Help From Above: UAV-Empowered Network Resiliency in Post-Disaster Scenarios

Christian Esposito
University of Salerno, Italy
esposito@unisa.it

Gianluca Rizzo
HES-SO Valais, Switzerland, and
University of Foggia, Italy
gianluca.rizzo@hevs.ch

***Abstract*—Natural and man-made disasters have often consequences on service availability in a wireless access network, provoking a progressively degraded performance or even the lack of connectivity. However, given the growing importance of situation awareness, telehealth, and advanced rescue teams coordination services for the affected population, it is key to restore these services in a timely fashion, while guaranteeing the required QoS levels. To this end, UAV-mounted base stations have been recently proposed as a key instrument to achieve this goal. Nonetheless, this gives rise to the key issue of how to deploy them in a resource efficient manner, in a post-disaster context typically characterized by lack of infrastructure support and of power supply. In this work, we tackle the issue of how to jointly optimize drones deployment and user association in a QOS aware manner to efficiently cater for coverage holes and QoS degradation in a cellular network after a disaster. We formulate a network optimization problem, and we provide a two-step genetic algorithm which iteratively tunes UAV position, base station transmit power and user association in order to minimize the number of employed drones. Initial results on a realistic measurement based scenario show that our approach is able to effectively minimize the number of deployed drones while achieving a target minimum QoS.**

I. Introduction

Computer-based communications are at the basis of an inclusive digital society, and they have a transformative effect on society and economy. The key role of digital services has paved the way to the advent of various new concepts such as smart cities, industry 4.0 or personalized healthcare. This has caused a progressive need of people to stay connected and exchange data with others. A key enabler of this scenario is the extensive network of wireless antennas which compose present day and future cellular access networks, which are often prone to partial or total failures as a side-effect of the occurrence of such disasters as earthquakes, floods, blackouts, fires, to name a few, which either physically damage the base station itself or its backhaul connection, and/or make it unavailable due to a failure to its power source [1]. Natural and/or man-made disasters may compromise the networking infrastructure to the point that it becomes unavailable or offers degraded quality services [2]. In fact, on the one hand, severe disasters can cause temporary damages at the Internet or mobile networks' links and nodes, possibly recoverable through software-based mechanisms and network reconfiguration [3]. On the other hand, permanent link failures may also occur, requiring maintenance and component substitution to recover the full link availability. Furthermore, after disasters, local peaks of traffic demand may occur, often resulting into network saturation and service unavailability. This further worsen the performance of the network already compromised by the hardware failures. As a consequent users may perceive a degradation of the network quality of service during a situation when they are particularly vulnerable and demanding proper data to decide how to escape from the affected area and rescues themselves an safer places. The lack of proper information after a disastrous event is particularly critical, as it generates a host of issues related to disaster management and rescue operations. As an example, during the worst fire cases in the Portuguese history (June 2017)[1], a large amount of users were cut off from fixed-line or cellular telephone service, giving rise to serious network congestion. Moreover, the communications among the rescue teams had been severely affected, slowing down their operations. Bad communications are felt to have increased the overall number of causalities in terms of human life losses [2]. In order to mitigate these issues, it is therefore key to make access networks resilient to this kind of disruptions [4]. Network and service providers need to ensure diversity and redundancy in the hardware of network devices, in the networking topology, and employ resilient routing strategies, to endow the networking infrastructure with the ability to adapt to and recover from failures caused by disasters without compromising the target quality of service.

As current cellular networks transition to the 5G paradigm and beyond, their ability to flexibly adjust and reconfigure increases thanks to the adoption of SDN and NFV technologies. This has facilitated the gradual integration in the network infrastructure of moving elements, such as base stations on flying and ground drones and on cars [5], which enhance the ability to provide coverage, capacity and computing power when and where needed, while decreasing the need for dense deployments of static, dedicated infrastructure. These features, which are thus key to economic sustainability and for timely resource provisioning in future networks during normal operations, have the potential to play a key role in the aftermath of a disaster, when the (typically partial, and geographically sparse) unavailability of network resources calls for solutions which are able to make the most of the surviving network, by appropriately reconfiguring it to adapt it to the new needs arising from such scenarios.

