Computer Communications 181 (2022) 45–57

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Smart Unmanned Aerial Vehicles as base stations placement to improve the mobile network operations

Zhongliang Zhao [a,*,1], Pedro Cumino [b,c,1], Christian Esposito [d], Meng Xiao [a], Denis Rosário [c], Torsten Braun [e], Eduardo Cerqueira [c], Susana Sargento [b]

[a] Beihang University, Beijing, China
[b] University of Aveiro, Aveiro, Portugal
[c] Federal University of Pará, Belém, Brazil
[d] University of Salerno, Fisciano (SA), Italy
[e] University of Bern, Bern, Switzerland

ARTICLE INFO

Keywords:
Emergency and flash crowd situations
Unmanned Aerial Vehicles
Flying base stations
Artificial Intelligence

ABSTRACT

Future mobile communication networks need Unmanned Aerial Vehicles as Base Stations (UAVasBSs) with the fast-moving and long-term hovering capabilities to guarantee consistent network performance. UAVasBSs help 5G/B5G mobile communication systems to rapidly recover from emergency situations and handle the instant traffic of the flash crowd. In this context, multiple UAVs might form a flying ad-hoc network to establish a flying access network to enhance the network connectivity and service quality. Therefore, it is important to determine the optimal number and locations of UAVasBSs in a fast and efficient way to cover the target area to provide temporary yet reliable cellular connectivity. The use of Artificial Intelligence (AI) and network data analysis are key tools to fulfill the above issues. In this article, we propose a smart UAVasBS placement (SUAP) mechanism to improve the mobile network operations in flash crowd and emergency situations. We have modeled such an UAVasBS placement task as an optimization problem to obtain required network connectivity and system performance, and resolved it with a genetic algorithm using the network context information. Simulation results show that our proposal could cover 90% of mobile users, and it provides nearly 90% packet delivery ratio for users with a fast convergence rate.

1. Introduction

Smart cities are changing our society through disruptive technologies. Their primary goal is to provide a new set of verticals and personalized applications to increase the quality of life and well-being of their inhabitants [1]. In this context, future mobile networks play a crucial role in providing connectivity with Quality of Service (QoS) support to those applications, and its evolution needs to be continuous [2]. Despite the innovative solutions in upcoming mobile networks, future applications' performance can be affected by network congestion or overloads caused by emergency situations such as flash crowds and nature disasters [3]. Specifically, flash crowd events could be a social event, *e.g.*, concerts, sports events, parades, and other gatherings of people, which suddenly increase the number of connected users [3]. On the other hand, natural emergency situations, *e.g.*, earthquakes, floods, etc, or a human-made emergency situation, *e.g.*, terrorist attacks, industrial accidents, transportation failures, and others, could compromise correct behaviors of existing mobile communication infrastructures. Hence, flash crowd and emergency situations stress network resources beyond the standard-setting. In this way, such situations lead to high traffic demand resulting from a high concentration of users or a high number of user connection requests [4].

Existing wireless and mobile networks cannot provide QoS requirements during flash crowd and emergency situations in a way that mobile network operators are willing to support, *i.e.*, with low cost and efficient real-time service demand fulfillment. For instance, adding new Base Stations (BS) or small cells may not provide a flexible approach considering fast deployment, user mobility, QoS requirements, and monetary cost [5]. In this way, there is a vital need for a robust, fast, and low-cost communication infrastructure to deal with a large number of mobile-connected users and high traffic volume. New approaches are imperative to provide fast communication networks during flash crowd and emergency situations [6]. In this context, Unmanned Aerial Vehicle working as an aerial BS (UAVasBS) become a promising approach

* Corresponding author.
E-mail addresses: zhaozl@buaa.edu.cn (Z. Zhao), pedro.cumino@av.it.pt (P. Cumino), esposito@unisa.it (C. Esposito), xiaomeng@buaa.edu.cn (M. Xiao), denis@ufpa.br (D. Rosário), torsten.braun@inf.unibe.ch (T. Braun), cerqueira@ufpa.br (E. Cerqueira), susana@ua.pt (S. Sargento).

[1] Authors of equal contributions.

https://doi.org/10.1016/j.comcom.2021.09.016
Received 23 January 2021; Received in revised form 23 June 2021; Accepted 18 September 2021
Available online 2 October 2021

to provide temporary communication to ground users to recover the mobile network operations in emergency situations, or to satisfy the sudden demands (hotspots) caused by flash crowd events [7]. For instance, there are ongoing standardization activities in 3GPP [8] for providing enhanced wireless connectivity to personal and commercial UAVasBS via mobile networks [9].

UAVasBS deployment has several advantages to provide fast connectivity support, such as the ability to facilitate on-demand deployment without highly constrained and expensive infrastructure (*e.g.*, cables), high flexibility by dynamically changing their positions to provide on-demand communications to ground users, and a better chance of having line-of-sight (LOS) communication links [10,11]. The control and management of UAVasBS movement and trajectory are essential for a UAV-assisted mobile network. This is because UAVasBSs need to be placed appropriately to provide temporary communication to ground users in a flash crowd and emergency situations to improve the mobile network operations [12]. Moreover, the correct placement of a UAVasBS depends on the number of users, application QoS requirements, number of available UAVs, and the cellular network state within the area. Thus, a set of UAVs could be orchestrated to work together with the available cellular network to improve the connectivity levels, QoS, and coverage areas for mobile users on the ground. However, it is important to design an efficient mechanism to deploy UAVasBSs by considering a lightweight solution and understanding users' network conditions, improving the network connectivity and QoS support in flash crowd events and emergency situations.

In this article, we propose a smart UAVasBS placement mechanism to improve the mobile network operations in flash crowd and emergency situations, called SUAP. We first model the UAVasBS placement as an optimization problem to determine the number and location of the UAVasBSs to obtain required aerial network connectivity and performance. Afterwards, we introduce the SUAP mechanism, which considers the position of the ground users, mobile user channel quality, and the positions of other UAVasBSs as input for a Genetic Algorithm (GA) to compute the number and location of UAVasBSs to be placed. Besides, SUAP minimizes the number of required UAVasBSs to provide connectivity to mobile users. Simulation results showed that SUAP could provide an average number of connected users (ACU) of 90%, and it can achieve a Packet Delivery Ratio (PDR) of nearly 90%. The core contributions of the article are summarized as follows:

- We propose a mechanism to deploy UAVs as aerial base stations to provide network connectivity, QoS support, and reliable communication in a flash crowd and emergency situations.
- We introduce a GA-based approach to determine the most suitable number and location of UAVasBSs without imposing an overwhelming complexity for the controller with a fast convergence rate.
- We perform simulation experiments to present the benefit and impact SUAP in a set of emergency and flash crowd situations. The results show that SUAP can effectively mitigate the challenges related to UAVasBS deployments by providing network connectivity with QoS guarantee and fast convergence.

The article is organized as follows. Section 2 discusses existing approaches for UAVasBS deployments. Section 3 describes SUAP to solve the UAVasBS placement. Section 4 details the simulation settings and evaluation results. Section 5 concludes the article and foresees future work.

2. Related work

UAVasBSs in public and civilian applications are getting more popular since UAVasBSs can be quickly deployed to provide on-demand services to improve mobile network performance. Several attempts have been proposed to determine the UAVasBS position and/or trajectories to meet application requirements. This section describes state-of-the-art research results on UAVasBS deployment mechanisms, and we discuss their strengths and weaknesses.

Reina et al. [13] presented UAVasBS deployment divided into initial and adaptation phases. In the initial phase, a centralized decision-making process aims to find a suitable position for UAVasBSs with limited information. In the adaptation phases, a distributed decision-making is adopted, in which the UAVs exchange information among them to improve the UAVasBS deployment position. Sharma et al. [14] introduced a cost-based neural model to assign UAVasBSs to a particular geographical area subject to high traffic demands. Their results showed that leveraging multiple UAVasBSs not only provides long-range connectivity but also better load balancing and traffic offloading. Wu et al. [15] proposed a cooperative mobile access network architecture to offload their traffic to other UAVasBSs. They formulated the UAVasBS placement and channel allocation problem in the cooperative UAVasBS assisted mobile access network architecture. Montero et al. [16] introduced an offloading scheme to guide UAVasBS deployment through void areas. In this sense, they identify clusters of users with low Signal to Noise (SNR) values and then deploy an UAVasBS into the cluster center.

Wu et al. [17] designed a QoS-aware UAVasBS placement and mobile user association strategy to jointly optimize UAVasBS deployment, user association, and bandwidth allocation such that the number of the served mobile users can be maximized. Akram [18] presented a mathematical model and a low complexity heuristic for the joint optimization of UAVasBS placement and user assignment to maximize the number of serviced users with a minimum number of UAVasBSs. Sharafeddine et al. [19] modeled 3D UAVasBS placement as a mixed-integer linear program (MILP) problem and proposed an unsupervised learning technique that relies on the notion of electrostatics with repulsion and attraction forces. Some works [20,21] introduced a proper deployment of UAVasBSs to extend the wireless coverage in rural areas, emerging countries, or places where BS density is not sufficient to cover the mobile user demands. Hayajneh et al. [22] introduced the use of UAVasBSs for network recovery and the design of public safety networks. Lyu et al. [23] introduced a hybrid network architecture that leverages the use of UAVasBSs, flying cyclically along the edge of the cell to offload data traffic at the edge of a BS. This approach paves the way to maximizing the minimum throughput experienced by all mobile devices by jointly optimizing UAVasBS trajectory, bandwidth allocation, and user partitioning. The work presented in Mirzaeinia et al. [24] described the application of K-means clustering to properly assign users to the UAVasBS. Also in Iellamo et al. [25], clustering techniques are used to optimally place UAVasBS to complement the capacity of an existing network.

Na and Yoo [26] presented a Particle Swarm Optimization (PSO) approach to improve the network throughput while reducing the power consumption through an efficient network topology. This work maximizes throughput by modeling each UAVasBS as an individual particle and adjusting UAVs' movement according to their utilities. Kalantari et al. [27] studied efficient deployment of UAVasBS to maximize the coverage performance, determining the minimum number of UAVasBS needed for serving all the ground users within a given area. This work also considers a PSO algorithm, which evaluates the altitude, location, and trajectory of the UAVasBS-cells and user communication coverage performance.

