has an underlying topology that is able to change, but it has a slower change rate than the DTN-like network considered in sections 3.2 and 3.3. In this situation, the DTN paradigm is not the most appropriate and a network paradigm shift is recommended. Therefore, in this chapter, the UAV network is assumed to adhere to another appropriate multihop ad hoc network paradigm, more appropriate, like the wireless mesh networking paradigm (WMN).

The network nodes are considered to exchange information during the entire mission development. As the information exchange occurs always that a pair of UAVs establishes a direct communication link and the network considered in this chapter is a connected network, the information exchange is far more frequent than in chapter 3. The information exchanged by the UAVs consists of the list of the victims that each UAV's is aware of, those victims that each UAV has under its wireless coverage area and the estimated position of these victims. Also, UAVs exchange their own positions with each other. This information is lightweight and it is supposed to be shared among all UAVs periodically during the mission. The idea behind sharing this information is that all UAVs in the network have the same aforementioned data related to the victims and other UAVs and based on this information each UAV can perform actions such as calculating the Jaccard distance with its Jaccard neighbours.

4.4 Simulation results

In this section, the results obtained from the simulation of the proposed Jaccard-based mobility model are introduced. The mobility model behaviour is tested on an urban scenario model. At the end of the section, several figures are shown, depicting the UAV network and the ground nodes' locations on the disaster scenario at different simulation times.

4.4.1 Simulation settings

In this section, the settings that were used for simulating the proposed Jaccard-based mobility model are shown. The results described later in this chapter correspond to the simulation settings shown in Table 10. It is worth highlighting that all the simulations results presented in this chapter were run in a tailored software simulator developed specifically for this research.

Table 10. Simulation settings

Number of UAVs	6
Number of victims	295
Scenario dimensions	1000 meters long and 1000 meters wide
Scenario events	2 groups of ground nodes disappear at t = 200 and t = 400 seconds (emulating a building collapse as described in section 4.2.1)
Simulation duration (T_{stop})	600 seconds
Simulation step	1 second
Mobility generation tool	BonnMotion [45] with tailored modifications merging features of several mobility models such as RWP mobility model [34] [111] [182] [186], Manhattan Grid mobility model [212] and Disaster Area mobility model [47]
Jaccard-based algorithm cycle period	30 seconds
Metaheuristics iterations	Each metaheuristic algorithm is executed with 10 iterations
Jaccard neighbour selection	Fixed and selecting the neighbour with the lowest Jaccard
Maximum number of Jaccard neighbours (NJn)	2

4.4.2 Performance evaluation metrics

The metrics considered for analysing the mobility model simulation results are presented in this subsection. These metrics are shown in Table 11.

Table 11. Performance evaluation metrics

Metric	Acronym	Description
Serviced nodes	*SERVN*	The total number of ground nodes within the UAV network wireless coverage area.
UAV network disconnections	*UDISC*	The number of situations in which the network suffered from a disconnection of one or more UAVs.
UAV locations	*UAVLOC*	Visually represents the UAV locations with respect to the ground nodes' locations, at different times of the simulation.

4.4.3 Mobility algorithm behaviour and metaheuristics comparison

4.4.3.1 Serviced nodes (SERVN)

The results corresponding to the *SERVN metric* are shown in Figure 59. Specifically, SERVN represents the variation of the total number of serviced ground nodes (i.e. victims) over time. The figure differentiates the serviced nodes for both metaheuristics described in section 4.3 and also for the random walk behaviour. It can be observed that the random walk-based algorithm is the worst performing one in terms of the SERVN metric. This behaviour is expected as the random walk algorithm does not perform any kind of optimization. The random walk algorithm randomly selects the Target Jaccard TJd and this does not guarantee that the Jaccard distances that the UAVs are trying to maintain are the best ones for maximizing the number of ground nodes under the wireless coverage area, i.e. for maximizing the SERVN metric.

Figure 59 shows a slight difference between the simulated annealing and the hill climbing performance (for the particular case shown in the figure). In the first time interval, i.e. between 0 and 100 seconds approximately, the simulated annealing algorithm shows a better performance than the hill climbing, i.e. reaching higher values for SERVN faster than the hill climbing algorithm. On the contrary, from the time frame that goes from $t = 100$ seconds onwards, the situation is the opposite and the hill climbing has slightly higher values than the simulated annealing algorithm. However, the difference between them is relatively small: the hill climbing algorithm is servicing 10 more victims than the simulated annealing algorithm.

There is one important aspect behind this fact of the hill climbing algorithm outperforming the simulated annealing. The hill climbing algorithm usually exploits the search space in search for a maximum, either it is global or local, without accepting worse candidate solution during the process. Accepting worse solutions is a mechanism for exploring several search space regions and avoids getting stuck in local maxima. The simulated annealing though may accept worse candidate solutions under specific circumstances. According to the description provided in section 4.3 and the fitness function defined in (18), the only aspects considered in the optimization problem proposed are the number of ground nodes under the wireless coverage area and the UAV network disconnections. According to the results shown in Figure 59, Target Jaccard values close to $TJd = 1$, which are common in the hill climbing algorithm, seem to perform better. This explains the better performance of hill climbing, as the simulated annealing algorithm may accept worse candidate solutions, and there will be situations in which TJd will take values smaller than 1 and therefore the serviced nodes will be fewer than in the case of the hill climbing.

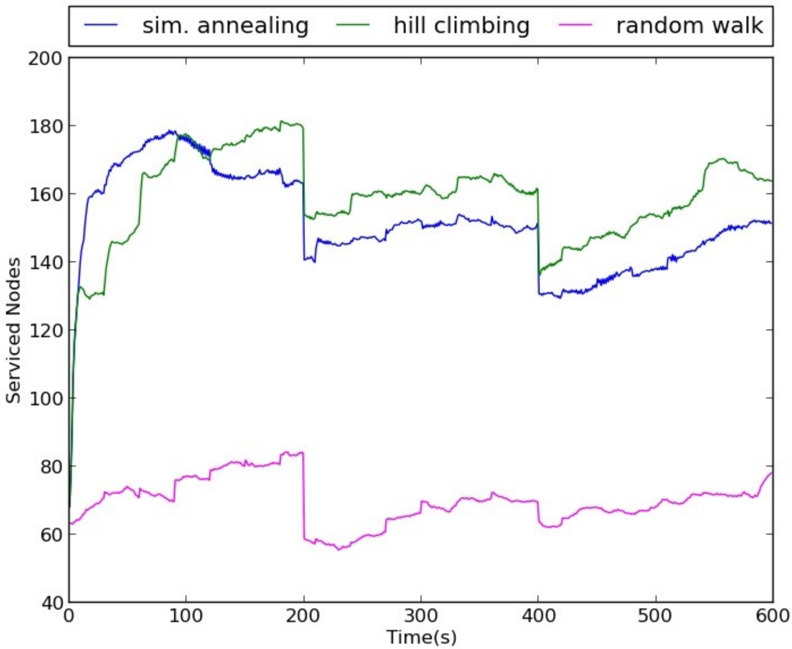


Figure 59. Serviced nodes metric (SERVN)

There are 2 *scenario events* at $t = 200$ and $t = 400$ seconds emulating *building collapse* events as it was described in section 4.2.1. These events have been modelled by groups of victims disappearing from the scenario, specifically from the area where the building was located. Both simulated annealing and hill climbing algorithms show a decrease on the SERVN metric values at the specific times at which these events occur. Also, the random walk approach is affected considerably by the first group of disappearing victims, however, the second vent have only a slight effect on the algorithm. This is due to the fact that the UAVs network is less spread with the random walk algorithm and the second group of victims disappearing is not entirely under the UAV wireless coverage area at the time they disappear.

There is also a common behaviour shown by both the simulated annealing and the hill climbing that is worth mentioning. Both algorithms actually spread out the UAVs network and, in this process, they present two main aspects: i) a tendency for increasing the number of serviced victims and ii) slight oscillations around some values once they reach a maximum. In Figure 59, in the time frame between $t = 0$ and $t = 200$, there is a clear tendency to increase the serviced nodes, as a result of the UAV network initial self-deployment. Within this time frame, the UAV network reaches its highest SERVN value which is between 160 and 180. This represents a percentage between the 54% and 61% of victims, taking into account that the total number of victims in the scenario is 295.

From $t = 200$ p to $t = 400$ seconds both algorithms present slight oscillations between the 150 and 160 serviced victims. This represents a percentage of serviced victims around the 56%, taking into account that the total number of victims is 275, after the first 20 victims disappeared from the scenario at $t = 200$. Finally, from $t = 400$ seconds up to the end of the simulation there is an increase tendency that ends up in servicing between 150 and 160 victims. This represents a percentage of SERVN around the 60%, taking into account that the total number of victims is 255, after the second group of 20 victims disappeared at $t = 400$.

Due to the fact that the disaster scenario, the mobility of the ground nodes and also the metaheuristics implemented have random aspects, it is considered normal to find oscillations around specific values. These oscillations may correspond then to the fact of ground nodes entering and going out of the UAV network wireless coverage area. Despite these oscillations, the Jaccard-based mobility model proposed together with the metaheuristics show that the UAV network actually spreads out and adapts to the scenario changes.

4.4.3.2 UAV network disconnections (UDISC)

The second objective for the Jaccard-based mobility model proposed is to keep the UAV network always connected. This is monitored by the *UAV network disconnection (UDISC) metric*. As described in section 4.3, the fitness function shown in (18) has a component that penalizes the network disconnections. Specifically, the penalty is represented by giving the fitness function $f(TJd)$ taking the value -1 when there is a UAV disconnecting from the network. The fitness function values of both metaheuristics have been logged in order to detect values equal to -1 corresponding to situations in which the UAV network is not a connected network anymore.

Figure 60 shows the comparison of metaheuristics, the hill climbing and the simulated annealing algorithms, with their respective fitness functions values over time. As it can be observed at no time of the simulation the fitness function takes the value -1. This is a signal that the UAVs network does not suffer from disconnections and therefore $UDISC = 0$ for both metaheuristics. In the case of the simulated annealing algorithm, a candidate solution characterized by a network disconnection could be possible as the algorithm may take worse candidates as a selected solution when it tries to escape local maxima. The hill climbing algorithm on the contrary is not accepting, by definition, worse candidates as valid solutions. However, in both cases, the disconnection avoidance mechanism described in section 4.3.1.4.1 is present during the simulations. This disconnection avoidance mechanism guarantees that at no time the UAV network becomes a non-connected network and therefore the fitness function will not take values equal to -1. This is depicted in Figure 60 for the simulated annealing and the hill climbing algorithms. It is worth mentioning that the random walk algorithm is also represented in this figure. Although the random walk is not an optimization algorithm per se, the fitness function values for this algorithm have been also represented in order to detect network disconnections. The situation is the same that happens with both metaheuristics, the disconnection avoidance mechanism guarantees that there are no network disconnections for the random walk algorithm.