In this work, we make an initial step towards tapping into this potential of future networks for enhanced service availability and post-disaster communications support. Specifically, we tackle the issue of how to jointly optimize drones deployment and user association to efficiently cater for coverage holes and QoS degradation in a cellular network after a disaster, to make up for failed and damaged antennas. We formulate the network optimization problem, and we provide a two-step genetic algorithm which iteratively tunes UAV position, transmit power, and user association in order to minimize the number of employed drones in the area of interest in a QoS aware fashion. Initial results on a realistic measurement based scenario show that our approach is able to effectively minimize the number of deployed drones while achieving a target minimum QoS.

II. System model

We consider a region of the plane, and a set of base stations (BS) located in the plane according to an arbitrary distribution. The signal power received from the $s-th$ base station by a user at a distance d from it is given by

$$p_{r_s}(d) = p_{t_s} G \left(\frac{10}{d}\right)^3 \quad (1)$$

where d denotes the Euclidean distance between the user device and the antenna, p is the BS transmit signal power and G is the antenna gain. When a device is associated to an antenna, the perceived QoS depends not only on received signal power, but also on the number of associated devices, as the antenna serves them according to a round robin scheduling. Therefore, we can model the QoS for a given user u in terms of its perceives throughput as follows:

$$t_s(u) = \frac{c_s(u)}{N_s} U_s \quad (2)$$

where N_s is the total number of users served by the $s-th$ base station, U_s is the BS utilization, while $c_s(u)$ is the channel capacity, which can be formulated according to the Shannon formula:

$$c_s(u) = Blog_2\left(1 + \frac{p_{r_s} d}{WB + i_s(u)}\right) \quad (3)$$

where B is the bandwidth, N is the additive white Gaussian noise and $i_s(u)$ is the interference affecting the communications between the user and the serving BS, given by

$$i_s(u) = L \sum_{s' \neq s} p_{r_{s'}} d(s', u) \quad (4)$$

where L is the antenna attenuation, given as $1-G$. Therefore, the average throughput provided by a BS is

$$\bar{t}_s = \frac{\sum_{u \in A_s} t_s(u)}{N_s} \quad (5)$$

We assume each base station aims at delivering a target throughput τ_0. Then we assume each base station is active for a fraction of time U_s such that the average throughput coincides with the target value, and it is idle for the remaining time. U_s is the base station utilization, which is related to the mean consumed power e_s by the following energy model [6]:

$$e_s = k_1 + U_s[k_2 + k_3(p - p_{min})] \quad (6)$$

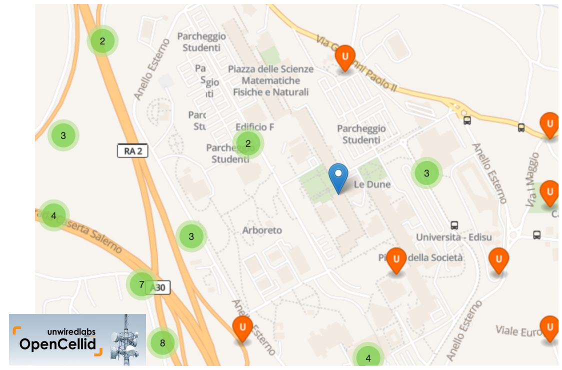

Fig. 1: Campus scenario at the UNISA, Italy, with base station locations (from OpenCelliD).

