# Descripción general de comunicaciones habilitadas por UAV en escenarios de emergencia posterior a un desastre

## An overview of UAV-enabled communications system in post-disaster emergency scenarios

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**Resumen:** Mantener las comunicaciones y brindar servicios a los usuarios son cruciales después de un desastre natural debido al daño de las redes de comunicaciones tradicionales. Las redes de emergencia mediante vehículos aéreos no tripulados (UAVs: *Unmanned Aerial Vehicles*) resuelven este problema debido a su rápido despliegue y configuración. En este contexto, este artículo presenta una descripción general de los retos y soluciones relacionados con la factibilidad de operación de sistemas de comunicaciones basados en UAVs, incluyendo los desafíos asociados para planificación de la ruta y posicionamiento. En este artículo además se describen las tecnologías para realizar la red principal, así como también las redes implementadas asociados a los UAVs.

***Palabras clave:*** *Vehiculos Aéreos No Tripulados, Comunicaciones de Emergencia, Desastres Naturales, Redes de UAV.*

**Abstract:** Maintaining communications and providing services to users is crucial after a natural disaster due to the damage to traditional communications networks. Emergency networks using UAVs solve this problem due to their rapid deployment. This article presents an overview of the challenges and solutions related to the feasibility of emergency communication systems in different scenarios, path planning, and positioning. Besides, It describes the technologies to realize the core and implemented networks associated with UAVs.

***Keywords:*** *Unmanned Aerial Vehicles, Emergency Communications, UAV Networks, Natural Disaster.*

## 1. Introduction

Natural disasters are unpredictable and happen anytime, anywhere. Natural disasters include earthquakes, tsunamis, floods, and forest fires. A timely response can save human lives and prevent material damage from these events. Moreover, maintaining user communications and real-time disaster information allows for timely and effective decisions.

Wireless communications networks are constantly evolving, and one of the first developed is ad-hoc networks [1], which provide node-to-node communication. If these networks present mobility, they are called VANETs (vehicular ad hoc networks) [2], and their main objective is to provide communications to moving vehicles. If the nodes can fly through Unmanned Aerial Vehicles (UAVs), the networks are denoted as Flying ad-hoc networks (FANETs) and provide ground user service [3].

There are different applications of UAVs [4], such as agriculture, logistic, and engineering, and they can support when a natural disaster happens because that UAVs have increased their flight autonomy and payload capacity over the years. Moreover, several models of UAVs include single rotor, multi-rotor, and fixed wind.

The architecture of a network using UAVs comprises the ground base station (GBS) and the nodes (UAVs). GBS gets information from the nodes (UAV) deployed in the area of interest. The UAV can work as a final node or router, and they are responsible for communicating between GBS and the end nodes that provide a service. The network helps in different scenarios of natural disasters, and they can take pictures in real-time of the affected area and send them to the ground station. Besides, they can give communication services to ground users.

Deploying a UAV-enabled network is necessary to solve issues such as path planning and optimal placement of UAVs over the service region. Path Planning calculates the optimal route from the ground station to its destination, and the optimal placement improves coverage range. Moreover, features such as the selected channel model, carrier frequency, path losses (e.g., free space loss, path diffraction loss), and distance between the user and UAVs are involved in the computation of the path planning and the optimal placement of UAVs. Thus, they must be considered in the deployment of a FANET. Energy consumption is another important characteristic in the operation of UAVs, and its optimal use must be ensured to achieve a desired availability level of the communication services. This paper aims to describe the issues that can affect the deployment of communications services enabled by UAVs in emergency scenarios, including the existing approaches and solutions.

## 2. Communication Systems with UAVs

A UAV-enabled communications system provides data or voice services to users on the ground and composes a single UAV or several UAVs, depending on the service area. It can be used complementary to the cellular network by increasing coverage and bandwidth to users. Moreover, UAVs can be treated as clients of the cellular network and used to solve the problem of path planning and position [5]. A natural disaster can destroy the cellular network, so it is necessary to deploy fully autonomous UAV emergency networks. Fig. 1 shows a UAV-enabled communications system.