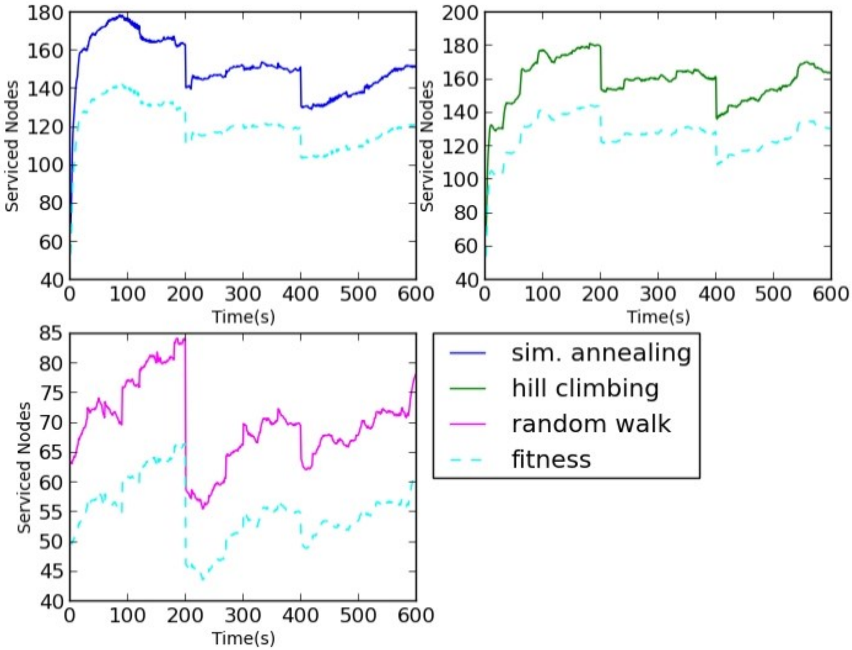
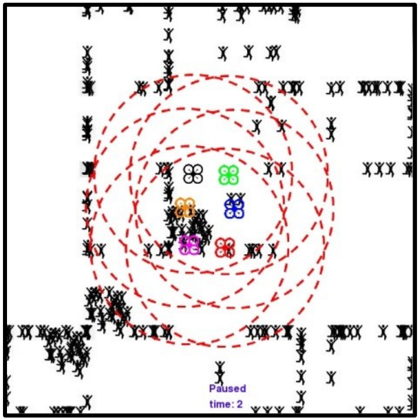


Figure 60. Metaheuristics (solid lines) and fitness (dashed lines)

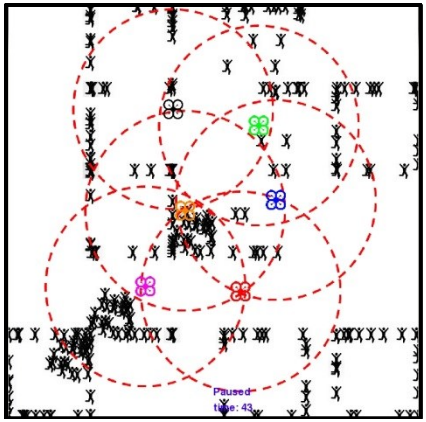
4.4.3.3 UAVs locations (UAVLOC)

Figure 61 corresponds to the *UAV locations metric (UAVLOC)* for the particular case of the simulated annealing algorithm. This figure shows the UAVs locations together with the victims' locations at different time stamps of the simulation. The dashed red lines represent the UAVs coverage areas using the disk model mentioned in section 4.2.2.2. The reason for using simulated annealing results in this section is to demonstrate that, even with the simulated annealing algorithm which is slightly outperformed by hill climbing, it is possible to notice that the Jaccard-based mobility model is able to make the UAV network self-deploy and spreading over the scenario maximizing the number of ground nodes under the wireless coverage area.

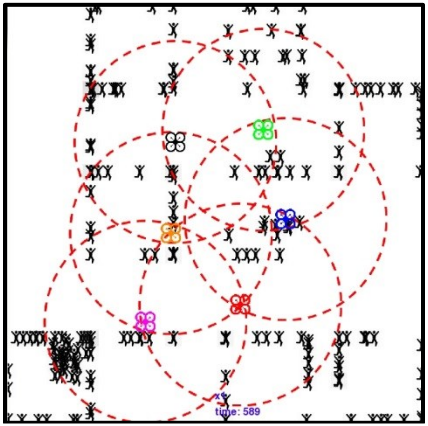
Figure 61a shows how the UAVs are close to each other at the beginning of the simulation, specifically when the simulation time is $t = 2\ seconds$. This situation is expected as, per design, it is assumed that the UAVs start the simulation from a small area located in the centre of the disaster scenario. Figure 61b shows how the UAV network has spread out during the first part of the simulation, specifically corresponding to the simulation time $t = 43\ s$, which corresponds to the second cycle of the Jaccard-based mobility model. It is noticeable that the area covered by the UAV network is bigger in this case in comparison to the one shown in Figure 61a. Therefore, this situation corresponds to a bigger number of ground nodes being serviced by the UAV network. Finally, Figure 61c shows the UAVs positions at the end of the simulation, specifically at the simulation time $t = 589\ s$, which corresponds to the 20th cycle of the Jaccard-based mobility model. It can be noticed that the changes from Figure 61b to Figure 61c are subtler than those observed between Figure 61a and Figure 61b. The reason is that when the UAV network starts to spread out, the UAVs' optimal locations generated by the Jaccard-base mobility model are usually far from the initial positions of the UAVs. When the UAV network is already spread out, the optimal positions generated by the mobility model are usually close to the current positions of the UAVs. Therefore, as the simulation time goes on, the changes in the UAVs' positions are smaller. Another aspect that affects to this situation is the disconnection avoidance mechanism. There is a higher risk of disconnection when the UAVs are spread out as the distance among them is bigger and the UAVs may be already located close to the disconnection security distance rings of their Jaccard neighbours. Thus, the disconnection avoidance mechanism will be likely acting on the movement vectors applied to the UAVs, moderating them in order to avoid network disconnections. Although the movements are smaller when the UAV network is already spread out, by looking at Figure 61b and Figure 61c it can be noticed that there are changes in the locations of the black and pink UAVs with respect with the scenario layout. There are also small changes in the coverage areas depicted on Figure 61c , which are displaced towards the lower part of the scenario where a major accumulation of victims is located (the bottom-left corner).



a) UAVs positions at simulation time t = 2 s



b) UAVs positions at simulation time t = 43 s



c) UAVs positions at simulation time t = 589 s

Figure 61. UAVs positions (UAVLOC) at different simulation time instants

It is also noticeable in Figure 61, that there are ground nodes that have not been covered by the UAV network wireless coverage area. With this scenario and the selected simulation settings (i.e. the number of UAVs and the wireless coverage area radius, among others), it is not feasible to cover the entire scenario area without disconnecting the UAV network. This is a known consequence when providing wireless coverage services in scenarios with larger area size and with a limited number of UAVs with connectivity constraints [55]. However, the Jaccard-based mobility model has demonstrated to adapt to the scenario changes (i.e. to the movement of the ground nodes), maximizing the number of victims under the wireless coverage area and avoiding network disconnections.

4.5 Discussion of results

This section gathers the main details of the work described in this chapter and the results shown in previous sections. The only purpose of this section is not to introduce new data but only to summarize and organized the information described.

This chapter has proposed a mission-based mobility model for a UAV network. The mission context corresponds to an emergency relief operation in a disaster-stricken scenario. The scenario context corresponds to an area where a group of victims are waiting for an emergency response team. The scenario considered is an urban-like scenario and the victims are moving along streets, around buildings and all over open areas. The UAV network mobility model aims at meeting two main objectives: i) providing communication services to the maximum number of victims as possible, and ii) maintaining the UAV network as a connected network. The main contributions of this chapter are listed below:

- A new algorithm called Jaccard-based mobility model has been proposed as a mission-based mobility model for a UAV network meeting the objectives described above.
- The Jaccard-based mobility model is based on the concept of the Jaccard distance Jd, the Target Jaccard distance TJd and several metaheuristics that are used as optimization algorithms. Basically, the Jaccard distance Jd is a metric that offers a way to measure whether a pair of UAVs is providing communication services to the same group of ground nodes or if they are

efficiently providing communication services to different ground nodes and therefore maximizing the UAV network service. The Target Jaccard distance TJd is defined as the optimal Jaccard distance value that UAVs should have with each its Jaccard neighbours in order to maximize different communication aspects, i.e. the number of ground nodes under the UAV network coverage in this case. The metaheuristics are used for calculating the Target Jaccard distance TJd.

- Several metaheuristics have been used for comparison purposes, namely hill climbing and simulated annealing. A random-walk based algorithm has been used as a benchmark. Both the hill climbing and simulated annealing algorithms outperform the random walk algorithm, so it is proven that a guided approach is needed. Also, when the number of ground nodes under the UAV network wireless coverage area is the main aspect optimized, the hill climbing algorithm is slightly the best performing algorithm as it does not accept worse candidate solutions and guide the UAV network towards a Target Jaccard distance $TJd = 1$. The simulated annealing may yield values for the Target Jaccard distance different than 1, as it accepts worse candidate solutions under specific circumstances. In the case of considering other aspects for the optimization problem such as the robustness of the network or load balancing the network traffic among all the UAVs (in the case that some UAVs are overloaded) the simulated annealing or other metaheuristics may be more appropriate.
- The concept of Jaccard neighbour is defined for each UAV in the network. A Jaccard neighbour of UAV_i is a network neighbour which has an effect on UAV_i movement. This effect is based on the difference between the current Jaccard distance Jd between UAV_i and its Jaccard neighbor and the Target Jaccard distance TJd. There are different mechanisms that can be used for selecting the Jaccard neighbours of each UAV in the network. The selection mechanism and the number of Jaccard neighbours per UAV is a design parameter. Depending on the number of Jaccard neighbours assigned to each UAV and how these Jaccard neighbours are selected, the UAV network will have the ability to stretch in order to cover ground nodes organized in the scenario with an extended shape or not.
- The virtual forces algorithm (VFA) has been used based on the Jaccard

distances existing between the Jaccard neighbours. This algorithm acts provoking attraction and repulsion forces between Jaccard neighbours nodes so their Jaccard distances Jd get closer to the value of the Target Jaccard distance TJd. Specifically, virtual repulsion forces are applied to those UAVs that have a Jaccard distance Jd smaller than the Target Jaccard distance TJd. On the contrary, virtual attraction forces are applied to those UAVs that have a Jaccard distance Jd bigger than the Target Jaccard distance TJd.

- A disconnection avoidance mechanism has been proposed as an addition to the aforementioned VFA algorithm in order to avoid UAVs to disconnect from its Jaccard neighbours. This mechanism defines a disconnection security distance area or Sda_i, with the form of an annulus or ring area, which is defined for each UAV of the network. A UAV which enters in the disconnection security distance area Sda_i of its Jaccard neighbour will be applied with a virtual attraction force towards its Jaccard neighbour in order to reduce the disconnection probability.
- An urban disaster-like scenario has been modelled composed by different regions such as streets, building blocks, open areas such as parks, and prohibited areas. Also, several details that are typical from disaster-stricken areas have been modelled, such as blocked roads and buildings collapse events. The different regions composing the scenario, the blocked roads and collapse events have different effects on the mobility of the victims with specific details in each case. This scenario has been used for validating the Jaccard-based mobility model.
- Several metrics have been used in order to assess the validity of the Jaccard-based mobility model for the goals established for the aforementioned mission. The metrics are the total number of serviced nodes (SERVN), the UAV network disconnections (UDISC), and the UAV locations (UAVLOC). According to these metrics, the proposed mobility model has proven the ability to meet the mission objectives by maximizing the number of ground nodes under the wireless coverage area up to the 60% of the total number of ground nodes, at the same time that maintains the UAV network as a connected network, i.e. avoiding UAV disconnections.

In conclusion, the model proposed, called the Jaccard-based mobility model, can be considered one of the few mission-based mobility models for UAV networks found today in the literature, complying with the requirements of maximizing the number of ground nodes under a UAV network wireless coverage area and maintaining a connected UAV network. The proposed mobility model has also shown good performance according to the several metrics used.