where P_{min} is the minimum transmission power, and the remaining constants describes the features of the antennas. Coefficients k_1, k_2 and k_3 depend on the specific technology used, on the hardware and software architecture of the BS, and on the size of the cell (e.g. femto, micro, macro). In order to consider a realistic scenario, we have considered the campus scenario depicted in Figure 1, in which BS geographical coordinates are derived via OpenCelliD[1]. Such a database contains not only BS locations, but also some key information such as the kind of technology (GSM, UMTS, LTE), the estimated coverage radius, and the identifier of the mobile operator owning it. These data can be used in order to place antennas onto a Cartesian plane, as in Figure 2 by using the latlon2local offered by MATLAB. Afterwards, users need to be inserted within the area and associated with the available towers. Typically, users are distributed based on the buildings located in the area, and the attractiveness of certain places with respect to the others. The literature contains many models [7], [8] able to express the spatial distribution of users in various kinds of areas, spanning from commercial and residential complex to university and school campuses. For a first evaluation of our approach however, we have used a uniform distribution of users. By assuming an initial condition in which users associate to the BS offering the strongest received signal, we have obtained the configuration shown in Figure 2, where BS and associated users have the same color. The last aspect of the system model is the model of failures caused by disasters at the antennas. Despite many complex models are available within the current literature [9], we have decided to take a simple approach by introducing a *worsening coefficient* to the antenna performance, namely w_s, taking a value in the interval $[0, 1]$ where 0 indicates a fully functional base station, while 1 indicates the complete destruction of the BS and its unavailability. The selection of such coefficient for each base station is done stochastically by defining two probabilities, respectively P_{damage} and $P_{destruction}$ where $P_{destruction} < P_{damage}$, so that per each antenna a random number $P_s \in [0, 1]$ is selected and the worsening factor is

[1] https://www.opencellid.org/

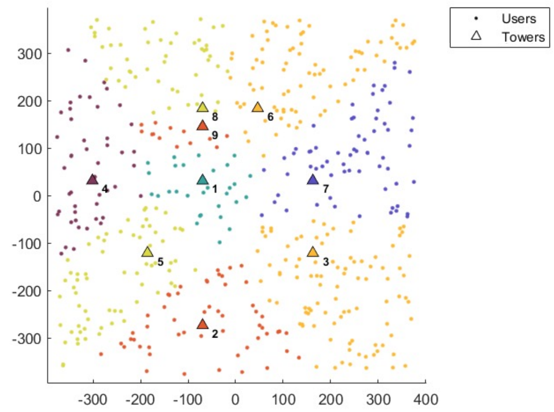

Fig. 2: Representation of the campus scenario with the location of users and of base stations.

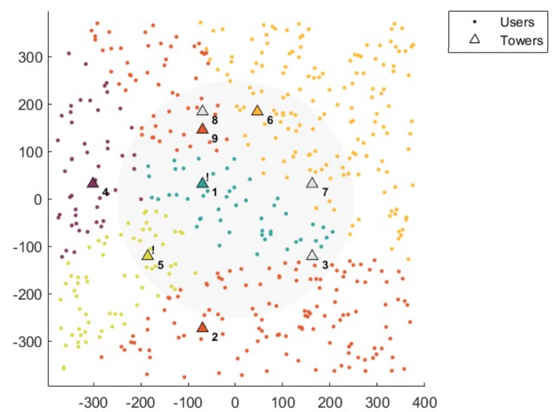

Fig. 3: Representation of the campus scenario after a disaster, with the damaged base stations.

determine according to this formula:

$$w_s = \begin{cases} 1,\ if\ P_s \leq P_{destruction} \\ x,\ if\ P_s \leq P_{damage} \\ 0, otherwise \end{cases} \quad (7)$$

where x is a random number within $[w_{min}, w_{max}]$. Such a coefficient indicate the state of an antenna, indicated as $h_s = 1 - w_s$, and it determines an upper limit to the utilization factor: $U_s \leq h_s$. We have assumed disaster to be associated to the center of the considered area (the disaster's *epicenter*), and that the only BSs susceptible of damage are those which are located within a given distance from the center, as represented in Figure 3.

III. Approach and Numerical Evaluation

In order to determine the position of the UAVs, we have adopted a Genetic Algorithm (GA) [10], where the chromosome is composed by a binary part indicating the number of UAVs deployed within the area and the permutation part