Existing works [28–30] applied the typical GA steps by properly representing UAVasBS placement and movement planning by using chromosomes. They also adapt fitness functions to represent the achievable wireless coverage, perceived latency/throughput, or other measures of communication QoS. However, they do not consider the possible integration of UAVasBS with existing cellular networks or their possible failures tolerated by exploiting the UAVs. Rodríguez-Cortés et al. [31] and Peng et al. [32] considered the problem of maximizing UAVasBS coverage, minimize the data volumes that each community of UAVasBSs carries out, or optimize the communication probability among two

users within a damaged area. Also, Reina et al. [33] designed a GA that solves the network coverage problem by deploying a set of UAVasBS as a wireless network. Coverage, fault-tolerance, and redundancy are considered by the fitness functions to find the optimal deployment positions based on a theoretical unit disk model under the known node locations. The work in Fotouhi et al. [34], further improved in Fotouhi et al. [35], proposed the use of game theory for a decentralized optimization of drones movements so as to serve as UAVasBS a set of users within an area of interest and improve spectral efficiency.

Based on our analysis of the state-of-the-art summarized in Table 1, UAVasBS deployment typically improves QoS in normal conditions or to support emergency communications. The current literature has scarcely investigated the problem of their deployment to support network recovery after a disaster. However, flash crowd and emergency situations can be characterized by a substantial increase in the number of mobile user connectivity and traffic demand. Such situations stress network resources beyond the standard-setting by exceeding the capacity of the base stations and access failure, leading to performance degradation [4,6]. In addition, the acquisition and evaluation of network metrics are crucial to understand users' network conditions to provide a suitable solution. In this sense, during the decision-making process, evaluating the number of users to be attended, their location and distribution are important metrics to define the required number of UAVasBSs to be deployed, the location of the UAVasBS, and the network coverage. Once a suitable number and locations are defined, it is possible to improve service provisioning quality and longer lifetime. Channel modeling is also important once the users' mobility, the UAVasBSs' flying pattern, and the environment indeed interfere in how effective the messages are being carried from the sender to the receiver, which can lead to QoS variation during the service provisioning. Hence, we conclude that designing a more efficient solution to deploy UAVasBSs by considering a lightweight solution and understanding users' network conditions is essential to provide network connectivity and QoS support to improve network operations in flash crowd events and emergency situations. The efficiency comes during UAVasBS deployment by reducing the decision-making latency and collecting mobile user and local environment data for enriching network analytic and automation. To the best of our knowledge, as shown in our analysis presented in Table 1, none of the previous work integrated a lightweight solution that analyzes users' network conditions to define the number and optimized locations of UAVasBSs, while only SUAP combines every critical feature previously mentioned not provided by existing UAVasBS deployment mechanisms.

3. Smart UAVasBS placement mechanism to improve the mobile network operations in flash crowd and emergency situations

This section introduces the SUAP mechanism to determine the most suitable number and location of UAVasBSs, improving the mobile network operations during flash crowd and emergency situations. We model UAVasBS placement as an optimization problem based on the network statistics of BS and mobile user requirements. In this way, it is possible to determine the most suitable number and location of UAVasBSs to provide network connectivity and QoS support. More details are provided in the next subsections.

3.1. Network model and architecture

Flash crowd events and emergency events stress network resources beyond the standard-setting since such events lead to high traffic demand resulting from a high concentration of users per unit area or a large number of user connection requests [4]. Specifically, natural or human-made disasters, *e.g.*, earthquakes, floods, or human-made disasters, *e.g.*, terrorist attacks, industrial accidents, transportation failures, etc., could compromise correct BS behaviors caused by damaging antennas and other equipment or even disrupt energy supply. In addition, a social event may incur gathering of people, *e.g.*, concerts, sports events, parade and gathering in 5G networks, which suddenly increase the number of connected users [3]. In this scenario, UAVasBSs could fly to specific locations to provide connectivity and QoS to mobile users on the ground. Fig. 1 depicts a set of UAVasBSs deployed to provide temporal mobile access as soon as the standard communication infrastructures are unavailable.

We consider a scenario composed of a set of mobile users $U = \{u_1, u_2, \dots, u_o\}$ with an individual identity ($k \in [1, o]$), and a set of cells $B = \{b_1, b_2, \dots, b_m\}$ with an individual identity ($j \in [1, m]$) deployed in fixed known locations (x_j, y_j). We consider a core network with high capacity fibers connected to avoid congestion on backhaul links [36]. A set of UAVasBSs $V = \{v_1, v_2, \dots, v_n\}$ with an individual identity ($i \in [1, n]$) could be deployed to offload cellular traffic from a existing mobile network infrastructure based on a UAVasBS placement mechanism, such as SUAP. Each UAVasBS v_i and mobile user u_k are aware of their location within the space of interest at a given timestamp t employing a positioning system, *e.g.*, GPS or Galileo. For instance, the location of each UAVasBS v_i, $L_{i,t}$ is defined as a 4-tuple of geographical coordinates(x_i, y_i, z_i, t) in a 3D space, *i.e.*, Cartesian coordinates, and altitude over the ground since UAVasBSs fly in a 3D space.

Each UAVasBS (v_i) flies with a given speed s_i ranging between a minimum (*e.g.*, s_{min}) and a maximum (*e.g.*, s_{max}) speed limit towards a given trajectory ($traj_i$). The trajectory $traj_i$ is defined as an ordered sequence of locations that a given UAVasBS v_i flies between two pairs of location, which is denoted as $traj_i = \{L_{i,0}, L_{i,1}, \dots, L_{i,t}\}$, indicating that a given UAVasBS v_i arrives at location $L_{i,t}$ at timestamp t. Finally, each UAVasBS v_i has a battery with initial energy ($E_{v_i}(0)$), and it spends energy to transmit a packet, to receive a packet, and to fly with a given speed s_i, as introduced by Cumino et al. [37]. It should be highlighted that UAVasBS movements require much more energy than for packet transmissions. Finally, each UAVasBS v_i is able to compute the remaining energy at a given timestamp t as the ratio between the initial energy $E_{v_i}(0)$ over the current energy level $E_{v_i}(t)$.

We considered an SDN architecture applied to UAVNet (SD-UAVNet), such as introduced by Zhao et al. [38]. SD-UAVNet provides flexibility to network management by separating the network infrastructure into distinct planes, where each plane can be programmed to meet particular application requirements. Specifically, SD-UAVNet is divided into three planes, namely, application, control, and forwarding planes. The application plane supports different applications, while the forwarding plane is composed of (re)configurable nodes connected to a centralized controller. Finally, the control plane relies on a centralized controller node (CN) responsible for all control functions to manage the mission-specific decisions based on global network context information. For instance, CN is responsible for dynamically determine the most suitable number and locations of UAVasBSs to obtain suitable network connectivity and performance, which can be performed by SUAP. CN can be deployed in a ground station or the air, and it is aware of the global network conditions to optimize the network operations.

3.2. Problem formulation

The optimal UAVasBSs placement consists of determining the number and locations of UAVasBSs to be deployed over the area of interest to guarantee good network connectivity and QoS support in flash crowd events and emergency events. The UAVasBS location depends on the number of users, application QoS requirements, number of available UAVs, and the cellular network state within the area. In this sense, a 3D position $L_{i,t}$ must be calculated for each UAVasBS v_i such that most mobile users U could obtain a desired level of QoS. For instance, QoS can be represented by multiple properties, such as latency, jitters, or success rate. Hence, our objective is to provide an optimal UAVasBS placement solution such that the mobile user u_k is connected to a UAV-assisted mobile network with high packet transmission rates.

Table 1
Summary of analyzed UAVasBS placement mechanisms to Improve the Mobile Network Operations.

Ref.	Used approach	Drawback
[13]	Evolutionary deployment divided into centralized and distributed adaptation phase.	Optimization of the area coverage in disaster scenarios without considering networking needs.
[14]	A cost-based neural model is used to find where UAVs can be placed to cope with high traffic demands in macro cellular networks.	The model is not applied in case of network recovery after disasters, but only consists in detecting areas with higher demands within which placing a drone.
[15,17]	It optimizes multiple UAVasBS placement and channel allocation for increased data rate by using a heuristic algorithm.	The approach does not consider BS failure due to a disaster, but only aims at supporting user traffic with UAVasBS added to the existing cellular network.
[16]	The solution groups unserved users in clusters where to place UAVasBS to increase network coverage and QoS.	UAVasBS deployment is not considered for network recovery after a disaster.
[18]	It optimizes user connectivity with the minimum deployed drones with a low complexity heuristic.	UAVasBS deployment is not considered for network recovery after a disaster.
[19]	UAVasBS deployment is made as a mixed integer linear program to optimize traffic offloading and network recovery.	This work copes with network recovery, and uses a greedy approach which does not guarantee optimal solutions.
[20]	An optimal placement of UAVasBSs is found to cover the maximum number of users with the lowest transmit power.	UAVasBS deployment is not considered for network recovery after a disaster.
[21]	The optimal user partitions with which associating UAVasBS is approached with optimal transport theory.	UAVasBS deployment is not considered for network recovery after a disaster.
[22]	The clustered deployment of UAVasBS around a destroyed BS is resolved with stochastic geometry.	Basically, user coverage is considered, neglecting network QoS, and BS failure dynamics due to disasters are not considered.
[23]	UAVasBS deployment is studied for traffic offloading.	Network recovery after a disaster is not considered in the problem formulation.
[24,25]	Clustering techniques are used to optimally place UAVasBS to complement the capacity of an existing network.	UAVasBS deployment is not considered for network recovery after a disaster.
[26]	PSO is exploited for UAV deployment to optimize sensing capabilities.	Networking demands after a disaster are not considered.
[27]	UAVasBS deployment is optimized with a heuristic algorithm so as to serve all the users not uniformly distributed in an area.	UAVasBS deployment is not considered for network recovery after a disaster.
[28–30,33]	GA is used to maximize wireless coverage by placing UAVasBS.	UAVasBS deployment is not considered for network recovery after a disaster.
[31,32]	UAV are used to provide emergency communications after a disaster.	The works do not consider the use of UAVs as BS and their exploitation to restore network QoS in case of failed BS.
[35]	Game theory is used to decentralize UAV control and optimize their placement to serve as UAVasBS.	UAVasBS deployment is not considered for network recovery after a disaster.