## 3. Challenges and solutions

The literature shows different challenges and solutions for the UAV-enabled emergency networks. Some investigations aim to solve trajectories, position, and energy-related problems in various application scenarios. Moreover, some works propose that UAVs can replace destroyed tower communication to assist the users. This replacement can consider response time, propagation delay, channel capacity, life battery, types of service, UAV transport capacity, and routing algorithms.

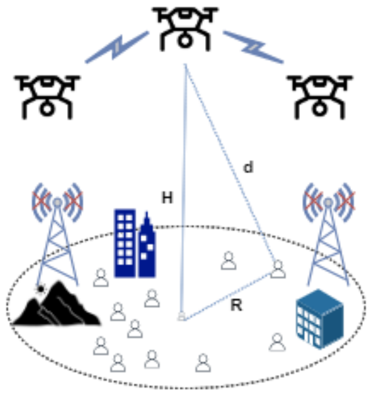


**Figure 1**. Example of a UAV-enabled communications system in emergency scenarios as an alternative infrastructure of a mobile network. H: Height from area to UAV, R: Coverage area radius, d: Distance between user and UAV.

### *3.1. Optimal path planning and position*

Different approaches address efficient path planning and positioning; the most relevant categories are described below.

#### 3.1.1. Optimization theory

The optimal path planning and suitable positioning of UAVs have been studied in the literature using optimization theory. For instance, [6] assumes knowing the position tower and placing a UAV in the exact location. It uses a cognitive-radio-based solution to determine if there is interference between towers and nodes. Moreover, the proposed algorithm in [6] sends more UAVs to cover the geographic area when a single UAV cannot provide all coverage needed.

In [7], the authors present two scenarios. In the first scenario, the communication network is partially damaged. In this case, the UAVs are used as ground BSs (GBS) to provide wireless coverage and collaborate with the survival GBS (e.g., cellular network). Meanwhile, in the second scenario, there is no GBS and uses UAVs are used as a single BS using multi-hop communications to the emergency communication vehicle (end-user). The first case optimizes the communication schedule, so the UAV has a slot of time to transmit information when the GBS is out. This optimization problem is non-convex, so the problem is relaxing into sub convex problem. In the second case, the UAVs must have multiple antennas to deploy a multi-hop network to reach the ground users. The authors identify overage and limited lifetime due to battery limitations in both scenarios.

In [8], the authors deal with the trajectory and power optimization problem in Multi-UAV networks. They propose a one-way hover-fly-hover method that considers the power allocation and is solved by a convex algorithm. Although the problem is non-convex, the authors decompose the original problem into two sub-problems by applying successive convex approximation techniques. Convex optimization seeks to minimize convex function over convex set [9]. The system model assumes that all UAVs use the same frequency band, fly at a fixed altitude, and have the same communication period.

Furthermore, each UAV has assigned a user group to offer communication. The simulation results are presented by varying the number of UAVs from one up to three UAVs flying at a fixed altitude of 100 meters and a flight speed of 10 m/s and considering eight users randomly distributed in a square area of one square kilometer. The results show that the average rate per unit area increases with the number of UAV increasing. Conversely, the average rate per unit area decreases as the number of users increases.

In [10], the authors study the optimization of the backhaul access link. They propose the resource allocation algorithm UPR to maximize the availability of the system. In the simulation, the UAVs are treated as base stations and relay nodes to provide backhaul links. This work considers that the UAVs are not directly connected to the base station. Therefore, it is necessary to deploy UAVs as intermediate routing nodes to provide backhaul links for other UAVs. The optimization algorithm uses the minimum feasible distances between UAV routers to optimize the coverage area.

3.1.2. Genetic algorithm

Path planning and energy consumption design are studied using genetic algorithms. For instance, in [11], the authors consider a cellular network supported by UAVs as Aerial Base Station (ABS). They assume that all these ABS transmit at the power and hover at the same height, while the user equipment (UE) locations are modeled as a two-dimensional Poisson point process. A UE is considered within communication coverage if its average throughput per unit bandwidth is more significant than a threshold. In [11], a genetic algorithm (GA) is used to compute the optimal position for deployed ABS, ensuring the best version of the network. The GA considers total network damage, and the user is unevenly distributed. Results of the genetic algorithm show a decrease in the amount of BS (UAV) needed to deploy a given service.