5. CONCLUSIONS & FUTURE WORKS

"After a certain high level of technical skill is achieved, science and art tend to coalesce in esthetics, plasticity, and form. The greatest scientists are artists as well"
Albert Einstein

This chapter summarizes the *conclusions* regarding the work developed for this thesis. These conclusions are presented in an organized manner, on one hand, the advancements corresponding to the mobility model for an *exploration mission*, on the other hand, those corresponding to the mobility model for an *adaptive coverage mission*. Also, this chapter describes *future research lines* that have been identified during the work carried out. These have been organized into three categories, namely, future research works for the *exploration strategy*, for the *adaptive coverage strategy* and *other* future research works (the former can be considered common future research for both the exploration and the adaptive coverage strategy). The author's desire is to keep working on this research area and keep contributing, even if it is a small bit, to the future of UAV networks and its applications. Also, the author looks forward to this work to be useful for other researchers, so they can build up their research from the contents of this document and the research material related.

5.1 Conclusions

Within the numerous aspects that can be studied in the field of UAV networks, mobility is one of the aspects that have attracted the attention of the research community. UAV mobility can be addressed from the perspective of different disciplines such as electronics, robotics and computer science, among others. In the case of multihop ad hoc networks with mobile nodes, it is a common practice to study the network and the behaviour of the nodes from the point of view of a mobility model. In a similar way, as it occurs in the motion planning research area, mobility models aim to imitate the movements of the mobile nodes that form a network. The multihop ad hoc research highly depends on the mobility models to validate the routing algorithms and networking solutions proposed. Therefore, the final goal of mobility models research is to provide a tool for the analysis of the networking properties of multihop ad hoc networks, either this is a MANET, a VANET or an AANET. Although there are some examples of research papers addressing the area of mobility models for UAV networks, such as [34] [39] [24] [55], these are still few. UAV networks are claiming a place within the networking paradigms of the future and therefore more research on UAV networks mobility models is required.

Within the existing research of mobility model for UAV networks, it is common to find works that adapt MANET mobility models for UAV networks. MANET mobility models are easy to implement and simple, however, these usually fail to represent the main purpose of UAV flights. This means that UAV networks are commonly used in missions in which both the UAV team and also each UAV individually have to accomplish specific goals. This requires that each UAV is assigned specific tasks and has to move in a precise manner to perform these tasks. Taking this into account, models inherited from generic MANETs such as the Random Walk (RW), the Random Waypoint (RWP), the Random Direction (RD) or the Gauss-Markov random mobility models do not represent fairly this mission-oriented behaviour of UAVs teams.

Some other research works have proposed new mobility models specifically designed for UAV networks such as the Semi-Random Circular Movement (SCRM) mobility model, the Three-Way Random (TW) mobility model or the Pheromone Repel (PR) mobility model, among others. Although these mobility models are specific for UAV networks and are better than MANET models in capturing aerial vehicles mobility dynamics, they still present very basic UAV movements and therefore are far from imitating mission-oriented movements of a UAV team. Also, it is worth mentioning that, usually, an important number of works proposing mobility models specific for aerial vehicle networks try to reproduce smooth trajectory changes typical from fixed-wing aerial vehicles [34]. However, some aerial vehicles such as multicopters are able to perform sharp turns and movements due to their mechanical capabilities. This is an aspect that has not received enough consideration within the research devoted to aerial vehicles mobility models.

Apart from the research working expressly in mobility models for UAV networks, there are research works in other disciplines like path planning and motion planning, which have proposed solutions for the mobility of UAV teams by using metaheuristics. These works are usually considered as mission-based as the UAV team is assigned a mission, which is typically associated with finding a feasible trajectory for the UAVs. Many of these works do not consider the UAV team as a UAV network and nor consider the networking aspects. However, the approach of using metaheuristics for a UAV team performing a specific mission is worth to be taken into account. The reason for this is that metaheuristics approaches have demonstrated its validity for generating mission-based trajectories of a team of UAVs and at the same time many of them are easy to implement.

The work carried out in this thesis consists of the development of two mission-oriented mobility models specifically for UAV networks. The proposed mobility models capture the mobility of a UAV network in two specific missions, with greater detail than MANET-adapted mobility models and non-mission-oriented aerial mobility models. Moreover, the proposed mobility models make use of metaheuristics for generating the UAV trajectories in a similar manner than some path planning approaches. Among the two mission-oriented mobility models proposed, the first one considers an exploration mission and the second one an adaptive wireless coverage mission. Regarding the mobility model proposed for the exploration mission, the main goals are two: i) to make the UAV network to explore the scenario and discover the ground nodes' locations, and ii) to make the UAVs converge to the clusters in which the ground nodes are organized in. In the second mobility model proposed, the main goals for the adaptive coverage mission are two: i) to make the UAV network provide communication services to as many ground nodes as possible, adapting to the mobility of the ground nodes, and ii) maintain the UAVs as a connected network during the entire mission. Both mobility models have been validated via simulations in disaster-like scenarios in which the ground nodes are considered victims or first responders. This section summarizes the conclusions with respect to both mobility models proposed: the one corresponding to the exploration mission (described in sections 3.3 and 3.4) and the one corresponding to the adaptive coverage mission (described in sections 4.3 and 4.4).

5.1.1 Mobility model for an exploration mission

The reader can refer to section 3.5 for a detailed description of the advancements with respect to the state of the art and a discussion of the results. The list below is a summary of the main findings related to the work developed in chapter 3:

- A distributed mission-based mobility model, called dPSO-U, has been proposed for a UAV network performing an exploration mission in a disaster scenario. The proposed mobility model is based on the well-known PSO algorithm with several modifications such as dynamic values for the inertia, local best and neighbour best weights together with controlled randomness. The mission assigned to the UAV network has two main objectives: i) explore the disaster scenario gathering information about the ground nodes' locations, and ii) make the UAVs converge to the nodes clusters discovered during the exploration phase. The proposed mobility model is able to capture the mobility of the UAV network in a mission with the aforementioned objectives.
- The dPSO-U mobility model has been characterized for different value sets of the inertia, local best and neighbour best weights of the algorithm. Several metrics, which are described in section 3.4.2, have been used for assessing the exploration, convergence and connectivity abilities of the dPSO-U algorithm. These metrics have been useful as well for identifying the value sets that respond better to the mission requirements.
- One of the best performing cases identified in the characterization has been used for validating the dPSO-U mobility model in simulations in which the number of ground nodes clusters in the scenario varies from 1 to 10. The dPSO-U mobility model has been able to meet the two

aforementioned objectives of the mission with a different number of clusters.

- Finally, one of the best performing cases identified in the characterization of the dPSO-U has been compared with the Lawnmower algorithm. The Lawnmower algorithm offers the guarantee of sweeping the entire scenario area, discovering almost all the ground nodes, then having the possibility to converge to the ground nodes clusters. The dPSO-U mobility model has demonstrated its ability to overcome the Lawnmower in terms of the exploration and convergence time (which has been reduced) and at the same time discover a high percentage of ground nodes. Also, the dPSO-U algorithm is able to provide better communication service in terms of the number of connections with the ground nodes since the first stages of the mission.

5.1.2 Mobility model for an adaptive coverage mission

A detailed description of the Jaccard-based mobility model results was presented in section 4.5. This section summarizes the conclusions related to the work developed in chapter 4 in the form of a list:

- A Jaccard-based mobility model has been proposed which captures the mobility of a UAV network carrying out an adaptive coverage mission in a disaster scenario. A combination of the virtual forces algorithm, the Jaccard distance between UAVs and metaheuristics such as hill climbing or simulated annealing have been used in this mobility model. The mission assigned to the UAV network has two main objectives: i) to maximize the number of ground nodes (i.e. victims) that are under the UAV network wireless coverage area, and ii) to maintain the UAVs as a connected network, i.e. avoiding UAV disconnections. The proposed mobility model is able to capture the mobility of the UAV network in a mission with the aforementioned objectives.
- The Jaccard-based mobility model has been validated in an urban-like disaster scenario with details typical of disaster-stricken areas such as blocked roads and buildings. Several metrics, which are described in section 4.4.2, have been used for assessing the mobility model behaviour

corresponding to the two mission aforementioned objectives. The proposed mobility has the ability to reach a percentage of ground nodes under wireless coverage of approximately (on average) the 60% of the total number of ground nodes.

- Different metaheuristics such as the hill climbing and the simulated annealing algorithm have been used for optimizing the Jaccard distance that the UAVs should have in order to maximize the number of ground nodes under the wireless coverage area of the network. The performance of the hill climbing and the simulated annealing algorithm has been compared by using the metrics described in section 4.4.2. A random-walk based algorithm has been used as a benchmark for validating the fact that a guided approach brings benefits to the mobility model. As a result of the comparison and considering that the main aspect optimized is the number of ground nodes under the UAV network wireless coverage area, the hill climbing algorithm has been the best performing algorithm. In the case of considering other aspects in the optimization problem, such as the robustness of the network or load balancing the network traffic among all the UAVs (in the case that some UAVs are overloaded), the simulated annealing may be more appropriate.

5.2 Future works

This section describes potential research topics that are considered as *open issues* in the area of mobility models for UAV networks. These have been organized into three categories. First of all, the *future works* that correspond to the mobility models focusing on exploration strategies. Second, those corresponding to mobility models centred on adaptive coverage missions. Finally, another subsection presents the potential research work that can be developed in generic areas related to UAV networks. Any of the future works described in this section are considered as the next steps to take for continuing with the work developed in this thesis, as well as a reference for other researchers working in related areas.

5.2.1 Exploration strategies

The dPSO-U mobility model proposed for the exploration strategy has been validated based on different metrics that are described in section 3.4.2. In a first approximation to implementing the dPSO-U mobility model, the set of metrics used has been limited, the fact that the focus was on validating the mobility model rather than studying every possible aspect. Nevertheless, other metrics can be used in order to gather more information about the behaviour of the proposed mobility model and refine its implementation. Defining new performance evaluation metrics and implementing the required changes on the software to measure them is considered a first-priority future research work.

Also, the dPSO-U mobility model has been based on the original PSO algorithm. However, there are other candidates, either metaheuristics or other algorithms, which could perform well in the specific exploration and convergence mission considered. Examples of these are the swarm intelligence algorithms such as the ant colony optimization (ACO) or the firefly algorithm [213]. Even changes in the current implementation, such as considering levy walks [214] [215] for improving the exploration phase of the mission instead of random direction changes for the UAVs when they reach the scenario border could be interesting approaches for improving the mobility model. Investigating other algorithms and comparing them with the proposed dPSO-U mobility model is another research topic open to improvements.

Another potential research line would be to consider an area division mechanism for organizing the scenario in different regions. This mechanism could be used before the exploration phase and, based on this, each UAV would be assigned the task of sweeping only one of the regions. Afterwards, and during the convergence phase, the UAVs will be allowed to move all over the scenario in order to exchange the information that each one has gathered about its own region. This area division mechanism is applied in some path planning approaches and could be an improvement worth to consider, as the dPSO-U mobility model has shown difficulties in exploring the entire scenario area and discovering all the ground nodes.

Regarding the second objective of the mission, i.e. making the UAVs converge to the different ground nodes clusters found, instead of having a simple convergence phase, the mission could require the UAVs to meet another requirement. Examples of such requirements would be: i) making each UAV to fly to a specific victim cluster so every cluster has a UAV assigned, and ii) having the UAVs connected as a relay network able to establish communication services between victims or first responders located in different clusters, among others. These new requirements could bring more benefits to the communication between victims or first responders. A potential research line would be to consider the implementation of the aforementioned requirements or additional features such as clustering techniques.