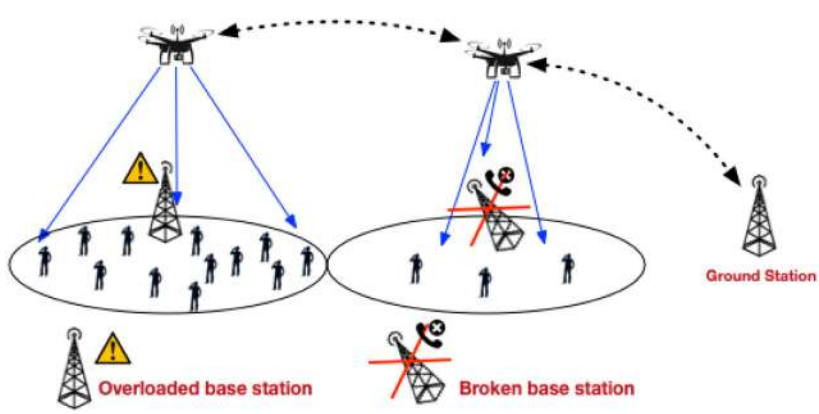


Fig. 1. UAVasBS deployed in flash crowd and emergency situations to provide temporary mobile network access.

A given mobile user u_k experiences a nominal non-zero loss rate. In this sense, the packet loss rate can achieve a value ranging from 0 (*i.e.*, all sent messages are delivered to their intended destinations, which is a sporadic case in wireless networks) to 1 (*i.e.*, none of the sent messages can reach their destinations, due to congestion phenomena or hardware damages in a given BS b_j). We denote $\Lambda_{k,j}$ as the nominal packet loss rate of the kth mobile user connected to the jth BS D, and Δ_j as the additional path loss caused by a faulty behavior of a BS b_j. This faulty behavior is modeled as a random value within a certain interval (*e.g.*, from 0 to 0.5). The upper bound has to be lower than 1, as soon as the BS is completely unavailable. Hence, we compute the experienced packet loss rate of a given BS $\Lambda^D_{k,j}$ based on Eq. (1).

$$\Lambda^D_{k,j} = \begin{cases} \Lambda_{k,j} + \Delta_j & \text{if BS } b_j \text{ is reachable but has issues} \\ 1 & \text{if BS } b_j \text{ is no more reachable} \end{cases} \tag{1}$$

The damage of a given BS b_j can be modeled using a Poisson point process with a thinning operation [22]. In this sense, the BS b_j is tagged as damaged with a given probability π_D, which is greater than a predefined threshold τ and depends on the number of damaged BS to be introduced in the experiments. The additional path loss due to a faulty behavior is denoted as Δ_j Therefore, we model the packet loss rate $\Lambda^D_{k,j}(\pi_D)$ of a faulty BS by restructuring Eq. (1) to include such probabilities, as shown in Eq. (2).

$$\Lambda^D_{k,j}(\pi_D) = \begin{cases} \Lambda_{k,j} + (0.5 \cdot \pi_F) & \pi_D \leq \tau \\ 1 & \pi_D > \tau \end{cases} \tag{2}$$

The signals emitted by the UAVasBS v_i or the mobile user u_k can be reached along the LoS path with probability $P_{LoS}(v_i, u_k)$ and/or the

non line-of-sight (NLoS) path with probability (1-$P_{LoS}(v_i, u_k)$), as a consequence of refraction or reflection phenomena. In this sense, the signal path loss $\Lambda^{v_i|u_k}$ of a given mobile user u_k to the reachable UAVasBS v_i (from which the packet loss rate can be inferred) is modeled by using two contributions, one along the LoS path namely $L_{LoS}(v_i, u_k)$, and one along the NLoS path $L_{NLoS}(v_i, u_k)$, as shown in Eq. (3).

$$\Lambda^{v_i|u_k} = P_{LoS}(v_i, u_k) \cdot L_{LoS}(v_i, u_k) + (1 - P_{LoS}(v_i, u_k)) \cdot L_{NLoS}(v_i, u_k) \quad (3)$$

The probability that a connection among UAVasBS v_i and mobile user u_k is established along the LoS path ($P_{LoS}(v_i, u_k)$) is formulated based on Alzenad et al. [20], as shown in Eq. (4). We denote a and b as two constant variables indicating the Radio Frequency (RF) pollution and obstacles in the environment, respectively, where we consider these values from Al-Hourani et al. [39]. We denote $v_i(3)$ as third component of UAVasBS position (*i.e.*, its altitude), and $d(v_i, u_k)$ as the Euclidean distance between UAVasBS v_i and mobile user u_k.

$$P_{LoS}(v_i, u_k) = \frac{1}{1 + a \cdot exp(-b(\frac{180}{\pi} tan^{-1}(\frac{v_i(3)}{d(v_i,u_k)}) - a))} \quad (4)$$

We define the loss rate along the LoS or NLoS path ($L_{LoS}(v_i, u_k)$ and $L_{NLoS}(v_i, u_k)$, respectively), as shown in Eq. (5), based on Alzenad et al. [20]. It is computed based on Euclidean distance $d(v_i, u_k)$ between UAVasBS v_i and mobile user u_k, carrier frequency f_c, the speed of light c in a vacuum, as well as two textcolorblueconstants related to loss rates for LoS and NLoS conditions, *i.e.*, η_{LoS} and η_{LoS}, respectively. We consider the values of these constants based on Al-Hourani et al. [39]. It is not possible to precisely estimate the path loss in NLoS conditions as computing the possible obstacles beforehand is not possible. For this reason, we preferred to have a random model represented in Eq. (5), by using a variation of the classic Friis transmission equation used in telecommunications engineering.

$$\begin{aligned} L_{LoS}(v_i, u_k) &= 20log(\frac{4\pi f_c d(v_i,u_k)}{c}) + \eta_{LoS} \\ L_{NLoS}(v_i, u_k) &= 20log(\frac{4\pi f_c d(v_i,u_k)}{c}) + \eta_{NLoS} \end{aligned} \quad (5)$$

Afterwards, we need to convert the path loss rate from decibel to percentage, as shown in Eq. (6)

$$\begin{aligned} L_{LoS}(v_i, u_k) &= 10^{(\frac{L_{LoS}(v_i,u_k)}{20})} \cdot 100 \\ L_{NLoS}(v_i, u_k) &= 10^{(\frac{L_{NLoS}(v_i,u_k)}{20})} \cdot 100 \end{aligned} \quad (6)$$

The kth mobile device could select to be connected to BS b_j or UAVasBS v_i according to the computed path loss rates with one of them. In this way, the mobile user u_k chooses the lowest path loss rates between the loss ratio of BS b_j $\Lambda^D_{j,k}$ and a UAVasBS v_i $\Lambda^{v_i|u_k}$.

$$\Lambda_k = min(\bigcup_{b \in B} \Lambda^D_{j,k}, \bigcup_{v \in \mathbb{V}} \Lambda^{v_i|u_k}) \quad (7)$$

Therefore, the overall UAVasBS placement problem can be determined as the minimization of the path loss rates for all relevant mobile user u_k by selecting the most useful vectors Λ_k, and the number of deployed UAVasBS over the available ones. These can be expressed as the number of non zero locations in the Λ_k vector computed by a counting function named as $c()$, under the constraints that each path loss will be below a given threshold Λ and only one UAVasBS can be placed in a given position, as shown in Eq. (8). Hence, the objective is to minimize the set of path losses and the number of UAVasBSs, whose maximum number is defined beforehand as n, where only one UAVasBS can be deployed in a given location.

$$\min_{\bar{v}} \bigcup_{k \in \mathbb{K}} \Lambda_k, c(\bar{v}) \quad (8)$$

s.t.

$$\Lambda_k \geq \Lambda \quad \forall k \in \mathbb{K} \quad (9)$$

$$c(\bar{v}) \leq n \quad (10)$$

3.3. UAVasBS deployment: A GA solution

We assume fixed altitude for each UAVasBS v_i, and thus the position to be selected is only the Cartesian 2D coordinates of each UAVasBS location Li, t. This issue reduces the complexity of the deployment task running at the controller CN, which has limited battery and computing resources. The UAVasBS deployment problem can be solved by a GA approach [40], which searches for optimal solutions by simulating natural evolutionary processes, such as mutation, crossover, and selection [41]. GA has the advantages to be simple, converging rapidly, and providing a solution with good quality, which fits well to run on a controller CN with limited resources. In a GA, each candidate solution (*i.e.*, number of UAVasBSs and their locations) has a set of properties (its chromosomes) that can be mutated and altered to obtain new solutions.

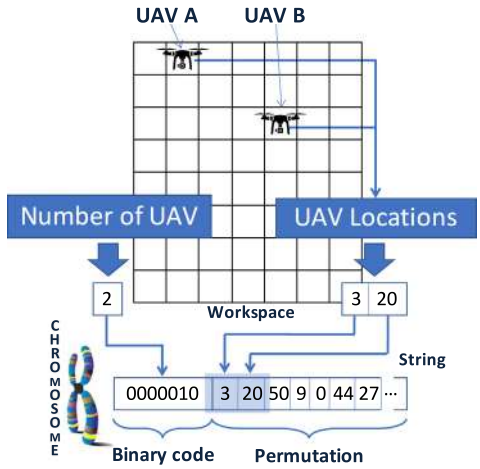
In each mutation, the chromosomes are evaluated based on an objective function to find the optimal solutions. A chromosome is characterized by two parts, namely, Binary code and Permutation, as depicted in Fig. 2(a). As we have two sets of decision variables within the optimization (*i.e.*, the number of UAVasBSs and their solution within an area of interest), the proposed GA has chromosomes with a binary part (representing the number of UAVasBSs to be deployed) and the permutation part (representing the UAVasBSs locations). For instance, a binary number of 2 means that only the first two identifiers in the permutation part are assumed as the locations of the two UAVasBSs to be placed, as shown in Fig. 2(a). The fitness of chromosomes is computed by considering both parts to return solutions optimizing the defined objective function defined over these decision variables.