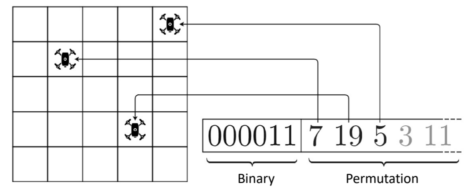

Fig. 4: Chromosome representation

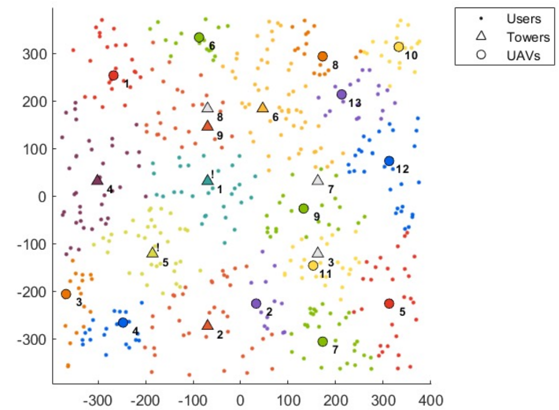

Fig. 5: UAVs placement within the damaged area after a disaster

indicates the location ids of those UAVs, as depicted in Figure 4. The objective function to be optimised by this GA implemented in MATLAB is

- the ratio between the number of deployed nodes (*i.e.*, the number represented in the binary part of the selected chromosome) and the maximum number of deployable UAVs; If we indicate with $e_v(c)$ the energy consumption of the UAVs formulated according to Equation 6, the overall energy consumption can be formulated as:

$$e(c) = \frac{e_s(c) + e_v(c)}{E_V + E_S} \quad (8)$$

where the denominator contains respectively the energy consumption of static BS and UAVs when their utilization factor is equal to 1.
- the penalty to have not properly served users, *i.e.*, their throughput is lower than the given threshold. If we define the set V_c as the number of available BS with users having a throughput below a threshold, then the penalty function is formulated as follows:

$$p(c) = \begin{cases} 1 - \max_{x \in V_c} \frac{\bar{t}_x}{T} & if\ |V_c| > 0 \\ 0 & otherwise \end{cases} \quad (9)$$

These three contributors are properly weighted by considering three constants whose sum needs to return 1: $w_{capex} + w_{opex} + w_{penalty} = 1$.

We have assessed our approach by considering the BS managed by the Vodafone IT mobile operator, with 500 users

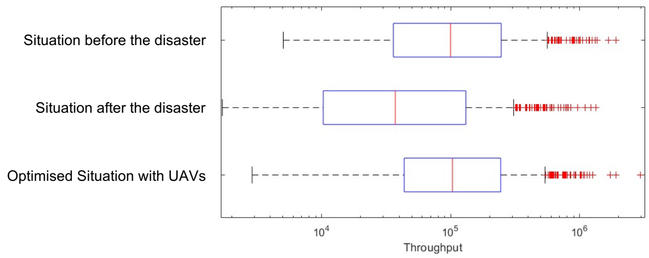

Fig. 6: Throughput assessment after the disaster.

in the area (corresponding to typical peak user density in the campus area), bandwidth of 20 MHz, antenna gain of 0.8 and transmission power for BS and UAVs respectively of 10W e 0.5W, as derived from the OpenCelliD database. We assumed a target mean throughput T is of 200kb/s, sufficient for satisfactory performance of such service as real-time video for medical consulting. Before the disaster all the users are able to keep up with the target throughput, according to the user association in Figure 2. When the disaster occurs, we assume it damages an area within a radius of 250m (see circle in Figure 3) from the epicenter, which models a disaster such as a fire or a flood. As a consequence of our failure model, BS numbered as 3, 7 e 8 in the figure are completely inactive, while those with id 1 e 5 are only partially available, with a maximum utilization factor of 34.1% and 38.6%, respectively. Such a failure situation cause a change in the user association: user devices previous assigned to the inactive towers are now associated with the remaining ones with stringer signal strength. This causes BS 2 and 7 to be overwhelmed and fully used, providing a mean throughput of 75 kb/s and 76 kb/s, respectively. Despite not fully used, also BS 1 and 5 cannot guarantee the target throughput, due to the received damages, and respectively offers 160kb/s and 140kb/s to the associated users. This implies a lowering of the quality as evident by comparing the first two bars in Figure 6. When the optimization is executed by using the following configuration $w_{capex} = 0.2$, $w_{opex} = 0.4$ and $w_{penalty} = 0.4$, where the energy consumption and penalty optimization are equally important to be minimized sacrificing the number of UAVs, and having the maximum number of deployable UAVs equal to 48, after running 100 generations of a population with 25 chromosomes we obtain a solution represented in Figure 5, where UAVs are mainly located far from the active BS (*i.e.*, those not affected by the disaster), which is intuitive. This allows a recover of the quality previously exhibited by the network, as evident by comparing the first and last bar in Figure 6.