5.2.2 Adaptive coverage strategies

The Jaccard-based mobility model proposed for the adaptive coverage strategy has used several metrics for assessing its behaviour in an adaptive coverage mission. These metrics, which are described in section 4.4.2., are limited and there is room for defining new metrics that can bring more information about the proposed mobility model behaviour. As a matter of fact, some of the metrics that were used in chapter 3 could be applied to the Jaccard-based mobility model, such as those related to the number of connections between ground nodes and UAVs (NCONN) and the time elapsed between consecutive connections among ground nodes and UAVs (TECONN). Using new metrics for gaining insights into the Jaccard-based mobility model behaviour is considered an important future research work.

The main parameter that the Jaccard-based mobility model optimizes is the number of ground nodes under the wireless coverage area of the UAV network. According to the implementation described in section 4.3 and the results that are shown in section 4.4 the hill climbing algorithm demonstrated the best performance by being the one that optimized the Target Jaccard distance TJd closer to the value 1. Let's recall that a Jaccard distance $Jd = 1$ between two UAVs is the situation in which these are maximizing the ground nodes under their wireless coverage area. An interesting research line would be to include more aspects in the optimization. Potentials aspects to be optimized are to consider load balancing the UAV network traffic, or providing robustness against UAV failures. Considering these aspects will yield in having optimal values for the Target Jaccard distance TJd which are not always 1 because, for example, a specific rate of victims will be required to be under the wireless coverage of more than one UAV. The analysis of the hill climbing and simulated annealing (and even other algorithms) performance in these conditions are of interest for continuing with the development of the proposed mobility model.

One aspect of importance for the Jaccard-based mobility model is the mechanism used for selecting the Jaccard neighbours. Two approaches have been tested in chapter 4, specifically, having predefined Jaccard neighbours selected before the mission starts or letting the UAVs to select the Jaccard neighbours autonomously. The latter consist of each UAV gathering information about the Jaccard distance with all the other UAVs that are within its wireless coverage range (i.e. those that are network neighbours) and select as Jaccard neighbour the one with the least Jaccard distance. This technique can be improved and other mechanisms can be used for selecting the Jaccard neighbours that maximize the mission objectives.

A side effect that has been observed in the results described in section 4.4 is that the UAV network, once is deployed and with a high number of ground nodes under wireless coverage, may leave unattended the nodes that are on the surroundings of the UAV network and out of its wireless coverage area. Other works have demonstrated the difficulty of exploring an entire scenario while providing wireless coverage services to ground nodes [55]. Basically, when a UAV network has constraints of avoiding network disconnections it is not possible for the UAVs to separate from each other to reach the scenario borders. An interesting research line is to complete the proposed mobility models with role-based mechanisms in which certain UAVs play the role of explorers while the rest of the UAV network remains to provide communication services to ground nodes [162] [55]. These explorer UAVs may be assigned the task of following release-and-return trajectories such as the ones described in [55]. In these trajectories, the explorer UAVs will gather information from unknown scenario zones, such as the locations of other ground nodes, while they are separated from the UAV network. Once the explorer UAVs return to the UAV network, the network as a whole can update its knowledge about the scenario from the information gathered by the explorers.

In relation to the previous paragraph, another future research line would be to consider more relaxed constraints with regard to the network. The Jaccard-based mobility model has considered that the UAV network should be a connected network during the entire mission duration. However, it is possible that other networking paradigms could benefit the communication services provided to ground nodes. An example would be to consider a trade-off between a wireless mesh network (WMN) and a delay tolerant network (DTN). In this case, the scenario could be divided into several regions and each UAV will be assigned to move over a specific region and also periodically to connect to other UAVs so the communication between regions is possible. This is just an example approach and for sure there are others that could bring benefits to the communication service provided to the ground nodes.

5.2.3 Other

The mobility models described in sections 3.3 and 4.3 have been validated through simulations with software developed specifically for this research. As of now, this software consists of independent software pieces, one for the exploration mission and another one for the adaptive coverage mission. These software pieces have been developed mainly in Python language and can be run in any machine running a Debian-based OS distribution. The main output of the software is a file with a tailored format, containing the UAVs positions together with other data such as the ground nodes under the wireless coverage area. However, in order to provide these mobility models as a tool for other researchers, future efforts will have to be put into integrating them with a consolidated software network simulator like ns-3. This would require translating the output file to comply with ns-3 mobility files.

In relation to the previous paragraph, integrating the proposed mobility models with a realistic network simulator such as ns-3 would allow simulating with different wireless communication technologies models. As the simulations carried out for this thesis have been somehow technology-agnostic from a wireless communication point of view, the fact of studying the mobility model behaviour with the specific features of different wireless communication technologies would bring a deeper understanding of the mobility models. This is considered an important research line.

Also, integrating the proposed mobility models with a realistic network simulator such as ns-3 would allow simulating the proposed mobility models with different routing algorithms. As the focus of this thesis has been to study the mobility aspects of a UAV network performing different missions, the routing algorithms have been modelled in a very simplified manner. Studying the mobility model behaviour when different routing algorithms are used is considered a very important future research work.

Focusing on the optimization techniques that are used in both of the proposed mobility models, the results have shown that in different situations, there are several aspects that need to be optimized at the same time. Some examples are: i) the number of ground nodes under the wireless coverage area while minimizing network disconnections (in the case of the adaptive coverage mission), and ii) the area swept by the UAVs exploring the scenario and the time spent in converging to a cluster (in the case of the exploration and convergence mission), among others. In many cases, one of the aspects of interest that need to be optimized may have a negative impact on another aspect. For this reason, the usage of multi-objective optimization techniques is a very interesting line of work for refining the implementation of the proposed mobility models.

Appendix B briefly describes the work that has been carried in parallel to this thesis. With respect to the hardware, a set of 3 UAVs have been built from scratch (i.e. using different pieces) and are operative as RPAS (piloted by a human). An interesting research line will be to finish 2 more UAVs that are waiting to be built and arrange all the aspects required for using these UAVs as a test-bed for UAV networks research. Performing tests with these real UAVs will allow validating the proposed mobility models in more realistic scenarios and will provide valuable information about the mobility and networking aspects.

Regarding the scenario model used, it has been noticed in the literature revised that disaster scenario models usually are simplistic and far from reality, not representing the mobility of the victims with enough details. The disaster scenario models used in this thesis are also simple as they have been used as a way to validate the concept of new UAV mobility models. However, a future research line is to use more realistic disaster scenario models as a base for the UAV network mobility models. In this regard, there are two potential ways to follow: i) to investigate more realistic and existing victim mobility models and integrate these with the mobility models proposed, and ii) to contribute to the design of new victim mobility models and therefore to new disaster scenario models. These are research lines that are not within the UAV network research area per se, however, they have an indirect impact on it.

Similar to the disaster scenario model, the model used for the UAVs is very simplistic and does not include specific details of the UAVs dynamics. Also, depending on the type of UAV used, e.g. a fixed-wing or a multicopter, the mobility models proposed can behave differently. An open research line is to use more realistic UAV models and with specific dynamics features of each type of vehicle. This way the behaviour of the proposed mobility models can be categorized for each type of aerial vehicle that an emergency response team may have. Also related to the aforementioned matter, the usage of UAVs from different vendors and with different capabilities may be a common practice in reality. The ability to simulate the proposed mobility models taking into account that some UAVs have different physical capabilities may bring useful information for future real-life operations with UAV networks.

Finally, considering other aspects such as the battery life of the UAVs in the two mobility models is also interesting as an open research line. Battery-life varies depending on aspects such as the type of vehicles, the size or the payload, among others. Considering different value sets for the battery life of the UAVs as a constraint of the mobility model will be challenging. Another interesting approach will be to implement in the mobility models a monitoring mechanism that allows the UAVs to return to a charging location during the mission in the case that its battery is about to be empty.

A. Fundamental Concepts

"There is a crack in everything
That's how the light gets in"
Leonard Cohen

In this appendix the fundamental concepts upon which the research described in this thesis are described.

A.1. Multihop ad hoc networks

A *wireless ad hoc communication* is defined as a direct communication link established between two devices, without the need of any other pre-deployed infrastructure. This type of communication is commonly called *peer-to-peer* or *single-hop* ad hoc [216]. When this type of communication occurs among multiple devices, a multihop ad hoc network appears. Depending on each node location and the communication capabilities (e.g. wireless communication range, interferences, etc.), each node will usually have in range several nodes of the network (called network neighbours or simply neighbours). Under such conditions, when two separated nodes that cannot establish a direct communication link with each other want to exchange information, they will have to use other nodes as intermediaries. Therefore, the source node, in order to send a packet to a destination node, which is out of its range, will send first the packet to its neighbours (one hop). Then, the neighbours of the source node will forward the packet to its respective neighbours (two hops), and this mechanism will be repeated until the packet reaches the destination node (after n hops). This is why these networks are known as multihop networks. These conditions force the network nodes to act as terminal nodes (in the case they are the source or the destination of the communication), and as intermediary nodes (routing packets) at the same time. The main characteristics of wireless *Multihop Ad Hoc Networks (MANETs)* [216] [217] can be summarized as follows: i) there is no pre-deployed communication infrastructure, ii) the nodes are able to establish peer-to-peer communication links using wireless technologies, and iii) the nodes act as terminal and router nodes. In the case that the nodes are mobile, as it usually happens in these networks, the number of neighbours of a node may vary over time. In this case, these networks receive the name of *Mobile Ad Hoc Networks (MANETs)* [216] [217], sharing the acronym with Multihop Ad Hoc Networks. Figure 62 shows the different Multihop Ad Hoc Network types that are described later in this section classified according to two aspects: i) the main purpose of the network, and ii) the node type.

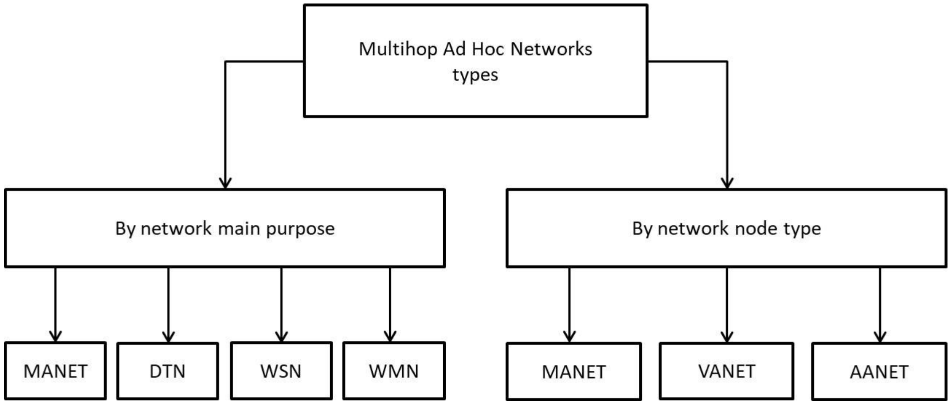


Figure 62. Multihop Ad Hoc Network types

a. Mobile Ad Hoc Networks

MANETs were one of the first wireless multihop ad hoc networking paradigms for civilian applications that emerged back in the 1990s. MANETs were conceived originally as a way of connecting wirelessly different portable devices, such as mobile phones and laptops located close to each other. An Internet Engineering Task Force (IETF) working group was created for studying MANETs in 1997 [216] [218]. This group received the name Mobile Ad-hoc Networks working group, or simply MANET WG. Despite the fact that MANETs are general-purpose by design, the first devices considered for creating these networks were portable devices, which means that were carried by a person, and therefore the mobility of these devices was originally associated with the mobility patterns of a walking person. The wireless technologies commonly used in MANETs are Wi-Fi (IEEE 802.11) and Bluetooth (IEEE 802.15.1), among others.