Fig. 2(b) depicts the schematic execution of GA to define the number and location of UAVasBS, which is composed of 5 steps:

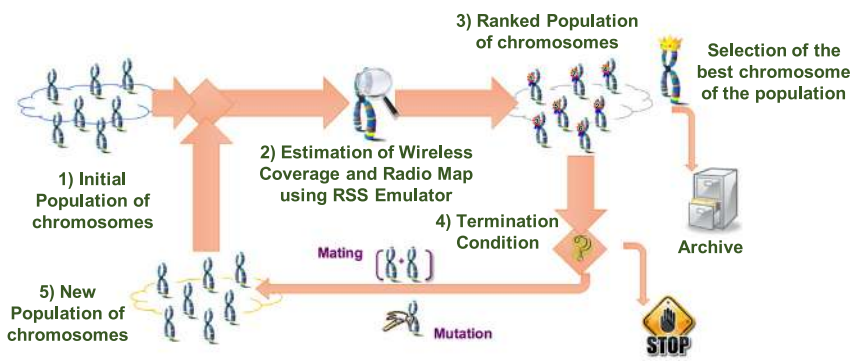
- Step 1: Initial population of chromosomes;
- Step 2: Wireless coverage and radio map estimation;
- Step 3: Ranked population of chromosomes;
- Step 4: Checking the termination condition;
- Step 5: New population of chromosomes;

GA starts by selecting a random set of admissible chromosomes, indicated as Step 1, where the chromosomes' binary and permutation parts are randomly determined. Later on, in Step 2, each chromosome's fitness value is determined by using the previous equations. It is possible that certain chromosomes are not admissible. In this case, there are two possible ways to handle inadmissible chromosomes [42]: these chromosomes have associated the worst possible fitness value so as to be excluded from the selection process (*i.e.*, $+\infty$ in case of a minimization problem or $-\infty$ for a maximization one), or a chromosome repairing operator can be defined to increase the number of admissible UAVasBS placements in each population by converting inadmissible chromosomes to admissible ones. We have decided to use the first approach as it is simpler to be implemented. Within the context of our problem formalized in Eq. (8), the admissibility of a chromosome depends on the case if the sum of the binary part of all the chromosomes does not have to exceed the maximum number of UAVasBSs defined a textcolorbluepriori, denoted as n, so as to cope with the constraints in Eq. (10). Therefore, chromosomes whose binary part exceed n have assigned $+\infty$ as fitness. Such value is also assigned to those chromosomes whose permutation parts share even a single number in their first positions. Specifically, if within the population there is a couple of chromosomes matching such last rule, the one with higher value in the binary part gets $+\infty$ as fitness, while the other one undergoes the assessment of its fitness. This is needed to have diverse placements under consideration within the same population and prevent premature convergence [43,44].

The fitness value represents the degree of goodness of the given solution in exhibiting the optimal value for the objectives to be minimized expressed in Eq. (8), and comparing the fitness of two solutions indicates the dominance of a solution concerning another one as stated



(a)



(b)

Fig. 2. (a) Placement representation in a chromosome, and (b) GA schematic execution flow.

in the literature. We define the fitness value as a tuple, where the first part is the computed averaged path loss $\Lambda^{v_i|u_k}$ based on Eq. (3) and using the permutation part of the chromosome, and the second part is the number of UAVasBSs within the solution represented by the binary part of the chromosome. After assigning a fitness value for all chromosomes, at step 3, it is possible to find those with the best value or dominate all the other ones, *i.e.*, the lowest value of average path loss and number of UAVasBS.

If a given termination condition is not met, whose verification is conducted in Step 4, the sets of chromosomes, or population, are used to obtain new solutions (Step 5). This is achieved by applying the mating processes (*i.e.*, a percentage of current solutions are mated by obtaining two new chromosomes by recombining two of the existing ones) and the mutation process (*i.e.*, a new chromosome is made by arbitrarily changing one value in one of a subset from the existing one) according to the following operators:

- *One-point crossover* for the binary part: A single crossover point, namely π, is selected. All binary digits beyond that point in both chromosomes are swapped between the two parent chromosomes;
- *OX cross-over* for the permutation part: Two cross-over points, namely π_1 and π_2, are randomly selected. Everything between the two points is swapped between the parent chromosomes, rendering two-child chromosomes;
- *Bit-flip* for the binary part: a point of mutation, namely μ, is randomly selected, and the binary digit in that place is changed to the opposite value, according to a given probability;
- *Reciprocal exchange* for the permutation part: two points of mutation, namely μ_1 and μ_2, are randomly selected. The order of everything between the two points is inverted, according to a given probability.

GA iterates until a termination condition is reached, such as the maximum number of iterations or the number of updates to the non-dominated archive (Step 4). The non-dominated chromosomes' archive content is assumed as the solutions found for the given problem, and one of them is assumed as the UAVasBS deployment. The GA runs on the CN using the network context and application requirements to keep calculating the optimized locations of UAVasBSs.

The analytical study of the convergence probability and speed for a GA has been widely studied within the current literature, as described in Gutjahr [45]. Our proposed optimization approach exploits time-invariant mating, crossover, and selection operators, which is known to converge if it devises an elitist strategy by always keeping the solution with the highest fitness value. Our algorithm visits the globally optimal set within a finite number of iterations by starting from any initial population. In our approach, archiving the best solutions found at each iteration and removing those dominated by the novel inserted solutions allows achieving such an elitist strategy. Moreover, applying the operators on the worst solutions allows the novel population to have the global optimal set elements. The use of two different crossover/mutation operators for the two parts of the chromosome guarantees diversity within the population, as mating among individuals in a homogeneous population may imply the genetic

Table 2
Main simulation parameters.

Parameters	Value
Simulation duration	100 s
Simulation area	200 m × 200 m
Number of UEs	55
Number of UAVs	[5…16]
Number of BS	4
Mobile user speed	[1…2] m/s
UAVasBS speed	[1…5] m/s
Base station failure time	10 s
Coverage ranges of BS, UAVasBS	55 m, 20 m

algorithm to be trapped in a local minimum [46,47]. The effective convergence of the approach depends on the tuning of the parameters, *i.e.*, crossover/mutation probabilities, and termination criterion. Several runs with varying values for such parameters have been done to look for the most suitable choice.

4. Evaluation

This section introduces the simulation evaluation of UAVasBS deployment in a flash crowd and emergency situations, including the methodology, scenarios, metrics, and obtained results. We compare the performance of SUAP with existing UAVasBS deployment approaches. Our analysis explores the average number of connected users, packet delivery ratio, delay, remaining energy, and GA cost evolution.

4.1. Simulation description

We implemented a UAV-assisted mobile network by using an OMNeT++ framework [48] in a simulation scenario composed of 4 BSs and 55 mobile users over an area of 200 m × 200 m with a simulation time of 100 s (s). Each mobile user moves following the Random Waypoint mobility model with speed ranging from 1 to 2 m/s and considering pause time since this mobility model enables mobile users to stay in a location for a while. We generated the mobility model by the BonnMotion mobility generator [49]. We assume that only one BS is completely damaged at each time following a Poisson point process at a simulation time of 10 s, and such BS is unfeasible to provide services to mobile users within its coverage. We consider a scenario with 5 to 16 available UAVasBS to evaluate the impact of different numbers of UAVasBS on the performance of mobile network operations. The deployed UAVasBSs fly following a pre-programmed flight plan defined by the controller node CN with speeds ranging from 1 to 5 m/s.

We consider WiFi for the communication between UAVasBS and mobile users with Lognormal shadowing path loss model, also known as Log-Distant Path Loss Model [50]. We set the simulation parameters from the literature to allow wireless channel temporal variations, link asymmetry, and irregular radio ranges, as expected in a real scenario. We consider a video streaming application, where mobile users download a video with moderate complexity (the Highway video sequence) levels in terms of motion and spatial complexity, which is available in a well-known video-trace repository.[2] The video has a duration of 66 s, and it is encoded with H.264 and a bit-rate of 210 kbps. We conducted 33 simulation runs with different randomly generated seeds, and the results show the values with a confidence interval of 95%. Table 2 summarizes the main simulation parameters.

We conducted simulation experiments with the following configurations. The *without UAVasBS* approach means a standard network solution without UAV-BS deployment to assist the network, which serves as a benchmark performance. We implemented four UAVasBS deployment approaches, namely, $Circular$, $Random$, PSO, and SUAP. The $Random$ approach randomly deploys a set of UAVasBS over the damaged BS. The $Circular$ approach deploys UAVasBS flying in a circle along with the damaged BS, such as introduced by Lyu et al. [23]. The PSO approach optimizes the deployment of UAVasBSs based on a particle swarm optimization algorithm, such as introduced by Na and Yoo [26], Finally, SUAP enhanced network operation by deploying the UAVasBSs as introduced in Section 3.

[2] http://media.xiph.org/video/derf/.

Table 3
SUAP relevant parameters.

Parameters	Value
Number of generations	30
Population size	20
Initial number of UAVs	7
Mutation rate	7.5%
Elitism	30%

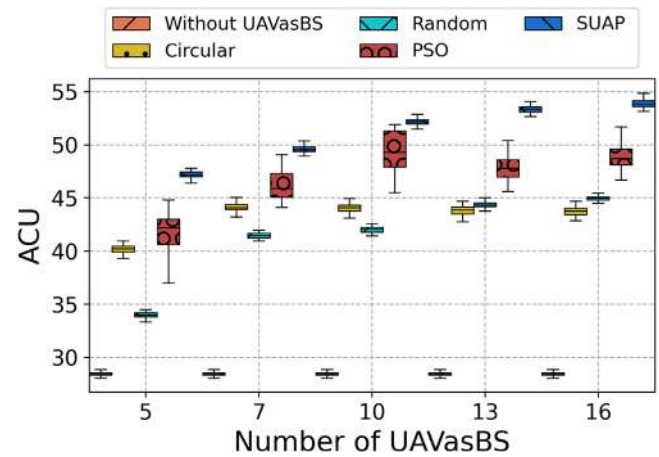


Fig. 3. ACU with different UAVasBS numbers and deployment approaches.