On the other hand, [12] show that one constraint is the life battery to provide wireless coverage because of flight lifetime. The authors propose a trajectory that minimizes the flight energy requirement of the UAV, which uses a GA to visit all BS for the UAV and return to a central node that acts as a gateway to the core network. The difference between [11] and [12] is the conception of the network. In this problem, the UAV travels around Truck-mounted Base Station to connect to a core network. In [12], the authors propose a fitness function and use genetic operators (selection, crossover, and mutation) to create populations of solutions that evolve over time. The result in [12] is given in terms of UAV speed and total energy consumed and shows a minimal energy consumption while using more computational capacity (in terms of CPU) and running time when the analyzed number of UAVs increases.

3.1.3. Machine learning

The use of machine learning techniques is an alternative to optimize path planning and position in the UAV domain. For instance, in [13], the authors design a UAV trajectory using a deep reinforcement learning (DRL) process, while in [14], the authors use a double deep Q network (DDQN) to improve the path of UAVs. In [15], the system model assumes that the user and the geographical features are known, and the scenario is distributed as a grid. The UAV alternate between hovering and moving to charge the battery to continue the lifetime network in this analysis. The result illustrates the average reward of the DDQN design with and without Transfer learning giving better trajectory results with transfer learning. Further, the battery capacity based on traffic demand improves using transfer learning.

In [16], the authors study the path planning and the coverage mapping problems in the UAV networks, which are unaware of the area and inhomogeneous user distribution. To provide a solution, the authors propose a deep learning model [17], which is evaluated through a Monte Carlo simulation [18]. In work, the authors analyze the path planning problem through a point-to-point process (PPP). The PPP model is more realistic due to considering a non-homogeneous model in natural environments. For example, more dismally populated users are in urban areas than in rural areas. Moreover, this model extends the points that UAVs can visit within an assigned grid representing a specific area with a large discretized area. It is better to plan the route that promptly collects information about the site and its population, allowing real-time tasks such as routing and services.

*3.2. UAV as Backbone technologies*

This section describes the combinations of the other technologies to provide communication service in a post-disaster scenario with a UAV-enabled communications system. For instance, [19] provides a network backbone solution based on UAV using WiMAX (mesh wireless networks). The idea is to create an ad-hoc backbone infrastructure, and the information travels through the UAV in a multi-hop network using WiMAX Technologies.

In [20], the authors describe an architecture consisting of a Software Defined Network (SDN) to provide centralized control on the edge and various public Safety PS-LTE services. SDN achieves an easy request by decoupling the control plane from the data plane. So the network routers/switches send packets following the flow table rules set by the control plane. Thus, SDN has become one of the most critical architectures for managing complex large-scale networks, which may require repetition or reconfiguration from time to time [21]. To convert the UAV as switch/router SDN, the authors propose three-Layers: an SDN-Layer, a UAV Cloudlet Layer, and a Radio Access Network (RAN) layer. OpenFlow protocol provides communication among SDN controllers and various network nodes (UAV), allowing network topology discovery. Furthermore, in the UAV Cloudlet Layer, the UAV must have a Cloudlet (Small data centers) to provide service. The proposed architecture decreases the delay compared with traditional architecture; simultaneously, the results show that the energy consumption of UAVs energy is dropped considerably.

In addition, [22] proposes a new three-dimensional algorithm to optimize the swarm UAV localization. This approach uses anchor UAV nodes, distributed randomly, and the optimization algorithm measures the distance between the anchor and new UAV nodes. In [23], the authors propose a new energy-efficient algorithm base on clustering.

### *3.3. UAV as support to other technologies*

Different technologies allow obtaining information in disaster areas, and the UAVs are supported to provide service to users [24, 25]. For instance, in [26], the authors propose a combination of IoT devices and UAVs to offer wireless service in broad areas. One problem is the battery lifetime of IoT devices. To solve this problem, the authors propose using a power transfer approach to extend the energy capacity. In this approach, a UAV exploits a multi-beam antenna array to transfer energy to an IoT device. The trajectory of UAVs is jointly optimized to maximize the power transfer. Thus, the UAVs transmit power and receive information about IoT devices.