After more than a decade, the MANET research community has been very active; however, the transference of pure MANET research to real scenarios has been slight and it did not have a broad market impact [216] [217]. This smooth impact on the market refers to several factors: i) very basic and wide initial assumptions (e.g. the aim of designing large scale MANETs for general-purpose applications), ii) lack of final user involvement in the research. Nevertheless, the success of MANETs came in the form of other networking paradigms adopting the MANET fundamentals [61]. These new MANET-related paradigms presented more specific application scenarios and therefore the acceptance is easier, in terms of the market and the end users. These networking paradigms are Delay Tolerant Networks (DTNs), Wireless Sensor Networks (WSNs), Wireless Mesh Networks (WMNs) and Vehicular Ad Hoc Networks (VANETs).

b. Delay Tolerant Networks

DTNs [219] [202] are also known for other names as Disruption Tolerant Networks Intermittently Connected Networks (ICN), Challenged Networks, and Opportunistic Networks. The architecture of DTNs was primarily designed for InterPlanetary Internet (IPN) [202] and deep space communications. Wireless communication in interplanetary scenarios is characterized by highly intermittent communication links and long propagation delays, among other features. Similar communication features as the ones aforementioned were also observed in some terrestrial networks, such as some specific MANETS, mobile WSNs (MWSNs), Battlefield Wireless Military Networks (BWMNs) or VANETs. Therefore, the research on DTNs attracted more attention, not only for space scenarios but also for terrestrial networks.

An Internet Research Task Force (IRTF) research group was created for studying DTNs in 2002 [220] [219]. This group received the name of Delay-Tolerant Networking Research Group (DTNRG). Nowadays, the IETF working group called Delay/Disruption Tolerant Networking continues the work of the DTNRG, which concluded its activities in 2016 [221]. Without loss of generality, DTNs are known for being low-density networks (a few nodes per area unit). In a DTN, nodes are considered to have high mobility and therefore communication links between nodes are intermittent and only occur when two nodes encounter with each other (this does not mean that some nodes may move with smaller speeds than others). These aspects make the DTN communication links and its topology to be highly variable with time. For this reason, when a source node wants to send a message to a destination node, the source node takes advantage of any encounter with other nodes (either the destination node or some intermediary nodes) for sending the message.

The main challenge of DTNs is to provide acceptable packet delivery ratio and end-to-end delays in disconnection-prone environments with non-guaranteed end-to-end connections. The communication strategy in DTNs is the well-known store-carry-forward policy. Under such circumstances, when a node receives a message, it keeps the message until it finds another node in the network to exchange messages with. Typical applications for DTNs are non-delay sensitive applications. DTNs are considered one of the best paradigms for satellite and spatial networking [222] and also for some specific MANETs and VANETs characterized by highly disruptive links and large propagation delays [219]. The wireless technologies used in DTNs range from typical Wi-Fi (IEEE 802.11) in terrestrial applications up to others such as satellite communication links in space applications, among others.

c. Wireless Sensor Networks

WSNs [61] belong to a networking paradigm in which nodes are sensing devices capable of communicating wirelessly with each other. WSNs are usually application-driven and have been successfully deployed for monitoring industrial processes or environmental phenomena, among others. The most common wireless technologies used are IEEE 802.15.4 (ZigBee or XBee) and Wi-Fi (IEEE 802.11). The common architecture in WSNs is as follows, a big number of nodes sense the environment and send the acquired data to a smaller subset of nodes, which are called sinks. Sink have usually more computing resources than normal nodes and also more communication interfaces in order to connect to other networks such as the Internet. In the last decade, sensors have been provided with the capability of movement as they have been embedded in small and medium-sized mobile robots. The mobility capability has been mainly applied to sink nodes, being the rest of the nodes static at specific locations. However, some research works have also considered WSNs in which all nodes are mobile [14] [223] [224] [20].

d. Wireless Mesh Networks

WMNs [61] are hybrid MANETs in which several nodes are fixed and others are mobile. There is a pre-defined hierarchy in WMNs, which was not considered as a possible design in a general-purpose MANET. This hierarchy is mainly built upon dedicated nodes that are called mesh routers. These mesh routers create a wireless backbone, which is connected to other networks such as the Internet. Other nodes of the networks are mainly mobile and connect to mesh routers in a multihop ad hoc fashion (either directly or through other mobile nodes). Traditional wireless technologies used in WMNs are the IEEE 802.11 standards family, IEEE 802.15 and IEEE 802.16 (WiMAX, Worldwide Interoperability for Microwave Access) [225]. Due to the fact that building a WMN backbone is less expensive than with the traditional infrastructure, WMNs have been proposed as an interesting alternative for extending Internet connectivity. Recently, WMNs have been built by integrating devices with routing capabilities in mobile robots thus having mesh routers with mobility capabilities as well. Mesh networking has been proposed as a solution for providing communications in disaster relief operations [217] [226] [227] [228]. Table 12 shows a classification of wireless multihop ad hoc networks according to the main purpose for which the network was designed for.

Table 12. Mobile ad hoc networks classified according to the network purpose

	Main purpose	Topology	Hierarchy	Mobility	Main Wireless Technologies
MANET	General-purpose network with mobile nodes and no pre-defined infrastructure	Variable	Flat	Low to medium	• IEEE 802.11 • IEEE 802.15.1
DTN	Forward non-delay sensitive information in disconnection-prone environments	Variable	Flat	High	Depends on the scenario (terrestrial vs spatial)
WSN	Sensing applications connected to other networks through sink nodes	Fixed nodes and mobile ones	Mainly hierarchical (sink nodes)	Low to high (mobile robots with sensors)	• IEEE 802.11 • IEEE 802.15.4
WMN	Extend Internet connectivity at lower costs	Fixed nodes and mobile ones	Mainly hierarchical (mesh routers)	Low to medium	• IEEE 802.11 • IEEE 802.15.4 • IEEE 802.16

e. Vehicular Ad Hoc Networks

Vehicular Ad Hoc Networks (VANETs) have been the first of mobile ad hoc networking paradigms to be specifically associated with the mobility of specific node types, i.e. ground vehicles as cars, in this case. Mobile ad hoc networking paradigms associated with specific vehicles are Vehicular Ad Hoc Networks (VANETs) and Aerial Ad Hoc Networks (AANETs), which are also known as Flying Ad Hoc Networks (FANETs).

VANETs [229] consist of a network built upon cars. VANETs arose as a solution for offering better monitoring and management services of road traffic both in urban and non-urban areas. The main objectives of VANETs are to increase road safety and the passenger's comfort. VANETs have a pre-defined infrastructure deployed along roads. This infrastructure connects with cars through fixed devices called Roadside Units (RSUs). This communication between RSUs and cars is commonly called Vehicle-to-Infrastructure communication (V2I). Cars are equipped with specific communication devices called On-Board Units (OBUs). Cars can also communicate with each other in a multihop ad hoc fashion, which is known as Vehicle-to-Vehicle communication (V2V) or Inter-Vehicular Communication (IVC). The most used wireless technology is the standard IEEE 802.11p. The upper layers of the communication stack have been standardized by the IEEE such as the Wireless Access in Vehicular Environments (WAVE) [230] and by the ISO CALM (Communications access for land mobiles) architecture [231] [232]. VANETs have similarities with several MANETs categories as the ones described in Table 12, for example, V2V communications in a low-density car scenario resemble DTNs, as usually occur in highways. VANETs also may resemble WMNs, as the RSUs can be considered fixed mesh routers which are part of a pre-deployed infrastructure that connects to other networks. Although VANETs have been supported by the industry and standardization organizations, the technologies and regulations needed are still under development. Apart from that, it is worth to mention that autonomous driving is a very close research field to VANETs and has been growing rapidly in the last years [233] [234]. Moreover, several private companies (e.g. Tesla Motors Inc., Google, Ford, and BMW among others) are pushing towards putting the first autonomous car in the market. Thus, great conjoint developments are expected in both VANET and autonomous cars areas and for sure this will bring many real and market implementations in the next few years.

f. Aerial Ad Hoc Networks

Aerial ad hoc networks are described in section 2.1.1 and are mentioned in this appendix only for completeness. Table 13 presents a classification of mobile ad hoc networks according to the type of node.

Table 13. Mobile Ad Hoc Networks classified according to the node type

	Node type	Vehicle name	Mobility	Speed	Topology	Main Wireless Technologies
MANET	Persons, robots	Node	Mainly free	Low to medium	Variable	• IEEE 802.11 • IEEE 802.15.1
VANET	Cars	Node, car	Limited to the road layout	Low to high	• Variable (cars) • Star (RSU)	• IEEE 802.11p
AANET	Aerial vehicles	UAVs	Free	Low to high	Application specific	• IEEE 802.11 • IEEE 802.15.4

A.2. MANET mobility models categories

MANET mobility models, as it has been proposed by [34], can be classified according to the following categories: i) *Random* mobility models, ii) Models with *temporal dependence*, iii) Models with *spatial dependence*, iv) Models with *geographic constraints*, and v) *Hybrid* models.

The random mobility models category includes models in which one or several parameters values of the trajectory are selected randomly. Examples of these models are the Random Walk (RW), the Random Waypoint (RWP) or the Random Direction (RD) [110], among others. In the case of the RD, each node selects random values for its direction and speed and maintains these for a specific amount of time. After this time, each node selects new random values and repeats the same process. The RWP model is similar, but the aspect that is selected randomly is the destination point that a node moves to. In the RD, the direction and speed are selected randomly as in RW, but the values selected are maintained until the node reaches the scenario borders.

The category of models with temporal dependence includes those that are characterized by the fact that the mobility pattern of a node depends on its previous mobility. Examples of these models are the Gauss-Markov (GM) random mobility model and the Smooth Random (SR) model [110] [146], among others. In both models, there is a correlation of the current movement of a node and its previous moves, which usually translates on nodes trajectories with smooth turns.

In the category of the models with spatial dependence, the main feature is that the mobility of the nodes gets affected by the presence of other nodes in the neighbourhood. These models are typically used for emulating the group mobility, i.e. the attributes of a set of nodes moving in a group. For example, in the Reference Point Group Mobility model (RPGM) [110], the nodes in the network are organized in groups and all the nodes in the group follow the mobility pattern of the group leader. Other examples of these models are the column mobility model or the pursue mobility model [110], among others.

In the models with geographic constraints, the nodes are allowed to move only on restricted sub-regions of the scenario. These models are used to represent the mobility of the nodes in a scenario with obstacles that impede the nodes to move completely free. Usually, the obstacle restricts the mobility of the nodes allowing only a few possible movements. An example in this category is the Pathway mobility model [235], which is typically used for representing the mobility of cars in a road layout.

Finally, in the hybrid models category, the models usually combine two or more characteristics of the aforementioned categories. A good example is the Disaster area mobility model (DA) [236] [47], which presents aspects of random, spatially dependent and geographically constrained mobility models.

Another common aspect used for classifying mobility models is the type of information used for generating the trajectories of the nodes. According to this aspect, mobility models can be classified in: i) synthetic [182] [178], and ii) trace-based [177] [184]. In synthetic mobility models, the trajectory of the nodes is generated artificially using a specific mathematical model which does not use as input real mobility traces. In trace-based mobility models, the mobility of the network nodes is based on traces taken from real movements, e.g. a human walking with a smartphone.

A.3. Jaccard distance

Dissimilarity and similarity coefficients are commonly used in cluster analysis techniques. *Dissimilarity or distance coefficients* evaluate the differences between objects, i.e. data sets. On the contrary, *similarity or proximity coefficients* evaluate the coincidences between data sets [237]. In both cases, the dissimilarity or similarity is evaluated in terms of a specific characteristic measured on the multiple objects under analysis. Dissimilarity and similarity coefficients have been used as a classifying technique in disciplines such as medicine, marketing, sociology, psychology, linguistics, biology and even archaeology.