We measured the performance of SUAP by evaluating the individual's population through four different costs, varying between 1 and 10, where 1 is the best and 10 is the worst cost value. Table 3 shows the main SUAP parameters. Besides, there are no general guidelines or standard deployment patterns that we can use for evaluating the SUAP for UAVasBS deployment. In this sense, it is possible to compute the Pareto Front solution of our optimization problem and determine the distance of the solution returned by our meta-heuristics, where the GA converges to the global optimum by returning points belonging to the Pareto Front [51]. Hence, we measure the network quality gains as an effect of UAVasBS deployment, which means that SUAP can meet its goal as soon as the mobile user establishes a reliable connection with an available UAVasBS, improving the connectivity and the QoS level.

We evaluate different solutions by collecting the ACU, PDR, delay, remaining energy of UAVasBS, and GA evolution rate. Specifically, ACU represents the number of mobile users in the range of a working infrastructure, either a working BS or a UAVasBS. The PDR represents the ratio between the number of successfully received packets over the number of transmitted packets. Delay represents how long it takes for a packet to travel from the mobile users to a working BS or UAVasBS, which considers propagation and waiting time of the packet. The number of connected users represents how many users are being served by the entire working network, including ground BSs and UAVasBS. Remaining energy means the ratio between the energy consumption to fly and to send/receive packets over the initial energy of a given UAVasBS. Finally, the GA evolution rate means how quickly the GA algorithm converges.

4.2. Simulation results

Fig. 3 shows the ACU according to the UAVasBS deployment approaches, and the number of UAVasBS available for each approach.

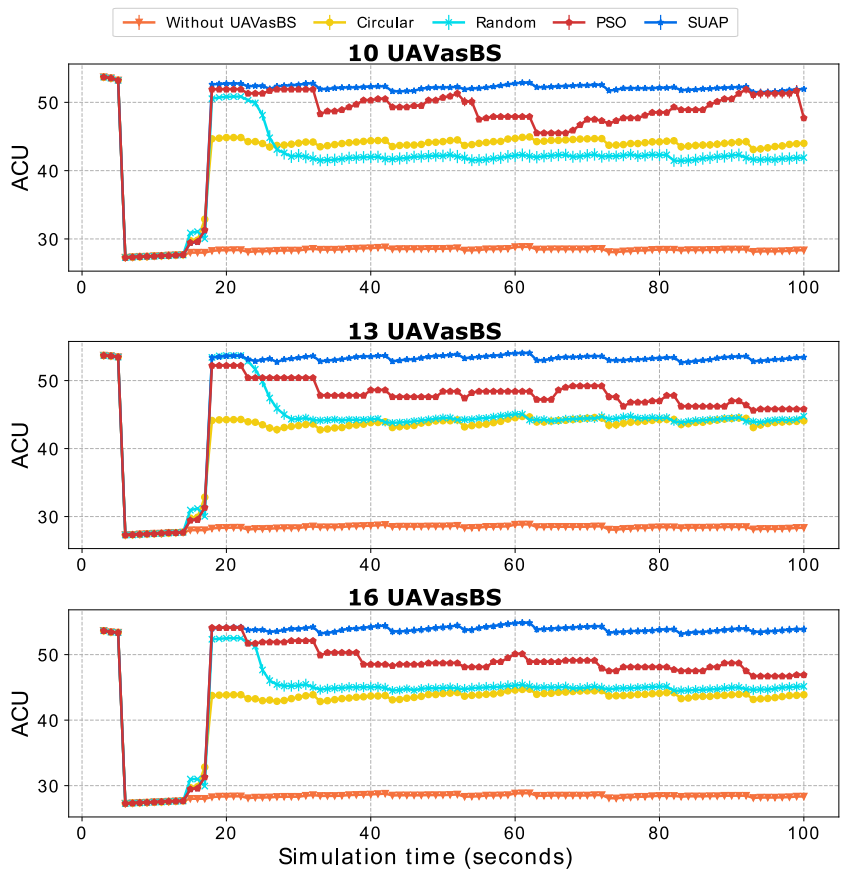


Fig. 4. ACU over time with UAVasBS deployment approaches.

By analyzing the results, we can observe that a standard network without any UAVasBS assistance can only provide network connectivity to 52.7% of the users (29 out of 55 users) after BS failures. In contrast, SUAP provides a higher ACU with short variation regardless of the number of available UAVasBS, where it provides a mobile user coverage ratio up to nearly 94% to 96% (52 to 53 out of 55 users) for 10 available UAVasBS. The reason it that SUAP determines the most suitable number and location of UAVasBSs based on the GA algorithm that considers network statistics from BS and mobile users in a flash crowd and emergency situations. Beyond that, SUAP also considers the position of the ground users, mobile user channel quality, and the positions of other UAVasBSs to evaluate the solutions. In other words, the deployed UAVasBS provides network connectivity to mobile users that are disconnected from the standard network and were in the range of the damaged BS. Similarly, *PSO* provides reasonable ACU results with a higher variation for each available UAVasBS. For instance, *PSO* provides ACU ranging from 80% to 89% of the users (44 to 49 out of 55 users) for 10 available UAVasBS. This means that all results of SUAP is within the 25% best results of *PSO* for 10 available UAVasBS. Besides, *Circular* and *Random* approaches cover between 72.7% and 74.5% (40 and 41 out of 55 users) and between 58.1% and 76.3% (32 and 42 out of 55 users) of mobile users, respectively. Despite providing UAVasBSs to support the mobile users, both methods do not rely on any other parameter other than the failed BS location, which is not enough to provide mobile users connectivity in a flash crowd and emergency situations.

Fig. 4 shows the number of users connected over time considering 10, 13, and 16 available UAVasBSs deployed with different UAVasBS placement approaches. This result is important to analyze how the approaches restore the number of connected users after a BS failure. It is important to highlight that the number of connected users on the network varies over time because users are continuously moving in the scenario, which leads to disconnection from a given ground BS as users move away. By analyzing the results, we can observe a short ACU variation over the time achieved by SUAP compared to *PSO* considering 10, 13, and 16 available UAVasBSs. The stability provided by SUAP makes it a better choice for the current scenario, not only because it is possible to attend more mobile user than the other approaches but also because the variation of connected mobile user is lower when employing SUAP. On the other hand, frequent disconnections can lead to poorer service provisioning. Specifically, after a BS failure at time 10 s, UAVasBS deployment increases the number of connected users once now a flying BS can reach the users of the damaged ground BS. However, the placement approach and the number of UAVasBSs can substantially impact the number of connected users. As the *Random* approach only considers the damaged ground BS area to deploy the UAVasBSs, it is not possible to consistently increase the number of connected users as they continuously move to different positions. The *Circular* approach tries to reach mobile users by applying a circular movement around the damaged BS location. Nevertheless, this approach does not significantly increase the number of connected users, as the users do not necessarily move only around the damaged BS. Then, differently, the UAVasBS placement was modeled as an optimization problem to determine the number and location of the UAVasBS to obtain required air network connectivity and performance, as in SUAP and *PSO*. These last two approaches also consider the user locations and update their status frequently to be as adaptive as possible. Specifically, SUAP provides mobile user coverage ratio almost constant nearly 90% after the first UAVasBS deployment for 13 available UAVasBSs. *PSO* provides in the best case 95% of user coverage, however, most of the time it provides nearly 83% of user coverage for 13 available UAVasBSs.

Fig. 5 shows the average PDR according to the deployment approach, and the number of UAVasBS available for each approach. It is possible to see the impact of varying the numbers of UAVasBSs, mainly

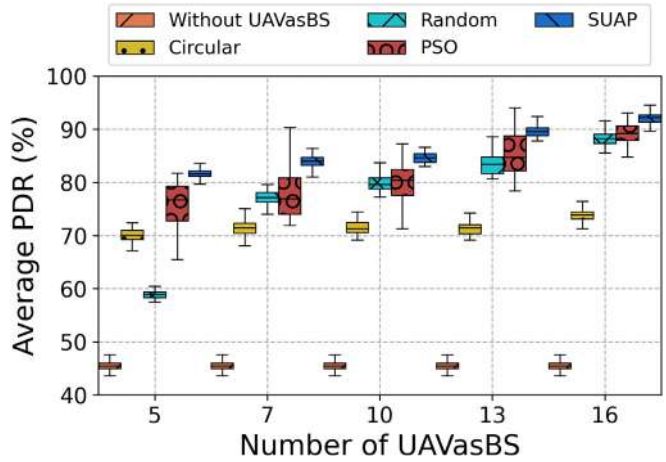


Fig. 5. Average PDR with different UAVasBS numbers and deployment approaches.

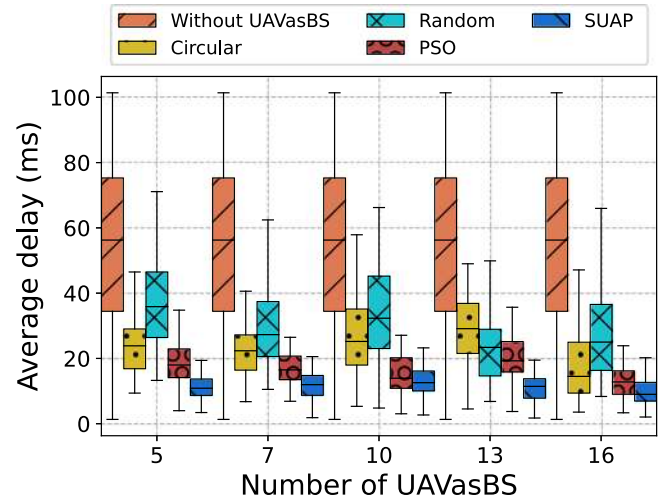


Fig. 7. Average delay with different UAVasBS numbers and deployment approaches.

when using the *Random* approach. It is expected that, when more UAVasBSs are available, the chance that a mobile user will be covered by a UAVasBS and transmit its packets successfully is higher. This also happens to SUAP and *PSO*. However, at a certain point, increasing the number of UAVasBSs does not improve the PDR performance anymore due to the optimized deployment. Besides, increasing the UAVasBSs number also increases the service cost and creates transmission interference. Moreover, because the *Circular* approach uses a single UAVasBS to get the users connected, the impact of the number of available UAVasBSs is not significant. Similar to ACU results, we can observe that SUAP provides higher PDR results with short variation, regardless of the number of available UAVasBS. For instance, all PDR results of SUAP is within the 25% best results of *PSO* for 10 available UAVasBS, which also happens to numbers of available UAVasBSs for each approach.