One of the most widely used technologies is WiFi. In [27], the transmission speed and delay in downlinks are analyzed, incorporating WiFi and buffer into UAVs to transmit data to the base station through millimeter waves [28]. In this approach, the users are connected to floating access points using Carrier Sense Multiple Access CSMA. The authors use a combination of stochastic geometry and queuing theory to solve the problem. To reduce the transmission delay, they incorporate a buffer in the UAV. The results show that the average delay decreases when the buffer size increases from 100 packets to 600 packets. Because UAVs can store more data packets, they can receive more information from users and transmit it to the base station, reducing the transmission delay. However, the average delay increased with the UAVs' flight height due to the deterioration of the channel conditions. On the other hand, the transmission delay decreases when the number of UAVs increases. However, the bandwidth of the base stations is fixed, and the bandwidth of the backhaul link decreases.

### *3.4. Implementation of UAV Network*

Currently, there are few implementations of UAV networks. In [29], the authors show the implementation of an emergency communication network based on UAV, constituted by physical (hardware), transport, and application layers. The hardware layer uses the UAVs and the Pixhawk autopilot system [30], including several sensors like an accelerometer, magnetometer, and barometer. The Transport layer uses a MAVLink protocol [31] that communicates between UAVs and ground stations, UDP protocol, and UART/radio link to send control and data information. The application layer is implemented in a python server that controls the network link with the MAVlink protocol.

In [32], the authors describe the implementation of an aerial communication network using an airship in disaster scenarios located in the Andes of Ecuador, specifically Ambato city. The proposed platform is oriented to help in geophysical or hydro-logical disaster scenarios. The frequency used is 5 GHz which links the ground station (GS) and the airship because this frequency belongs to the ISM band. The relationship between GS and airship is point-to-point, and the connection between airship and user is multiple. As the airship has a greater weight capacity, it has a battery bank and a communications system. The limitations are preparing the land, which takes around two hours, and a suitable place for launch. On the other hand, the cost of implementation is high compared to rotary-wing UAVs.

## 4. Trends

Research on UAV emergency networks has gained relevance due to technological progress. The trends in the subject are the integration of path planning with the optimal position and configuration of the nodes to provide maximal coverage. The lifetime of the network depends on the battery of the UAV. Therefore, it is necessary to determine the service type and the QoS requirements and make scheduling in time to replace the battery or the equipment (entire UAV).

The number of UAVs versus the number of users and users' localization is also a trend. The literature unknown their localization and number, so it assumes a probability distribution or that users are not on the move.

The replacement of the UAV battery or changing the equipment in time is necessary to keep the AID-UAV network's service; in this regard, the handover between UAVs is an open problem that is also under investigation. In addition, due to the UAV routing protocols depending on the position and weather conditions, the future proposals must consider a suitable path loss model and the uncertainty of UAVs or users' positions.

AID-UAV communication networks are composed of several nodes with a specific function. However, when one of them does not work correctly or fails, the communication network is down, so the network must have the ability to be self-configured to maintain communication or send a control signal to the GBS. The self-configuration network maximizes user coverage and keeps the communication between nodes. On the other hand, if the UAV network needs a backbone and fails, the transmission is down between the service area and GBS. The network has to reconfigure or design a backup.

Many UAV networks use GPS to determine their localization in the network. However, the system of GPS has errors in the calculation of localization. The error can be between 10m to 30m, and this error distance can change the topology, coverage, and the communication between UAVs is in danger. Finding a solution to this problem is a challenge, so this investigation is in progress.

## 4. Conclusions

This paper presents an overview of the technical considerations for the deployment of a UAV-enabled communications system in the scope of emergency scenarios. Particularly, this paper describes the issues related to optimal path planning, placement of UAVs in a given service region, and energy consumption-related problems. The paper provides information about the exciting approaches to cope with these issues, including a solution that uses optimization theory, genetic algorithms, or machine learning techniques. This paper also discusses additional application scenarios in which the UAVs can be used, some trends for future work, and open research problems.