According to the description provided in [237], in the case of nominal variables, like binary ones, similarity can be defined as follows. Let $X(n,p)$ be a matrix representing p measurements on n objects. Let x_i be the row i of this matrix, representing the object i and its p measurements. Let the measurement k on the object i be represented by x_{ik} which is considered a binary variable so that $x_{ik} \in \{0,1\}$. These definitions are shown in equations (26) and (27).

$$X(n,p) = \begin{pmatrix} x_{00} & \cdots & x_{01} & \cdots & x_{0p} \\ & \ddots & & & \\ \vdots & & x_{ik} & & \vdots \\ & & & \ddots & \\ x_{n1} & \cdots & x_{ni} & \cdots & x_{np} \end{pmatrix} \tag{26}$$

$$x_{ik} \in \{0,1\} \tag{27}$$

By comparing the measurement k of the rows i and j, the equations (28), (29), (30) and (31) show the 4 possible cases that may be found.

$$x_{ik} = x_{jk} = 1 \tag{28}$$

$$x_{ik} = 0, \qquad x_{jk} = 1 \tag{29}$$

$$x_{ik} = 1, \qquad x_{jk} = 0 \tag{30}$$

$$x_{ik} = x_{jk} = 0 \tag{31}$$

Let's define a_1, a_2, a_3 and a_4 as shown in (32), (33), (34) and (35).

$$a_1 = \sum_{k=1}^{p} I(x_{ik} = x_{jk} = 1) \quad (32)$$

$$a_2 = \sum_{k=1}^{p} I(x_{ik} = 0, x_{jk} = 1) \quad (33)$$

$$a_3 = \sum_{k=1}^{p} I(x_{ik} = 1, x_{jk} = 0) \quad (34)$$

$$a_4 = \sum_{k=1}^{p} I(x_{ik} = x_{jk} = 0) \quad (35)$$

The proximity between object i and j can be defined depending on two weighting factors δ and λ as shown in (36). Therefore the similarity among a set of objects can be defined by a matrix $D(n \times n)$ as shown in (37).

$$d_{ij} = \frac{a_1 + \delta a_4}{a_1 + \delta a_4 + \lambda(a_2 + a_3)} \quad (36)$$

$$D = \begin{pmatrix} d_{00} & \cdots & d_{01} & \cdots & d_{0p} \\ \vdots & \ddots & d_{ik} & \ddots & \vdots \\ d_{n1} & \cdots & d_{ni} & \cdots & d_{np} \end{pmatrix} \quad (37)$$

Different proximity coefficients can be defined depending on the values given to factors δ and λ. Specifically for the case of interest here, the Jaccard similarity coefficient is defined for $\delta = 0$ and $\lambda = 1$, so equation (36) results in (38).

$$d_{ij} = \frac{a_1}{a_1 + a_2 + a_3} \quad (38)$$

It is important to note that for each similarity coefficient d_{ij}, a dual dissimilarity coefficient d'_{ij} can be defined as shown in (39).

$$d'_{ij} = max_{i,j}\{d_{ij}\} - d_{ij} \quad (39)$$

Other similarity coefficients commonly used in science are Tanimoto, Simple Matching (M), Russel and Rao (RR), Dice and Kulczynski. These are defined from equation (36) using different values of δ and λ, as it is shown in Table 14 [237].

Table 14. Similarity coefficients definition

Coefficient	δ	λ	Definition
Jaccard	0	1	$\frac{a_1}{a_1 + a_2 + a_3}$
Tanimoto	1	2	$\frac{a_1 + a_4}{a_1 + 2(a_2 + a_3) + a_4}$
Simple Matching (M)	1	1	$\frac{a_1 + a_4}{p}$
Russel and Rao (RR)	-	-	$\frac{a_1}{p}$
Dice	0	0.5	$\frac{2a_1}{2a_1 + (a_2 + a_3)}$
Kulczynski	-	-	$\frac{a_1}{a_2 + a_3}$

The Jaccard distance is a dissimilarity coefficient that has been used in previous works on MANETs. For example, the Jaccard distance is used in [238] for assessing the similarity/dissimilarity of mobile nodes in terms of their neighbours. Following this example, two nodes are similar if the share many neighbours. In this case, these two nodes will have a Jaccard distance close to the value 0. On the contrary, if these two nodes share very few nodes or none they will be considered dissimilar and the Jaccard distance between them will be close to the value 1. The relation between the Jaccard coefficient and the Jaccard distance is shown in Table 7 and Table 8.

A.4. Metaheuristics

Metaheuristics [157] [158] are a subgroup of approximate optimization algorithms, which are characterized by several features: i) the ability to solve large and complex problems faster than optimal algorithms, ii) ease of design and implementation, iii) better relation between the cost of the equipment and the quality of the solution [108], and iv) flexibility, i.e. non-dependency from the problem to be solved. Examples of metaheuristics are Hill Climbing, Simulated Annealing, or Evolutionary Algorithms, among others.

A more formal definition of metaheuristics is provided in this section. Let $f(x)$ be a function which has an unknown shape with several local maxima and also flat regions (also known as *plateaus*). The aim of an optimization algorithm for this specific function $f(x)$ would be to find the value x that corresponds to the global maximum of $f(x)$. An example of a generic fitness function is shown in Figure 63. In most real-life problems $f(x)$ can be such a complex function that an analytic evaluation of the function is not possible due to several reasons: i) lack of information about $f(x)$ e.g. due to a very simplified model of the problem, ii) the dynamics of $f(x)$ which presents changes over time, and iii) insufficient computing resources or time to use exhaustive approaches (like evaluating all the possible values of x) among others. For these reasons, in the field of mathematical optimization, it is common to use a specific group of algorithms and techniques known as metaheuristics.

Metaheuristics belong to the *stochastic optimization* branch of mathematical optimization, in which algorithms make use of random and stochastic techniques in order to find an optimal solution (i.e. the global maximum) or a close-to-optimal solution. Due to the fact that these algorithms evaluate several candidate values in search of the optimal value, these algorithms are usually called search algorithms as well. The function $f(x)$ usually receives the name of fitness function due to the fact that the goal of these algorithms is to assess different values of x in search for the maximum value of $f(x)$, i.e. to evaluate the fitness of x for becoming the best candidate solution. It is also worth to mention that, there are two important features that a metaheuristic algorithm offers: i) exploration, which is known as the ability to explore widely the entire set of values that x can take, and ii) exploitation, which is known as the ability to vary slightly the values of x in search for the maximum value of $f(x)$.

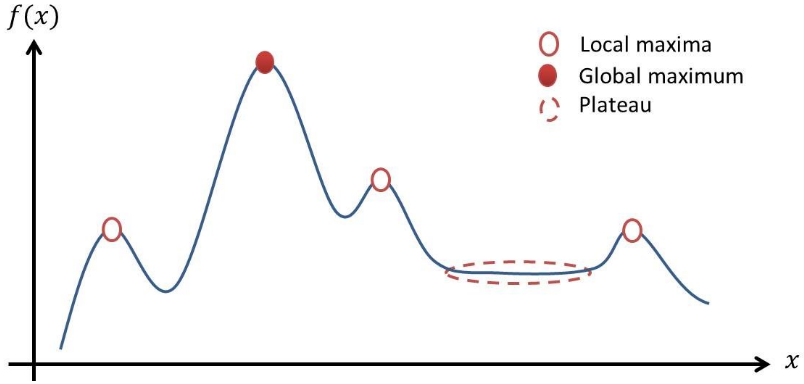


Figure 63. Generic fitness or objective function

Within the metaheuristics algorithms, there is a subgroup called *nature-inspired algorithms* which uses mechanisms that are present in natural processes or even in living organisms. A specific subgroup of nature-inspired algorithms focuses on the behaviour of groups of animals and the mechanisms they use for accomplishing tasks such as foraging or mobility, among others. These algorithms are called swarm algorithms [157]. The main potential of a swarm is that each individual performs simple actions and share its local information with its neighbours. Despite the individuals' actions are simple, the information sharing allows the group to develop complex behaviours and carry out challenging tasks. Examples of swarm algorithms are Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), among others.

a. Hill Climbing

Hill climbing (HC) [239] [240] algorithm is a simple local search algorithm guided towards finding one of the optimal values of a fitness function. Hill climbing algorithm is analogous to the *gradient ascent method* [241] but with one important advantage: it does not need to know the derivative or the gradient of the function under study. In its uphill version, the hill climbing algorithm is used to find the maximum of a function. The hill climbing algorithm also has a downhill version, which is used to find the minimum of a function. The downhill version would be analogous to the gradient descent method.

The hill climbing algorithm is considered as *single-state metaheuristic* [240] because it stores only one candidate solution at each algorithm step. Other works call this type of algorithms trajectory-based metaheuristics [242]. The hill climbing algorithm starts by selecting randomly an initial value as the initial candidate solution. Then, the algorithm uses a modification procedure to produce a new candidate solution (usually with a partially random operation). Usually, this is accomplished by modifying slightly the current best candidate solution. Afterwards, the algorithm compares the fitness of the current best and the new candidate solutions. The current state of the algorithm is updated according to the following rules: i) if the new candidate solution has higher fitness than the current best candidate solution, then the new candidate solution will be saved as the current state of the algorithm (i.e. the best candidate solution so far), and ii) if the new candidate solution has not higher fitness than the current best candidate solution, the new candidate solution is discarded and the best candidate solution remains. This updating procedure of the best candidate is usually known as the selection procedure of the algorithm. This procedure is repeated iteratively until a specific stopping criterion is reached. Examples of the stopping criterion are either a fixed number of iterations or until the fitness of the best candidate solution does not improve. A generic pseudocode corresponding to the hill climbing algorithm is shown in Figure 64.

Hill Climbing (HC)

```
Best ← Initial candidate solution
Define Stopping Criterion
WHILE (Stopping Criterion == False) do
  New ← Generate new candidate solution from Best
  IF (fitness(New) > fitness(Best) then
    Best ← New
  ENDIF
ENDWHILE
```

Figure 64. Hill Climbing algorithm

The main drawback of the hill climbing algorithm, as it has been defined in Figure 64, is that its final result could be a local maximum and not a global one. Also, this algorithm could get stuck in flat regions. For this reason, hill climbing is not considered a complete optimization algorithm [243] or a global optimization algorithm [240] as it cannot reach the global maximum always.

In order to overcome these limitations, several enhancements are used. As an example, instead of generating only one the algorithm can generate multiple new candidate solutions. The best candidate solution will be the one saved as the candidate solution for the next algorithm iteration. This enhancement is usually known as the Steepest Ascent Hill Climbing algorithm [240]. Another enhancement is to execute several times the hill climbing algorithm with different initial candidate solutions which are randomly generated. The final candidate solution will be the best among the solutions for the algorithm. This enhancement of the algorithm is called Hill Climbing with Random Restarts [240]. This enhancement can be seen as the merge of the random search and the hill climbing algorithms, which offers exploration (random search) and exploitation (hill climbing) capabilities. Hill Climbing with Random Restarts can be considered a very simple global search/optimization algorithm [240].

b. Simulated annealing

Simulated annealing (SA) is a metaheuristic that can be classified as a local search algorithm with probabilistic features [239], which mimics the annealing of solids. This algorithm was first formulated in 1953 and was known as the Metropolis algorithm [244]. In the metallurgy industry, the annealing process decreases the temperature of a metallic material gradually, keeping the material on each temperature value for a specific amount of time to allow the material's atoms to reach the lowest energy states possible. When used as a metaheuristic algorithm, simulated annealing is an algorithm that finds a global optimum for a fitness function. Similar to hill climbing, the simulated annealing algorithm is a single-state or a *trajectory-based metaheuristic*. Simulated annealing uses several design parameters according to [211]. These parameters are shown in Table 15.