Fig. 6 presents PDR results over time considering 10, 13, and 16 available UAVasBSs deployed with different UAVasBS placement approaches. This result helps to see how the UAVasBS deployment restores the PDR after a BS failure happens. As it can be seen, the PDR drops significantly when a BS failure happens, and then it starts to recover in 6 – 7 s after the BS failure, which is the time needed for a set of UAVasBS to reach the defined locations. Each time our proposal runs, the decision-making process involves identifying when a BS stops working and evaluating the number of disconnected mobile

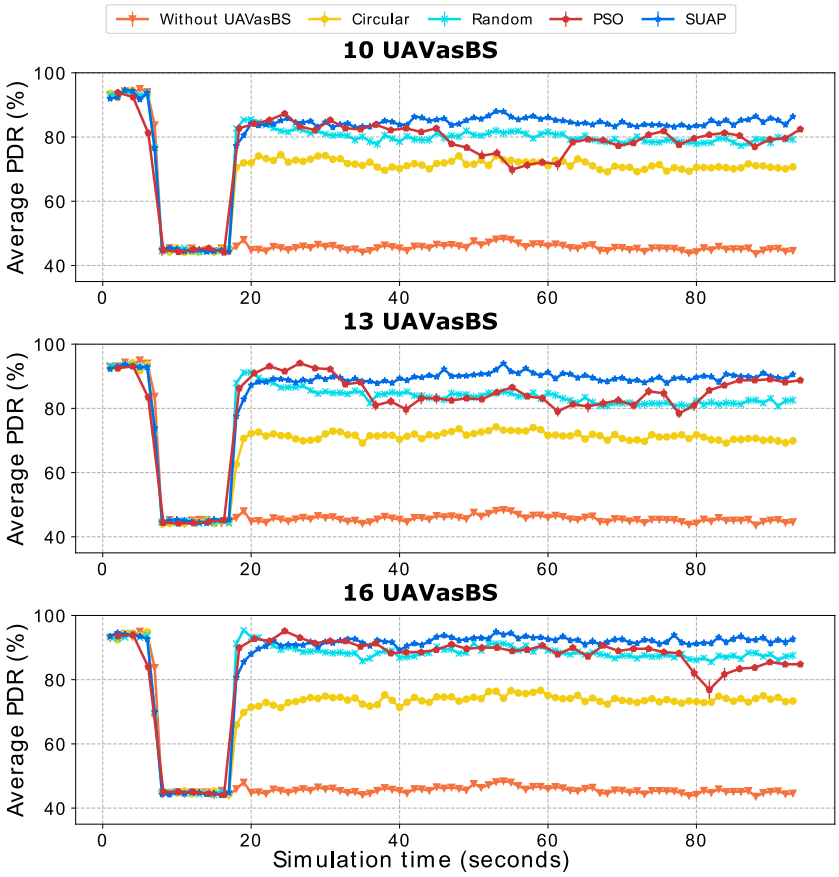


Fig. 6. Average PDR over time with UAVasBS deployment approaches.

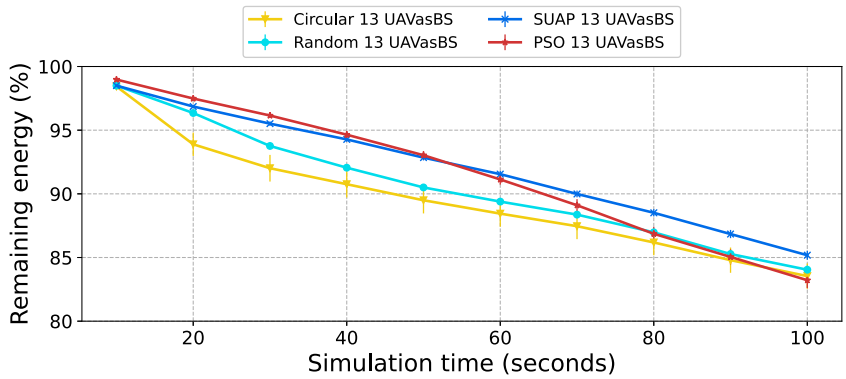


Fig. 8. Remaining energy of UAVasBS over time with UAVasBS deployment approaches.

users. Based on such information, SUAP determines the most suitable number and locations of UAVasBSs. *PSO* calculates optimized UAVasBSs' positions based on a set of available UAVasBSs. The *Random* approach also updates its solution accordingly, but this deployment does not consider users' locations, and, therefore, the PDR remains between 70% and 85%. The PDR in the *Circular* approach remains at approximately 70%. The *Random* approach performs better than the *Circular* one. This is because the *Circular* approach tries to cover all the damaged BS areas with a circular movement, which makes it cover much fewer users than the *Random* one. Moreover, we can see that the *PSO* performance varies over the simulation time, and it could reach a reasonable performance in the end. The SUAP approach delivers a better and almost constant PDR performance than the others approaches, For instance, it provides a PDR of 90% – 95% over time for 16 available UAVasBSs. It is possible to see once again that the variation of connected mobile users is inversely proportional to the network performance in terms of PDR. In other words, the higher the variation of connected mobile user, the lower the network performance in terms of PDR. SUAP achieves a better performance once it considers each user's current locations and the average distance between the set of UAVasBSs and the users, which makes it more adaptive than other solutions. As the one with the worst performance, when no additional UAVasBSs are deployed to provide network connectivity under BS failure scenarios, the PDR drops to approximately 41% and keeps at this low level over time.

Fig. 7 shows the delay performance with different UAVasBS placement approaches and the number of deployed UAVasBSs. We consider the delay values experienced by users with network connectivity provided by the working ground BSs that are not damaged or the deployed UAVasBSs. We can see that, even with the support of UAVasBS, the delay varies from one solution to another. However, the variation range is smaller when using SUAP approach. When there is no UAVasBS deployed, the highest delay is observed since users in the affected area can only be connected to a distant ground working BSs. *Random* and *Circular* can provide some improvements. However, as these solutions are not aware of the user positions, the delay performance does not reach a reasonable rate for some users.

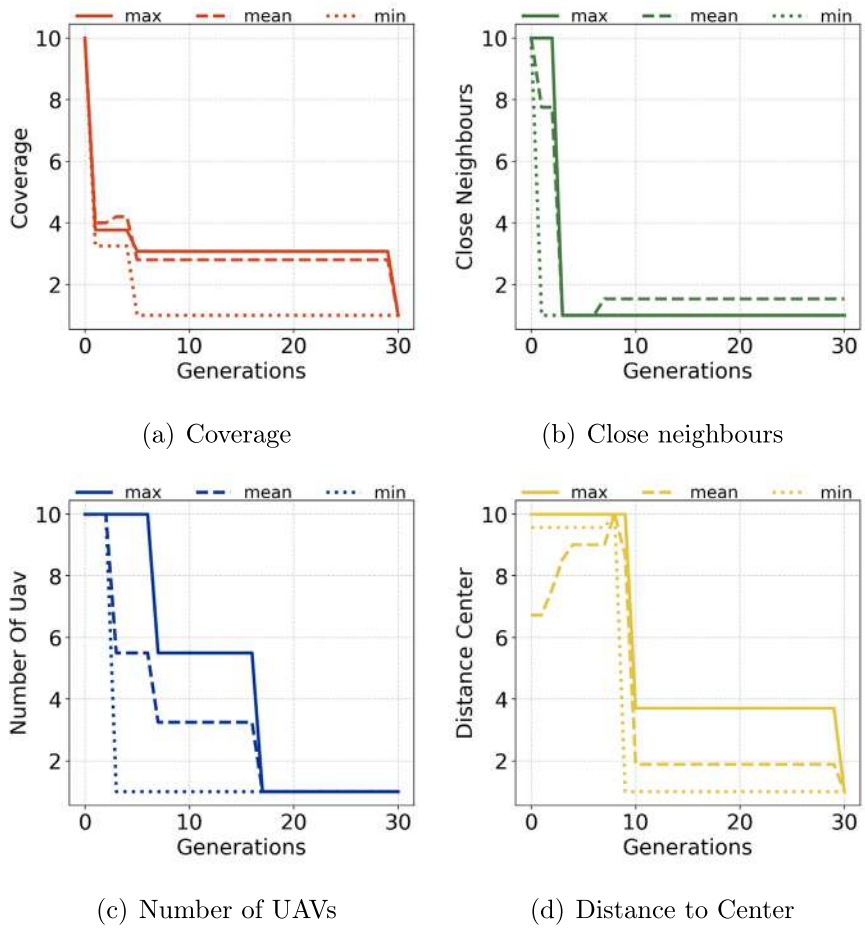
Fig. 8 shows the average remaining energy ratio of the UAVasBSs over time while using different UAVasBS deployment strategies. As described by Zhao et al. [38] and Cumino et al. [37], the remaining energy of each UAV decreases according to the amount of movement and the number of transmitted packets. The UAV movement is the most relevant energy consumption part. Moreover, when following the *Circular* mode, the energy consumption becomes very significant since UAVasBS starts to make constant circular movements to cover users, while *Random*, *PSO* and SUAP remain static. The subtle improvement of *PSO* and SUAP compared to *Random* is because, with *Random*, UAVasBSs tend to spend more energy to re-transmit packets that are lost due to the long distances between UAVasBS and users, while in *PSO* and SUAP, this packet loss is minimized as UAVasBS tends to stay closer to users.