IV. Conclusions and Future Work

In this work we have presented our approach to post disaster QoS-aware network reconfiguration, which determines UAVs number and location which minimizes the number of UAVs as well as the overall energy consumed by the network, providing a higher level of resiliency to cellular networks against disasters which damage antennas within a given area. Specifically, we have modeled in a simulator an area of interest where towers and users are located according to a realistic, measurement based model, and we have simulated the failures caused by a disaster. The issue of UAVs planning has been approached by using a genetic algorithm so as to find the optimal UAVs number and placement and assessed the QoS perceived by the users. We have shown how or approach is able to restore the QoS perceived by the users in a resource efficient manner.

In the continuation of this work, on one hand, we will substitute the centralised optimization approach with a distributed one based on the game theory so that each UAVs is able to independently take decisions on its route and location without needed a controller sending commands. On the other hand, we aim to use our simulator to investigate the opportunistic user association with more than one access point, as in the area a user device can be connected to an antenna an UAV or establishing an ad-hoc connection with other users, as in [11], and assess the impact of such an approach on the energy consumption and perceived QoS.

References

[1] L. Martins, R. Girao-Silva, L. Jorge, A. Gomes, F. Musumeci, and J. Rak, "Interdependence between power grids and communication networks: A resilience perspective," in *13th International Conference on the Design of Reliable Communication Networks*, 2017, pp. 1–9.

[2] S. Liew and K. Lu, "A framework for characterizing disaster-based network survivability," *IEEE Journal on Selected Areas in Communications*, vol. 12, no. 1, pp. 52–58, 1994.

[3] F. Palmieri, U. Fiore, A. Castiglione, F.-Y. Leu, and A. De Santis, "Analyzing the internet stability in presence of disasters," in *International Conference on Availability, Reliability, and Security*. Springer, 2013, pp. 253–268.

[4] J. Rak, *Resilient routing in communication networks*. Springer, 2015, vol. 118.

[5] F. Dressler, C. F. Chiasserini, F. H. P. Fitzek, H. Karl, R. L. Cigno, A. Capone, C. Casetti, F. Malandrino, V. Mancuso, F. Klingler, and G. Rizzo, "V-edge: Virtual edge computing as an enabler for novel microservices and cooperative computing," 2021.

[6] G. Rizzo and M. A. Marsan, "Qos-aware capex minimization in urban off-grid radio access networks," in *2016 IEEE 24th International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS)*. IEEE, 2016, pp. 179–188.

[7] S. Nousiainen, K. Kordybach, and P. Kemppi, "User distribution and mobility model framework for cellular network simulations," *VTT Information Technology*, pp. 518–522, 2002.

[8] X. Ge, J. Ye, Y. Yang, and Q. Li, "User mobility evaluation for 5G small cell networks based on individual mobility model," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 3, pp. 528–541, 2016.

[9] B. E. Helvik, P. Vizarreta, P. E. Heegaard, K. S. Trivedi, and C. M. Machuca, "Modelling of software failures," in *Guide to Disaster-Resilient Communication Networks*, ser. Computer Communications and Networks, J. Rak and D. Hutchison, Eds. Springer, 2020, pp. 141–172.

[10] C. Ramirez-Atencia, G. Bello-Orgaz, M. D. R-Moreno, and D. Camacho, "Solving complex multi-UAV mission planning problems using multi-objective genetic algorithms," *Soft Computing*, vol. 21, no. 17, pp. 4883–4900, 2017.

[11] C. Esposito, Z. Zhao, R. Alcarria, and G. Rizzo, "Game theoretic optimal user association in emergency networks," in *ADHOC-NOW 2019, Luxembourg, October 1-3, Proceedings*, ser. Lecture Notes in Computer Science, vol. 11803. Springer, 2019, pp. 18–31.