Table 15. Simulated annealing algorithm parameters

Parameter	Symbol	Description
Initial probability	P_s	The initial value of the probability of accepting a worse solution as a valid one. This is a value that we select for the algorithm implementation at the design stage.
Final probability	P_f	The final value of the probability of accepting a worse solution as a valid one. This is a value that we select for the algorithm implementation at the design stage.
Initial temperature	T_s	The initial value of the temperature parameter.
Final temperature	T_f	The final value of the temperature parameter.
Temperature factor	F	The factor that reduces the temperature in each cycle with respect to the previous cycle temperature.
Number of cycles	N	Number of times that the simulated annealing outer loop is executed. Each cycle corresponds with one value for the temperature. This term receives the name of *sa-cycle* in section 4.3 in order to avoid confusion with uses of the word *cycle*.
Number of trials	M	Number of times that the simulated annealing inner loop is executed. The inner loop corresponds to the execution of the algorithm for one specific value of the temperature.

The simulated annealing algorithm starts by selecting values for the parameters shown in Table 15 and also an initial candidate solution. The algorithm sets the temperature parameter to the initial temperature value and starts a *sa-cycle* (*outer loop* iteration). The algorithm starts a *trial* (*inner loop* iteration) by generating a new candidate solution from the current best solution using a modification procedure that involves certain randomness (the inner loop represents the behaviour of the solid's atoms when moving towards the lowest energy state for a specific temperature value). If the candidate is better than the previously accepted solution, then the new candidate replaces the accepted solution. If the candidate is worse, a random number r generated, and if r is smaller than the Boltzmann probability p (which is later defined in this section), then the candidate is accepted as a valid solution (despite being a worse solution than the previously accepted one); otherwise, the candidate is rejected. This trial procedure of generating new candidate solutions and evaluating their fitness is repeated M times. During a trial, the value of the temperature does not change. After a trial has finished, the temperature value is reduced by the temperature factor and a new cycle begins, consisting in M trials again. The algorithm finishes when N sa-cycles have been completed. Figure 65 shows the pseudocode of a generic Simulated Annealing algorithm.

Simulated Annealing (SA)

```
Select values for Ps, Pf, Ts, Tf, F, N, and M
temperature ← Ts
cycle, trial ← 0
Best ← Initial candidate solution
For cycle = 0 to N step -1
  For trial = 0 to M step -1
    New ← Generate new candidate solution from Best
    IF (fitness(New) > fitness(Best) then
      Best ← New
    ELSE
      p ← Calculate Boltzmann probability(temperature, ΔE, k_B)
      r ← Generate random number
      IF p > r
        Best ← New
      ENDIF
    ENDIF
  ENDFOR
  temperature ← Ts × F
ENDFOR
```

Figure 65. Simulated Annealing algorithm

The original *Boltzmann probability* equation for the annealing of solids is used for this algorithm but with slight changes. The Boltzmann probability for the simulated annealing algorithm is defined by the expression shown in (40).

$$p = e^{(-\Delta E / \Delta E_{avg} T)} \tag{40}$$

This probability depends on the following terms:

- *T*: It represents the temperature. Initial and final temperature values are selected as design parameters. The effect of the temperature on the algorithm is that with every cycle of the algorithm the temperature decreases and thus is more difficult to have worse solutions accepted as candidates.

- ΔE: It represents the difference between the previously accepted solution and the current candidate, i.e. the difference between the fitness function values of each one.
- ΔE_{avg}: It represents the average of all the accepted solutions so far. It is used to normalize the change in the fitness difference ΔE.

For the simulated annealing implementation, values for the initial probability (P_s), the final probability (P_f) and the number of cycles of the algorithm (N) must be selected. Usually, there might be several combinations of values for the parameters shown in Table 15 that can provide overall good results. These values are used for the calculation of the temperature parameters by using the expressions (41), (42), (43) and (44).

$$T_s = \frac{-1}{\ln(P_s)} \tag{41}$$

$$T_f = \frac{-1}{\ln(P_f)} \tag{42}$$

$$F = \left(\frac{T_f}{T_s}\right)^{\frac{1}{N-1}} \tag{43}$$

$$T_{n+1} = F \cdot T_n \tag{44}$$

The simulated annealing algorithm presents exploration capabilities as there is a certain probability of accepting worse solutions. Also, this algorithm presents exploitation capabilities as it accepts better solutions and the probability of accepting a worse solution decrease with lower values of the temperature.

c. Particle swarm optimization

Particle swarm optimization (PSO) is a nature-inspired optimization algorithm that was first presented in [204]. PSO belongs to the category of *population-based algorithms* [245]. Specifically, PSO is inspired by common *social behaviours* present on different groups of animals such as a *flock* of birds. The applications of the PSO algorithm have been numerous and it has been used in different optimization problems. For example, as stated by one of the latest papers reviewing the state of the art of PSO, this algorithm has been applied to artificial neural networks training, pattern classification [206], nodes placements in wireless mesh networks [246], among other problems.

As described in [206], there have been many variants of the original PSO algorithm. Even the inventors of the algorithms introduced a new variant of the PSO including the inertia weight coefficient ω in [247]. This variant is probably the most famous one and is known as the canonical PSO [203]. As defined by [247], the PSO algorithm consists of a population of particles that move over a search space S. Each particle position is a candidate solution for the problem to be solved. Considering a one-dimensional search space, each particle in the swarm updates its position according to (45).

$$x(t+1) = x_i(t) + v_i(t+1) \tag{45}$$

Where:

- t: represents the current iteration of the algorithm.
- $x(t)$: corresponds to the current position of particle i.
- $v_i(t+1)$: is the velocity vector applied to particle i at time t.

The particles' velocity vector has usually three components and is defined by (46).

$$v_i(t+1) = \omega v_i(t) + C_1\varphi_1(P_i(t) - x_i(t)) + C_2\varphi_2(P_{gi}(t) - x_i(t)) \tag{46}$$

Where the terms are as follows:

- $v_i(t)$: Current velocity of particle i.
- C_1 and C_2: Constants representing the intensity of the attraction of a particle towards its local best (C_1) or the global best (C_2).
- φ_1 and φ_2: Random values that represent the exploration and diversity component of the algorithm. They usually follow a uniform distribution within the range $[0,1]$.
- $P_i(t)$: The local best of particle i.
- $P_{gi}(t)$: The global best of particle i.

The left-most term represents the inertia component. The second term is usually known as the cognitive component and the third one is the social component. As defined in [247], the inertia coefficient ω decreases its values over time. At the beginning of the simulation process, when ω takes bigger values, the particles present more important exploration abilities, thus being able to explore extensively the search space. This resembles a global search process. As time goes on and ω has smaller values, the particles tend to focus on exploiting the space regions surrounding their local and global best solutions. This second phase is similar to the behaviour of local search algorithms. It is important to highlight that the global best is usually calculated by assuming that each particle can share its local best with all the particles considered in the algorithm. Thus, the global best would be the best of the local bests of all particles. This is the Gbest method defined in the original PSO paper [204] [203].

d. Virtual forces algorithm

The virtual forces algorithm (VFA) [117] [248] is a mechanism based on the idea of the electromagnetic forces applied to particles in physics. As an example, in the field of electrostatics, a particle with electric properties located on a space where other particles exist will experience attraction forces towards the particles with the opposite electric charge and repulsive forces from the particles with the same electric charge. In wireless sensor networks (WSN) the VFA algorithm has been used for maximizing the coverage of the network [117]. In this approach, a sensor in the WSN will exert attraction or repulsion forces to another sensor based on the existing Euclidean distance that separates them. Usually, a specific distance value is selected as a threshold. In the case of a pair of sensors being separated by a distance smaller than the threshold, each sensor will exert a repulsive virtual force to each other. On the contrary, if two sensors are separated by a distance bigger than the threshold, each sensor will exert an attractive virtual force to each other. In this case in a network with N nodes, the repulsive or attractive force that nodes i and j exert on each other is defined by $\underset{F_{i,j}}{\longrightarrow}$. Therefore, the i^{th} node experiments a total force $\underset{F_i}{\rightarrow}$ defined by (47).

$$\underset{F_i}{\rightarrow} = \sum_{n=1,n\neq i}^{N} \underset{F_{i,j}}{\longrightarrow} \tag{47}$$

Based on the previous definition, the distance threshold is selected with the goal of having the network sensors repelling each other so each sensor ends up separated from each other a distance close to the threshold. Usually, the threshold is selected as a trade-off between separating the sensors as much as possible from each other, and at the same time guaranteeing that a communication link can be established between sensors.

This basic idea has also been used in path planning problems for calculating the trajectory for a vehicle moving in a scenario with the presence of obstacles. In path planning approaches using the VFA, the vehicle will be considered a mobile particle, the origin location and the obstacles will exert repulsive forces on the vehicle while the destination location will exert an attraction force. This approach is known in path planning problems as the *artificial potential field (APF)* method [249].

B. MATERIALS

"Ever tried. Ever failed. No matter. Try Again. Fail again. Fail better."
Samuel Beckett

This appendix introduces the reader into the hardware and software tools used during the research described in this thesis.

B.1. Hardware

The software simulations were run in a server owned by the *ACE-TI research group*, at the Electronics Engineering department of the University of Seville. Specifically, the server used corresponds to an HP Proliant ML350 Gen9 server running a Debian distribution as its operating system.

Apart from using simulations, a possible alternative to carry out experimental activities with UAV networks is to develop small scale test-beds with UAVs communicating with each other. This approach allows for understanding the potential differences that may appear between a simulated scenario and a real one. Test-beds are important for refining the solutions developed via simulations in order to make them be applicable not only in simulated scenarios but also in the real world. For this reason, several multicopters have been assembled piece by piece in order to contribute to the development of a test-bed for UAV networks research. The efforts devoted to assembling the UAVs have been closely related to the activities carried out during the doctoral studies, however, this is an ongoing work that has not been finished yet. The main goal is to finish the UAV test-bed so the proposed mobility models simulated can be validated with real UAVs in a controlled scenario area. Hopefully, the test-bed will be completed out of the scope of this thesis and will allow validating the proposed mobility models in real-flights experiments.

The current status of the test-bed is as follows. Three UAVs have been assembled successfully and are operative as RPAS (i.e. remotely controlled by a human operator), and two more are in process. One of these UAVs is shown in Figure 66. The following steps are to install communication electronics devices in order to provide the UAVs with the ability to communicate wirelessly with each other and also with ground nodes.

Figure 66. Quadrotor UAV assembled under the work of this thesis

The hardware selected for wireless communications is the embedded system board Alix3d2 by PC engines. This board has 2 miniPCI slots for connecting two radio cards. The radio cards that have been used correspond to the model Mikrotik R52H 802.11AGB. These radio cards comply with the wireless communication standards IEEE 802.11a/b/g able to operate in both 2,4GHz and 5GHz bands. A picture of two alix3d2 system boards is shown in Figure 67 for specific communication tests performed.

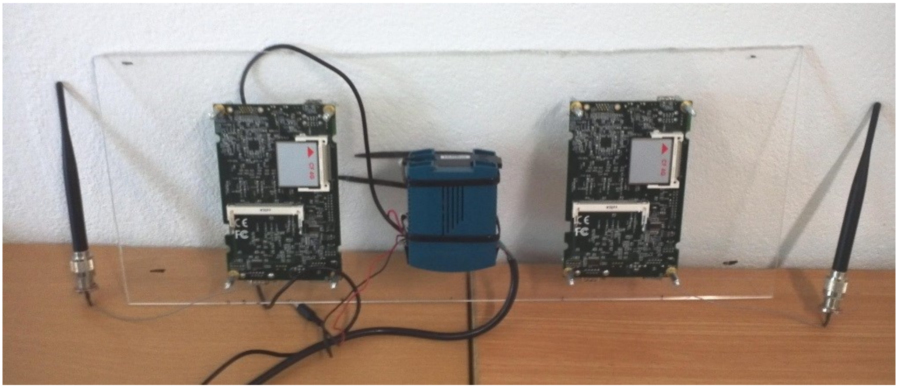


Figure 67. Alix3d2 system boards setup for communication tests

B.2. Simulation software

The proposed mobility models and all the simulations performed have been carried out using different software tools developed during the doctoral studies. A simplified diagram of the main components of the software developed is shown in Figure 68. It is important to mention that for the sake of simplicity Figure 68 represents a diagram close to the software architecture, but not adhering to any specific standard for this purpose. The only purpose is to represent the main components with their functions and relations. The main function of each of these components is shown in Table 16.