To further analyze the proposed GA-based solution's convergence rate, we present the GA cost evolution results. As it can be seen in Fig. 9, we assumed index values varying from 1 to 10 for each of the costs, these being Coverage, Proximity between neighbors, Number of UAVasBSs, and Distance concerning the central point of the area to be served. The Coverage index, shown in Fig. 9(a), represents how many UEs are sufficiently close to the set of deployed UAVasBS. The close neighbor index, as shown in Fig. 9(b), represents how close the UAVasBS are from each other. This index aims to evaluate how the distribution of UAVasBSs by considering that UAVasBSs concentration at a certain point can weaken the connectivity to UEs that may be moving at very distant points. The number of UAVs index, as shown in Fig. 9(c), is proportional to the number of UAVs being allocated to a given area. Finally, the Distance to Center Index, shown in Fig. 9(d), represents how close to the area's central midpoint the group of UAVasBSs are. The closer to the midpoint, the higher are the chances to cover most of the UEs affected by the BS failure. These results prove that SUAP can deliver an optimal UAVasBS placement solution with fast convergence, which is essential for UAVs to provide emergent flash crowd and emergency situations connectivity services with limited battery capacity.

5. Conclusions

In this article, we propose SUAP for UAVasBS deployment in flash crowd and emergency situations to provide temporary network connectivity. We explore an SD-UAVNet to manage the UAVasBS in a coordinated manner, where a controller node collects global context information for UAVasBS placement by SUAP, enhancing the network performance in flash crowd or emergency situations. SUAP considers a GA algorithm running on the controller using the network context and application requirements to generate the optimized locations of UAVasBS and provide aerial base station coverage to ground UEs. In this sense, we introduce a path loss model for communications between UAVasBS and mobile users as input for the GA decision-making. Simulation results show that SUAP can effectively mitigate the challenges of deploying UAVasBSs, and SUAP could recover the network with 90% of ACU and achieve a PDR of 90%.

In the future, we will extend the system to explore ground user mobility prediction to optimize the placement of UAVasBS further. We will also investigate the possibility of having a distributed management of the UAVasBS placement. When the number of deployed UAVasBS and the geographical area to be covered is large, a consistent view of the overall system state is theoretically unreachable due to the FLP impossibility proof [52], making it unfeasible to exploit a centralized resolution approach. By having each UAVasBS selecting its deployment point within the area of interest, based on the local knowledge (*i.e.*, the loss rate experienced by the neighboring user devices or base



(a) Coverage (b) Close neighbours

(c) Number of UAVs (d) Distance to Center

Fig. 9. GA costs evolution through the generations.

stations), a distributed management of UAVasBS placement can be realized by leveraging on a game-theoretic approach. For these reasons, we have studied the application of distributed resolution approaches for multi-objective optimization surveyed in [53].

CRediT authorship contribution statement

Zhongliang Zhao: Conceptualization, Methodology, Investigation, Supervision, Writing – original draft, Funding acquisition. **Pedro Cumino:** Software, Validation, Data curation, Writing – original draft. **Christian Esposito:** Methodology, Investigation, Writing. **Meng Xiao:** Methodology, Writing – review & editing. **Denis Rosário:** Conceptualization, Methodology, Investigation, Supervision, Writing, Funding acquisition. **Torsten Braun:** Investigation, Supervision, Writing – review & editing. **Eduardo Cerqueira:** Methodology, Supervision, Writing – review & editing, Funding acquisition. **Susana Sargento:** Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported by Beihang Zhuobai program, China with grant ID ZG216S2176, Brazil funding FAPESPA, Brazil with grant number 003/2017 and CNPq, Brazil, and EU's Horizon 2020 research with grant No. 813391, and EU's Horizon innovation program under the Marie Skłodowska-Curie ITN TeamUp5G.

References

[1] H. Kumar, M.K. Singh, M. Gupta, J. Madaan, Moving towards smart cities: solutions that lead to the smart city transformation framework, Technol. Forecast. Soc. Change 153 (2020) 119281.
[2] J. Nightingale, P. Salva-Garcia, J.M.A. Calero, Q. Wang, 5G-QoE: QoE modelling for ultra-HD video streaming in 5G networks, IEEE Trans. Broadcast. 64 (2) (2018) 621–634.
[3] S. Marinova, V. Rakovic, D. Denkovski, T. Lin, V. Atanasovski, H. Bannazadeh, L. Gavrilovska, A. Leon-Garcia, End-to-end network slicing for flash crowds, IEEE Commun. Mag. 58 (4) (2020) 31–37.
[4] P. Yang, X. Cao, C. Yin, Z. Xiao, X. Xi, D. Wu, Proactive drone-cell deployment: Overload relief for a cellular network under flash crowd traffic, IEEE Trans. Intell. Transp. Syst. 18 (10) (2017) 2877–2892.
[5] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, M. Debbah, A tutorial on UAVs for wireless networks: Applications, challenges, and open problems, IEEE Commun. Surv. Tutor. (2019).
[6] M. Yin, X. Chen, H. Wang, Q. Wang, C. Ma, X. Qin, An automatic event detection method for massive wireless access prediction, IEEE Access 7 (2019) 113404–113416.
[7] C.-C. Lai, L.-C. Wang, Z. Han, Data-driven 3D placement of UAV base stations for arbitrarily distributed crowds, in: IEEE Global Communications Conference (GLOBECOM), IEEE, 2019, pp. 1–6.
[8] 3GPP, Study on Remote Identification of Unmanned Aerial Systems (UAS), 3GPP TR 22.825. Rel. 16,, Tech. Rep., 2018.
[9] I. Bor-Yaliniz, M. Salem, G. Senerath, H. Yanikomeroglu, Is 5G ready for drones: A look into contemporary and prospective wireless networks from a standardization perspective, IEEE Wirel. Commun. 26 (1) (2019) 18–27.
[10] A. Merwaday, I. Guvenc, UAV assisted heterogeneous networks for public safety communications, in: Proceedings of the IEEE Wireless Communications and Networking Conference Workshops (WCNCW), 2015, pp. 329–334.
[11] D. Liu, Y. Xu, J. Wang, Y. Xu, A. Anpalagan, Q. Wu, H. Wang, L. Shen, Self-organizing relay selection in UAV communication networks: A matching game perspective, IEEE Wirel. Commun. 26 (6) (2019) 102–110.
[12] L. Ferranti, F. Cuomo, S. Colonnese, T. Melodia, Drone cellular networks: Enhancing the quality of experience of video streaming applications, Ad Hoc Netw. 78 (2018) 1–12.