## 5. References

[1] Ruiz, P., Bouvry, P. (2015). Survey on Broadcast Algorithms for Mobile Ad Hoc Networks. *ACM Computing Surveys, 48* (1), 1-35. https://doi.org/10.1145/2786005

[2] Ghori, M. R., Zamli, K. Z., Quosthoni, N., Hisyam, M., Montaser, M. (2018). *Vehicular ad-hoc network (VANET): Review*. IEEE International Conference on Innovative Research and Development (ICIRD), Bangkok, Thailand. https://doi.org/10.1109/ICIRD.2018.8376311

[3] Mukherjee, A., Keshary, V., Pandya, K., Dey, N., Satapathy, S. C. (2018). Flying Ad hoc Networks: A Comprehensive Survey. En S. Satapathy, J. Tavares, V. Bhateja, J. Mohanty (Eds.), *Information and Decision Sciences* (pp. 569-580). Springer. https://doi.org/10.1007/978-981-10-7563-6_59

[4] Fan, B., Li, Y., Zhang, R., Fu, Q. (2020). Review on the Technological Development and Application of UAV Systems. *Chinese Journal of Electronics*, *29* (2), 199-207. https://doi.org/10.1049/cje.2019.12.006

[5] Azari, M. M., Rosas, F., Pollin, S. (2019*).* Cellular Connectivity for UAVs: Network Modeling, Performance Analysis, and Design Guidelines. *IEEE Transactions on Wireless Communications, 18* (7), 3366-3381. https://doi.org/10.1109/TWC.2019.2910112

[6] Xiao, Y., Hu, F. (2008). *Cognitive Radio Networks*. CRC Press.

[7] Zhao, N., Lu, W., Sheng, M., Chen, Y., Tang, J., Yu, F. R., Wong, K. K. (2019). UAV-Assisted Emergency Networks in Disasters. *IEEE Wireless Communications, 26* (1), 45-51. https://doi.org/10.1109/MWC.2018.1800160

[8] Zhang, Y., Cheng, W. (2019). *Trajectory and Power Optimization for Multi-UAV Enabled Emergency Wireless Communications Networks*. IEEE International Conference on Communications Workshops (ICC Workshops), Shanghai, China. https://doi.org/10.1109/ICCW.2019.8756780

[9] Bertsekas, D. P. (2009). *Convex Optimization Theory*. Athena Scientific. http://web.mit.edu/dimitrib/www/Convex_Theory_Entire_Book.pdf

[10] Yuan, X., Tian, H., Nie, G. (2020). *Joint Access and Backhaul Link Optimization in Multiple UAV-Assisted Emergency Network*. IEEE/CIC International Conference on Communications in China (ICCC), Chongqing, China. https://doi.org/10.1109/ICCC49849.2020.9238878

[11]Peng, G., Xia, Y., Zhang, X., Bai, L. (2018). UAV-Aided Networks for Emergency Communications in Areas with Unevenly Distributed Users. *Journal of Communications and Information Networks*, *3* (4), 23-32. https://doi.org/10.1007/s41650-018-0034-1

[12]Sambo, Y. A., Klaine, P. V., Nadas, J. P. B., Imran, M. A. (2019). *Energy Minimization UAV Trajectory Design for Delay-Tolerant Emergency Communication*. IEEE International Conference on Communications Workshops (ICC Workshops), Shanghai, China. https://doi.org/10.1109/ICCW.2019.8757127

[13]Zhang, X., Zheng, G., Lambotharan, S. (2020*). Trajectory Design for UAV-Assisted Emergency Communications: A Transfer Learning Approach*. IEEE Global Communications Conference, Taipei, Taiwan. https://doi.org/10.1109/GLOBECOM42002.2020.9348212

[14]Arulkumaran, K., Deisenroth, M. P., Brundage, M., Bharath, A. A. (2017). Deep Reinforcement Learning: A Brief Survey. *IEEE Signal Processing Magazine, 34* (6), 26-38. https://doi.org/10.1109/MSP.2017.2743240

[15]Pan, S. J., Yang, Q. (2010). A Survey on Transfer Learning*. IEEE Transactions on Knowledge and Data Engineering*, *22* (10), 1345-1359. https://doi.org/10.1109/TKDE.2009.191

[16]Steiger, J., Lu, N., Sorour, S. (2020). *Learning for Path Planning and Coverage Mapping in UAV-Assisted Emergency Communications*. IEEE Global Communications Conference, Taipei, Taiwan. https://doi.org/10.1109/GLOBECOM42002.2020.9322190

[17]Kaur, M., Mohta, A. (2019). *A Review of Deep Learning with Recurrent Neural Network*. International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India. https://doi.org/10.1109/ICSSIT46314.2019.8987837

[18] Mooney, C. Z. (1997). *Monte Carlo Simulation*. SAGE.

