Game Theoretic Optimal User Association in Emergency Networks

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Abstract. The availability of effective communications in a post-disaster scenarios is key to implement emergency networks which enable the sharing of critical information and support the coordination of the emergency response. In order to deliver those levels of QoS suitable to these applications, it is vital to exploit the multiple communication opportunities made available by the progressive deployment of the 5G and Smart City paradigms, ranging from ad-hoc networks among smartphones and surviving IoT devices, to cellular networks but also drone-based and vehicle-based wireless access networks. Therefore, the user device should be able to opportunistically select the most convenient among them so as to satisfy the demands for QoS imposed by the applications and also minimise the power consumption. The driving idea of this paper is to leverage non-cooperative game theory in order to design such a opportunistic user association strategy in post-disaster scenario using UAV ad-hoc networks. The adaptive game-theorethic scheme allows to increase the QOS of the communication means by lowering the loss rate, and also keepts moderate the energy consumption.

Keywords: Game Theory · Disaster Resilient Networking · Emergency Networks · Vehicular Crowdcell.

1 Introduction

The current era is strongly characterised by the pervasiveness of ICT within our daily life and the ubiquitous accessibility of the Internet everywhere and every-time. Owing one or more smartphones and using for almost everything is extremely normal in the current digital society, so that human being feel lost without being able to access the web and its related services. However, large-scale natural and man-made disasters can negatively compromise the efficiency and effectiveness of the network, by causing failures of base stations composing cellular networks or truncating writes, causing permanent and/or temporary Internet inaccessibility or worsening. In post-disaster scenarios, being able to exchange data is particularly important for two main reasons. On the one hand, citizens need to inform their dear ones of their well-being, to know which of the possible escape routes is the best one to take, to ask for assistance/help or to receive updates on the current status of the neighbouring environment and/or situation. On the other hand, the rescue teams need good networking in order to access satellite images or on-field assessment data to determine the entity of possible damages, the causalities or people in needs, and to harmonize the recovery actions undertaken by the multiple teams involved in the damaged area. As a consequence, in the immediate aftermath of a disaster the traffic demand may be overwhelming, with a high possibility of causing congestion phenomena. If we also consider that the network operational status is affected by failures, we can have a glimpse of how the perceived Quality-of-Service is much lower than the nominal levels and cannot keep with the high demands from the users reaching the point that the Internet becomes unavailable or offers degraded quality services [1], [2]. This can have a negative impact on the correct conduction of the rescue operations and increase the number of troubles caused by a disaster. As a concrete example, in the worst wildfire in Portugal June 2017, a large number of users were cut off from using fixed-line or cellular communication services. This led to remarkable traffic congestion over the isolated areas, as well as affecting the emergency communications among rescue teams, which caused a large number of casualties.

We are witnessing a huge demand in resilient networking, as the occurrence of disasters is increasing, and their impacts are non-negligible [3]. Such a feature can be offered by properly rethinking the overall network by introducing redundant paths beforehand, or even by reacting to possible network saturation and service unavailability by deploying ad-hoc networking devices to substitute failed or overwhelming ones. This is the recent use of Unmanned aerial vehicles (UAVs) playing the role of relay node to support cellular or ad hoc communications and strengthening the accessibility to the Internet offered to user devices. In fact, the work described in [4] proposed to use UAVs as aerial base stations (UABSs) to assist public safety communications during natural disasters, as soon as parts of the communication infrastructure being damaged and dysfunctional. This leads to the case that a user device can have multiple possible base stations towards the network: (1) the first exploits ad-hoc connections established with other user devices, acting as forwarders, (ii) the second leverages on base stations to access the Internet through cellular networks, (iii) the last one makes use of UAVs for communication purposes, and the contacted UAV can exploit an ad-hoc network with other UAVs or have direct Internet accessibility by means of long-range cellular or even satellite communication means. A user device can select one of these three communication opportunities, or even more than one so as to realize multi-path routing, based on the offered QoS and the required cost in terms of consumed energy. If fact, each of them can provide a certain degree of performance and success rate, but the required power consumption is not uniform as each of them leverages on specific communication technologies. For example ad-hoc networks among user devices are built based on low-range RF technologies such as Bluetooth and WiFi, which exhibits a lower energy cost than the cellular ones to connect to a base station. Reaching UAVs demands long-range RF technologies, where the energy cost can be higher. Such a selection depends on the actual network conditions and demands, and cannot be determined once but must be continuously conducted over the time.