[13] D. Reina, T. Camp, A. Munjal, S. Toral, Evolutionary deployment and local search-based movements of 0th responders in disaster scenarios, Future Gener. Comput. Syst. 88 (2018) 61–78.
[14] V. Sharma, M. Bennis, R. Kumar, Uav-assisted heterogeneous networks for capacity enhancement, IEEE Commun. Lett. 20 (6) (2016) 1207–1210.
[15] D. Wu, X. Sun, N. Ansari, A cooperative drone assisted mobile access network for disaster emergency communications, in: IEEE Global Communications Conference (GLOBECOM), 2019, pp. 1–6.
[16] E. Montero, D. Rosário, A. Santos, Clustering users for the deployment of UAV as base station to improve the quality of the data, in: Proceedings of the IEEE Latin-American Conference on Communications (LATINCOM), IEEE, 2019, pp. 1–6.
[17] D. Wu, X. Sun, N. Ansari, An FSO-based drone assisted mobile access network for emergency communications, IEEE Trans. Netw. Sci. Eng. (2019) 1.
[18] T. Akram, M. Awais, R. Naqvi, A. Ahmed, M. Naeem, Multicriteria UAV base stations placement for disaster management, IEEE Syst. J. (2020) 1–8.
[19] S. Sharafeddine, R. Islambouli, On-demand deployment of multiple aerial base stations for traffic offloading and network recovery, Comput. Netw. 156 (2019) 52–61.
[20] M. Alzenad, A. El-Keyi, F. Lagum, H. Yanikomeroglu, 3-D placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage, IEEE Wirel. Commun. Lett. 6 (4) (2017) 434–437.
[21] M. Mozaffari, W. Saad, M. Bennis, M. Debbah, Wireless communication using unmanned aerial vehicles (UAVs): Optimal transport theory for hover time optimization, IEEE Trans. Wireless Commun. 16 (12) (2017) 8052–8066.
[22] A.M. Hayajneh, S.A.R. Zaidi, D.C. McLernon, M.D. Renzo, M. Ghogho, Performance analysis of UAV enabled disaster recovery networks: A stochastic geometric framework based on cluster processes, IEEE Access 6 (2018) 26215–26230.
[23] J. Lyu, Y. Zeng, R. Zhang, Uav-aided offloading for cellular hotspot, IEEE Trans. Wireless Commun. 17 (6) (2018) 3988–4001.
[24] A. Mirzaeinia, M. Mirzaeinia, M. Shekaramiz, M. Hassanalian, Placement of UAV-mounted mobile base station through user load-feature K-means clustering, in: AIAA AVIATION 2020 FORUM, 2020, p. 2925.
[25] S. Iellamo, J.J. Lehtomaki, Z. Khan, Placement of 5G drone base stations by data field clustering, in: IEEE 85th Vehicular Technology Conference (VTC Spring), IEEE, 2017, pp. 1–5.
[26] H.J. Na, S.-J. Yoo, Pso-based dynamic UAV positioning algorithm for sensing information acquisition in wireless sensor networks, IEEE Access 7 (2019) 77499–77513.
[27] E. Kalantari, H. Yanikomeroglu, A. Yongacoglu, On the number and 3D placement of drone base stations in wireless cellular networks, in: Proceedings of the IEEE 84th Vehicular Technology Conference (VTC-Fall), 2016, pp. 1–6.
[28] G. Liu, H. Shakhatreh, A. Khreishah, X. Guo, N. Ansari, Efficient deployment of UAVs for maximum wireless coverage using genetic algorithm, in: Proceedings of the IEEE 39th Sarnoff Symposium, 2018, pp. 1–6.
[29] Y. Hu, F. Zhang, T. Tian, D. Ma, Placement optimisation method for multi-UAV relay communication, IET Commun. 14 (10) (2020) 1005–1015.
[30] C. Lai, C. Chen, L. Wang, On-demand density-aware UAV base station 3D placement for arbitrarily distributed users with guaranteed data rates, IEEE Wirel. Commun. Lett. 8 (3) (2019) 913–916.
[31] G.L. Rodríguez-Cortés, A. Martínez-Vargas, O. Montiel-Ross, The deployment of unmanned aerial vehicles at optimized locations to provide communication in natural disasters, in: O. Castillo, P. Melin, J. Kacprzyk (Eds.), Fuzzy Logic Augmentation of Neural and Optimization Algorithms: Theoretical Aspects and Real Applications, Springer International Publishing, 2018, pp. 501–513.
[32] G. Peng, Y. Xia, X. Zhang, L. Bai, UAV-aided networks for emergency communications in areas with unevenly distributed users, in: Proceedings of the IEEE International Conference on Communication Systems (ICCS), 2018, pp. 25–29.
[33] D. Reina, H. Tawfik, S. Toral, Multi-subpopulation evolutionary algorithms for coverage deployment of UAV-networks, Ad Hoc Netw. 68 (2018) 16–32.
[34] A. Fotouhi, M. Ding, M. Hassan, Dynamic base station repositioning to improve performance of drone small cells, in: 2016 IEEE Globecom Workshops (GC Wkshps), IEEE, 2016, pp. 1–6.
[35] A. Fotouhi, M. Ding, M. Hassan, Flying drone base stations for macro hotspots, IEEE Access 6 (2018) 19530–19539.
[36] A. Costa, L. Pacheco, D. Rosário, L. Villas, A.F. Loureiro, S. Sargento, E. Cerqueira, Skipping-based handover algorithm for video distribution over ultra-dense VANET, Comput. Netw. (2020) 107252.
[37] P. Cumino, K. Maciel, T. Tavares, H. Oliveira, D. Rosário, E. Cerqueira, Cluster-based control plane messages management in software-defined flying ad-hoc network, Sensors 20 (1) (2020) 67.
[38] Z. Zhao, P. Cumino, A. Souza, D. Rosário, T. Braun, E. Cerqueira, M. Gerla, Software-defined unmanned aerial vehicles networking for video dissemination services, Ad Hoc Netw. (2018).
[39] A. Al-Hourani, S. Kandeepan, S. Lardner, Optimal LAP altitude for maximum coverage, IEEE Wirel. Commun. Lett. 3 (6) (2014) 569–572.
[40] T. Bäck, U. Hammel, H.-P. Schwefel, Evolutionary computation: Comments on the history and current state, IEEE Trans. Evol. Comput. 1 (1) (1997) 3–17.
[41] J. Li, D. Lu, G. Zhang, J. Tian, Y. Pang, Post-disaster unmanned aerial vehicle base station deployment method based on artificial bee colony algorithm, IEEE Access 7 (2019) 168327–168336.
[42] D.E. Golberg, Genetic algorithms in search, optimization, and machine learning, Addion Wesley 1989 (102) (1989) 36.
[43] B. McGinley, J. Maher, C. O'Riordan, F. Morgan, Maintaining healthy population diversity using adaptive crossover, mutation, and selection, IEEE Trans. Evol. Comput. 15 (5) (2011) 692–714.
[44] M. Črepinšek, S.-H. Liu, M. Mernik, Exploration and exploitation in evolutionary algorithms: A survey, ACM Comput. Surv. 45 (3) (2013) 1–33.
[45] W.J. Gutjahr, Convergence analysis of metaheuristics, in: Matheuristics: Hybridizing Metaheuristics and Mathematical Programming, Springer US, Boston, MA, 2010, pp. 159–187.
[46] J. He, L. Kang, On the convergence rates of genetic algorithms, Theoret. Comput. Sci. 229 (1) (1999) 23–39.
[47] J.A. Lozano, P. Larrañaga, M. Graña, F.X. Albizuri, Genetic algorithms: Bridging the convergence gap, Theoret. Comput. Sci. 229 (1–2) (1999) 11–22.
[48] D. Rosário, Z. Zhao, C. Silva, E. Cerqueira, T. Braun, An OMNeT++ framework to evaluate video transmission in mobile wireless multimedia sensor networks, in: International Workshop on OMNeT++, ICST, 2013, pp. 277–284.
[49] N. Aschenbruck, R. Ernst, E. Gerhards-Padilla, M. Schwamborn, BonnMotion: a mobility scenario generation and analysis tool, in: Proceedings of the 3rd International ICST Conference on Simulation Tools and Techniques, 2010, pp. 1–10.
[50] T.K. Sarkar, Z. Ji, K. Kim, A. Medouri, M. Salazar-Palma, A survey of various propagation models for mobile communication, IEEE Antennas Propag. Mag. 45 (3) (2003) 51–82.
[51] D.V. Veldhuizen, G. Lamont, Evolutionary computation and convergence to a Pareto front, in: Proceedings of the Genetic Programming 1998 Conference, 1998.
[52] M. Paterson, M. Fischer, N. Lynch, Impossibility of distributed consensus with one faulty process, J. ACM 32 (2) (1985) 374–382.
[53] Y.-J. Gong, W.-N. Chen, Z.-H. Zhan, J. Zhang, Y. Li, Q. Zhang, J.-J. Li, Distributed evolutionary algorithms and their models: A survey of the state-of-the-art, Appl. Soft Comput. 34 (2015) 286–300.

Dr. Zhongliang Zhao received his Ph.D. degree from the University of Bern in 2014. Since 2014, he holds an appointment of a Senior Researcher with the University of Bern. Currently, he is an associate professor with the School of Electronic and Information Engineering, Beihang University, China.

Pedro Cumino graduated in Computer Engineering and Master in Computer Science from the Federal University of Para. He is currently doing a PhD in Computer Engineering from the University of Aveiro, Portugal, as an Early Stage Researcher at Marie Skłodowska-Curie ETN TeamUp5G. His current research interests include: Smart Cities, Internet of Things, FANET, Quality of Experience and Software Defined Network.

Dr. Christian Esposito graduated in Computer Engineering at the University of Napoli Federico II, Italy. Currently, he is a tenured Assistant Professor at the University of Salerno, and was an Assistant Professor at the University of Napoli Federico II, a research fellow at the University of Salerno and The Institute for high performance computing and networking (ICAR) of the National Research Council of Italy (CNR), all of them in Italy. He has been involved in the organization of several international conference/workshops and the editorial boards of journals. His current research interests include the following: Network Resiliency, Secure Communications, Distributed Optimization and Game Theory, Internet of Things and Cloud Computing.

Meng Xiao

Dr. Denis Rosário received his PhD degree in Electrical Engineering at the Federal University of Pará, Brazil with joint supervision undertaken by the Institute of Computer Science and Applied Mathematics of University of Bern, Switzerland in 2014. Currently, he is a Professor at Federal University of Pará. His current research interests include the following topics: Multimedia adaptation, Wireless Networks, FANET, VANET, Mobility, Quality of Experience, and Software Defined Network.

Prof. Dr. Torsten Braun got his Ph.D. degree from University of Karlsruhe (Germany) in 1993. From 1994 to 1995, he was a guest scientist at INRIA Sophia-Antipolis (France). From 1995 to 1997, he worked at the IBM European Networking Centre Heidelberg (Germany) as a project leader and senior consultant. Since 1998, he is a full professor of Computer Science at University of Bern. He held an appointment of a vice president of the SWITCH (Swiss Research and Education Network Provider) Foundation from 2011 to 2019. He has been a Director of the Institute of Computer Science and Applied Mathematics at University of Bern between 2007 and 2011 as well as since 2019. He is serving as Deputy Dean of the Faculty of Science, University of Bern from 2017 to 2019. He received best paper awards from LCN 2001, WWIC 2007, EE-LSDS 2013, WMNC 2014, and the ARMS-CC-2014 Workshop as well as the GI-KuVS Communications Software Award in 2009. In the scope of EU funded projects, he was leading WPs of FP6-EUQOS and FP7-MCN. Moreover, he coordinated national projects such as SNSF SwissSenseSynergy and SNSF CONTACT.

Prof. Eduardo Cerqueira received his Ph.D. in Informatics Engineering from the University of Coimbra, Portugal (2008). He is an associate professor at the Faculty of Computer Engineering of the Federal University of Pará (UFPA) in Brazil, as well as invited researcher at the Network Research Lab at UCLA-USA and Centre for Informatics and Systems of the University of Coimbra, Portugal. His publications include 5 edited books, 5 book chapters, 4 patents and over than 180 papers in national/international refereed journals/conferences. He has been serving as a Guest Editor for 6 special issues of various peer-reviewed scholarly journals. His research involves Multimedia, Future Internet, Quality of Experience, Mobility and Ubiquitous Computing.

Dr. Susana Sargento is a Full Professor in the University of Aveiro and a senior researcher in the Institute of Telecommunications, where she is leading the Network Architectures and Protocols (NAP) group. She received her PhD in 2003 in Electrical Engineering in the University of Aveiro. She joined the Department of Computer Science of the University of Porto between 2002 and 2004, and she was a Guest Faculty of the Department of Electrical and Computer Engineering from Carnegie Mellon University, USA, in August 2008, where she performed Faculty Exchange in 2010/2011. She has been TPC-Chair and organized several international conferences and workshops, such as ACM MobiCom, IEEE Globecom and IEEE ICC. She has also been a reviewer of numerous international conferences and journals, such as IEEE Wireless Communications, IEEE Networks, IEEE Communications. In March 2012, Susana has co-founded a vehicular networking company, Veniam (www.veniam.com), a spin-off of the Universities of Aveiro and Porto, which builds a seamless low-cost vehicle-based internet infrastructure. Susana is the winner of the 2016 EU Prize for Women Innovators. Her main research interests are in the areas of self-organized networks, in ad hoc and vehicular network mechanisms and protocols, such as routing, mobility, security and delay-tolerant mechanisms, resource management, and content distribution networks. She regularly acts as an Expert for European Research Programs.