[19]Dalmasso, I., Galletti, I., Giuliano, R., Mazzenga, F. (2012). *WiMAX networks for emergency management based on UAVs*. IEEE First AESS European Conference on Satellite Telecommunications (ESTEL), Rome, Italy. https://doi.org/10.1109/ESTEL.2012.6400206

[20]Kaleem, Z., Yousaf, M., Qamar, A., Ahmad, A., Duong, T. Q., Choi, W., Jamalipour, A. (2019). UAV-Empowered Disaster-Resilient Edge Architecture for Delay-Sensitive Communication. *IEEE Network, 33* (6), 124-132. https://doi.org/10.1109/MNET.2019.1800431

[21]Hu, F., Hao, Q., Bao, K. (2014). A Survey on Software-Defined Network and OpenFlow: From Concept to Implementation. *IEEE Communications Surveys Tutorials, 16* (4), 2181-2206. https://doi.org/10.1109/COMST.2014.2326417

[22]Arafat, M. Y., Moh, S. (2019). Localization and Clustering Based on Swarm Intelligence in UAV Networks for Emergency Communications. *IEEE Internet of Things Journal, 6* (5), 8958-8976. https://doi.org/10.1109/JIOT.2019.2925567

[23]Chen, C. Y., Ye, F. (2012). *Particle swarm optimization algorithm and its application to clustering analysis.* 17th Conference on Electrical Power Distribution, Tehran, Iran. https://ieeexplore.ieee.org/document/6254579

[24]Chakraborty, B. (2002). *Genetic algorithm with fuzzy fitness function for feature selection.* IEEE International Symposium on Industrial Electronics (ISIE), L'Ayuila, Italy. https://ieeexplore.ieee.org/document/5730782

[25]Liu, M., Yang, J., Gui, G. (2019). DSF-NOMA: UAV-Assisted Emergency Communication Technology in a Heterogeneous Internet of Things. *IEEE Internet of Things Journal, 6* (3), 5508-5519. https://doi.org/10.1109/JIOT.2019.2903165

[26]Feng, W., Tang, J., Yu, Y., Song, J., Zhao, N., Chen, G., Wong, K. K., Chambers, J. (2020). UAV-Enabled SWIPT in IoT Networks for Emergency Communications. *IEEE Wireless Communications, 27* (5), 140-147. https://doi.org/10.1109/MWC.001.1900656

[27]Zhang, Y., Lu, G., Zhang, J. (2020). *Delay and Transmission Rate Analysis of Buffer-Aided UAV Networks for Emergency Communications*. International Conference on Wireless Communications and Signal Processing (WCSP), Nanjing, China. https://doi.org/10.1109/WCSP49889.2020.9299820

[28]Huang, K. C., Wang, Z. (2011). *Millimeter Wave Communication Systems.* John Wiley & Sons.

[29]Bupe, P., Haddad, R., Rios-Gutierrez, F. (2015*). Relief and emergency communication network based on an autonomous decentralized UAV clustering network*. SoutheastCon, Fort Lauderdale, FL, USA. https://doi.org/10.1109/SECON.2015.7133027

 

[30]Meier, L., Tanskanen, P., Fraundorfer, F., Pollefeys, M. (2011). *PIXHAWK: A system for autonomous flight using onboard computer vision.* IEEE International Conference on Robotics and Automation, Shanghai, China. https://doi.org/10.1109/ICRA.2011.5980229

[31]Atoev, S., Kwon, K. R., Lee, S. H., Moon, K. S. (2017). *Data analysis of the MAVLink communication protocol.* International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan. https://doi.org/10.1109/ICISCT.2017.8188563

[32]Jara-Olmedo, A., Medina Pazmiño, W., Tozer, T. Aguilar, W. G., Pardo, J. A. (2018). *E-services from Emergency Communication Network: Aerial Platform Evaluation*. International Conference on eDemocracy & eGovernment (ICEDEG), Ambato, Ecuador. https://doi.org/10.1109/ICEDEG.2018.8372336