The programming language chosen for developing this software program has been Python. The code has been stored and maintained in a remote repository during the entire time of the software development process. Currently, the software is being revised and released on one or both of the repositories listed below. These repositories are open to everybody and it is the intention of the author that is available for other researchers interested in the topic. Please understand that some parts are being refactored before being released, in order to make the software useful as a tool so other researchers can use it. The two repositories can be found at:

- https://github.com/jchanger
- https://github.com/mobmodel

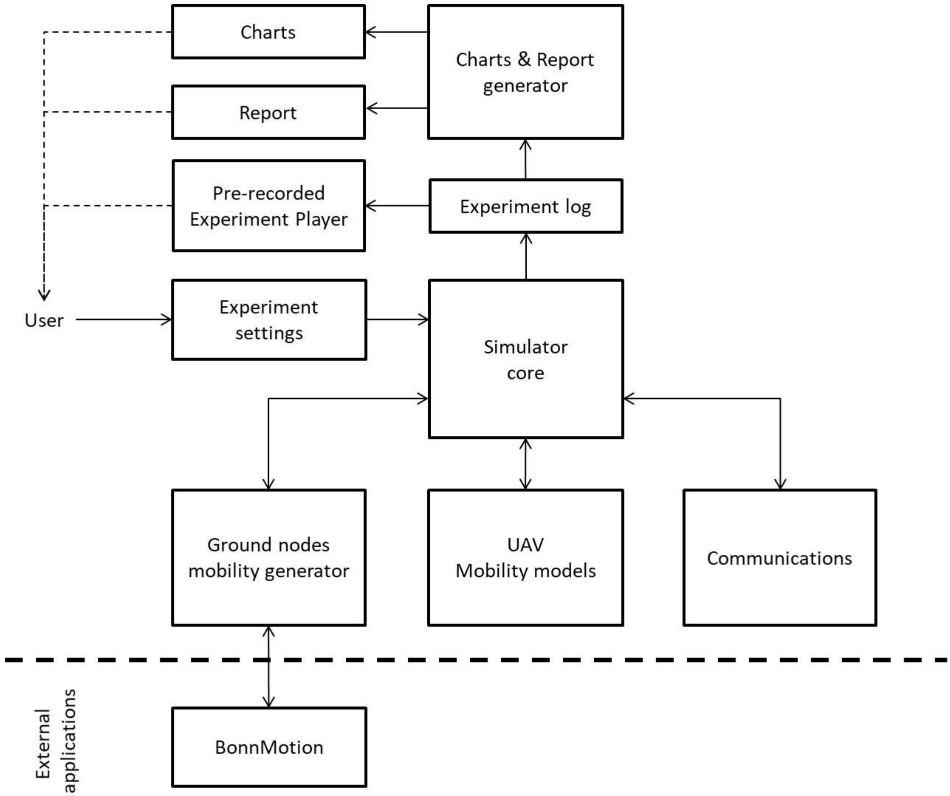


Figure 68. Architecture of the software developed

Table 16. Components of the software simulation tool developed

Component	Description
Simulator core	Acts as the orchestra director of the simulator, controlling the simulation time base and the events that have to take place in specific time slots and in a specific order.
Ground nodes mobility generator	Produces the mobility of the ground nodes that correspond to the scenario in which the UAV network works. In the specific case of disaster scenarios, the traces represent the mobility of the victims. This component works with the BonnMotion mobility generator [45], an external software application.
Mobility model algorithms	Calculates the UAVs next positions based on their current positions and the victims' positions and the specific constraints that the mobility model could present. The proposed mobility models would be implemented within this component.
Communications module	Simulate the network traffic flow between UAV-UAV and UAV-ground nodes. At the time of writing this thesis, this is modelled by the disk model which is simplistic but it has served the purpose of validating the proposed mobility models.
Experiment log	Records all the relevant information of the UAV network at each simulation time.
Charts and report generators	Parse the experiment log and calculate statistics and metrics that are represented in charts. Also, the most important metrics and information are used to produce an experiment report.
Pre-recorded experiment player	Plays an animation of the experiment with the movements of the UAVs and the ground nodes. It serves the purpose of visually analysing the experiment behaviour at specific time stamps.

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"The difficulty of literature is not to write,
but to write what you mean."
Robert Louis Stevenson

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Curriculum Vitae

"- I can't…
- No. You couldn't. Now keep trying."
Jesús Sánchez García

I was born in Seville, Spain, in 1984. Since 2012, I hold an MSc degree in telecommunications engineering from the University of Seville, Seville, Spain. In 2010, I started working as a software engineer intern in the Center for Advanced Aerospace Technologies (CATEC), specifically in the Avionics and Unmanned systems department. This was the first time I had the chance to be close up to a UAV. My MSc thesis is based on the work carried out during my internship at this research centre. Specifically, I developed the software for a prototype of a LIDAR-based embedded system able to scan the terrain surface during an aerial vehicle flight for building 3D terrain models of the terrain.

From 2010 to 2013 I worked as a software and project engineer in the R&D department of a privately owned engineering company. During this time, I had the chance to contribute to several R&D projects granted with funding from both the Spanish Government and the European Commission. During the last year in this company, I became project manager of some of these R&D projects, even being the project coordinator of a European R&D project funded under the Ambient Assisted Living European Programme. These years brought me a background on project proposal creation, project funding, project development, and also organizational and managerial abilities. It is worth to mention all the knowledge that I gathered from all the amazing people that I met during this time, working in technology companies, research centres, universities and public institutions.

In 2014 an opportunity came up at the University of Seville and I joined the ACE-TI research group from the Electronics department of the University of Seville as scientific personnel. Also, I took the chance to enrol in the doctoral studies in the area of Automatics, Electronics and Telecommunication Engineering, specifically in the area of mobile ad hoc networks. From that date, I have been doing research in the mobile ad hoc networks as a member of the ACE-TI research group. My work has been centred in the development and validation of mobility models for UAV networks. During this time, I have contributed to the process of building a real UAV test-bed for the research group. I also became a teaching assistant in the electronics department of the University of Seville. I really much enjoyed my time teaching different modules in several graduate degrees and master programmes in the Higher Technical School of Engineering of Seville, along two academic years.

Currently, I feel lucky for being part of a group of excellent and highly qualified people that works at Galgus. Galgus is a small engineering company devoted to doing big things such as maximizing the performance of WiFi technology in high-density environments. Specifically, my work at Galgus is as a software engineer developing the software for a specific wireless access point, using the IEEE802.11 standards, and which is mounted on planes all over the world.

In the near future, I really look forward to keeping working in the research area of UAV networks, merging my background on UAV networks mobility models, embedded systems and IEEE802.11 wireless access points to contribute to the research community that is building the future of UAV networks and its applications.

Publications

"Out of the night that covers me,
Black as the pit from pole to pole,
I thank whatever gods may be
For my unconquerable soul.

In the fell clutch of circumstance
I have not winced nor cried aloud.
Under the bludgeonings of chance
My head is bloody, but unbowed.

Beyond this place of wrath and tears
Looms but the Horror of the shade,
And yet the menace of the years
Finds and shall find me unafraid.

It matters not how strait the gate,
How charged with punishments the scroll,
I am the master of my fate,
I am the captain of my soul."
William Ernest Henley, Invictus

5.3 Publication list

This section contains the publications that the author of this thesis has produced as first author and co-author during its time as a doctoral student in the Automatics, Electronics and Telecommunication Engineering doctoral programme of the University of Seville. The publications are organized in several categories, specifically book chapters, journal papers and conference papers.

Book chapters

The author's publications as chapters on international books are shown in Table 17.

Table 17. Author's book chapters

Ref.	Title	Authors	Book	Year	Status
[250]	Application of Nature Inspired Algorithms for Wireless Multi-hop Ad hoc Network Optimization Problems in Disaster Response Scenarios	J. Sánchez-García, J. M. García-Campos, D. G. Reina, S. L. Toral and F. Barrero	Nature-Inspired Networking: Theory and Applications	2017	Published
[251]	A Simulation Methodology for Conducting Unbiased and Reliable Evaluation of MANET Communication Protocols in Disaster Scenarios	J. M. García-Campos, D. G. Reina, J. Sánchez-García and S. L. Toral	Smart Technologies for Emergency Response and Disaster Management	2018	Published

Journal Papers

The author's publications on international journal papers are shown in Table 18.

Table 18. Author's journal papers

Ref.	Title	Authors	Journal	Year	Status
[252]	A distributed PSO-based exploration algorithm for a UAV network assisting a disaster scenario	J. Sánchez-García, D. G. Reina and S. L. Toral	Future Generation Computer Systems	2019	Published
[253]	A survey on unmanned aerial and aquatic vehicle multi-hop networks: Wireless communications, evaluation tools and applications	J. Sánchez-García, J. M. García-Campos, M. Arzamendia, D. G. Reina, S. L. Toral and D. Gregor	Computer Communications	2018	Published
[254]	An Intelligent Strategy for Tactical Movements of UAVs in Disaster Scenarios	J. Sánchez-García, J. García-Campos, S. Toral, D. G. Reina and F. Barrero	International Journal of Distributed Sensor Networks	2016	Published
[255]	An Evaluation Methodology for Reliable Simulation Based Studies of Routing Protocols in VANETs	J. M. García-Campos, J. Sánchez-García, D. G. Reina, S. L. Toral and F. Barrero	Simulation Modelling Practice and Theory	2016	Published
[256]	On-siteDriverID: A Secure Authentication Scheme based on Spanish eID Cards for Vehicular Ad Hoc Networks	J. Sánchez-García, J. M. García-Campos, D. G. Reina, S. L. Toral and F. Barrero	Future Generation Computer Systems	2016	Published

Conference papers

The author's publications on international conferences are shown in Table 19.

Table 19. Author's conference papers

Ref.	Title	Authors	Conference	Year	Status
[257]	A Self-Organizing Aerial Ad Hoc Network Mobility Model for Disaster Scenarios	J. Sánchez-García, J. M. García-Campos, D. G. Reina, S. L. Toral and F. Barrero	8th International Conference on Developments in e-Systems Engineering	2015	Published
[258]	Evaluation of Dissimilarity-based Probabilistic Broadcasting Algorithms in VANETs	J. M. García-Campos, J. Sánchez-García, D. G. Reina, S. L. Toral and F. Barrero	8th International Conference on Developments in e-Systems Engineering	2015	Published

5.4 Publications correspondence with the text

The contents of this document are partially based on the author research work and its publications. Specifically, the correspondence between each chapter contents and the author's publications is shown in Table 20.

Table 20. Chapters and author's publications correspondence

Chapter	Chapter title	Ref.
1	Introduction	[254] [257] [250] [252] [253]
2	Background & Related works	[254] [257] [250] [252] [253]
3	Mobility models for Exploration	[252]
4	Mobility models for Adaptive coverage	[254] [257] [250]
5	Conclusions & Future Works	[254] [257] [250] [252] [253]