It is possible to model such an issue as an optimisation problem; however, it is intractable in a centralised manner, even with heuristic approaches such as genetic algorithms and so on. In fact, on the one hand, it is a well known result in the theory of distributed systems that within the context of a fully asynchronous system (such as the one using the Internet as communication means) there is no global consensus and reaching a consistent view of certain pieces of data among asynchronous distributed processes despite of possible failures (in fact, this is theoretically unreachable due to the FLP impossibility proof [5]). This means that a single node cannot collect a consistent view of all the QoS levels experiences along the links established by all user devices exploiting one or more of the three mentioned communication opportunities. On the other hand, even if this may be viable, the overhead to converge to a solution by resolving the optimisation problem can be overwhelming due to the large number of nodes to be considered, and the consequent enormous solution space to be explored. Even the possibility of using optimised solutions to deal with large scale problems, such as s genetic algorithm with multiple populations, may not lead to a tractable problem. Such a problem can only be resolved in a distributed manner by leveraging on a game theoretic approach, where each user device is considered as a player in the game, which picks up a given strategy (i.e., using one of the possible communication means or even more than one) by maximising the obtainable gain (in terms of meeting the demands of the applications and users in terms of performance and success rate) and minimising the consequent cost in terms of energy consumption. The driving idea of this work is to adopt a non-cooperative formulation of a resolution approach and this paper presents the design and challenges of the proposed system.

2 System model

We consider a set of N cellular users, moving within a region of then plane in which a number of static cellular base station (BS) are deployed. We assume in such a scenario there is also a set of vehicles (such as UAV and ground transportation vehicles) which carry cellular base stations, and which move according to a given mobility pattern. We consider the uplink channel of a cellular access network. We assume BS in the considered scenario belong to three classes. The first is represented by static cellular base station (BS). The second class is composed by moving base station (MBS), installed on UAV or a ground vehicles, and forwarding all traffic to a static BS via a wireless backhaul connection. Finally, we assume user devices can act as base stations too, relaying traffic originating from other user devices to a static BS. In this work we assume that backhaul links are one-hop only, though our approach can be easily extended to multi-hop backhaul connections.

In such scenario, we assume each user can associate to at most one BS for each class. This implies that each user can associate to at most three base stations at the same time. For instance, users may differentiate the access technology according to the QoS requirements of the traffic they exchange, sending delay sensitive traffic to a nearby static BS under high load while forwarding delay tolerant traffic to another, less loaded base station via multi-hop relaying. Note however that our approach can be easily extended to the case in which a user can associate to more than one BS for each class, as in the case of Heterogeneous Network (HetNet) [26], where in addition to selecting BS thee is also the problem of traffic splitting among the multiple BS.

We assume time to be divided into slots of equal duration, and let $t \in \mathcal{N}$ be the index of the t-th slot. Each of the access modes is characterised by a loss pattern, i.e. by a mean rate of packet loss, which is a function of time. For every slot t, we assume to know the mean packet loss rate for each possible base station. Specifically, for each user n in the considered region, and for each static base station s, the coefficient $\pi_{n,s} \in [0,1]$, which indicates the mean packet loss experienced by the n-th user when associated to the s-th static BS in the given time slot. Analogously, for each vehicular BS v and each user-based BS u we introduce the coefficients $\pi_{n,v} \in [0,1]$ and $\pi_{n,u} \in [0,1]$. However, while packet losses for the static base stations coincide with packet losses experienced on the link between the user and the base station, the packet loss coefficient associated to moving base stations (either vehicle or user) are the resultant of the link between the user and the moving BS, and of the backhaul link between the moving BS and the static BS. We assume that at the beginning of each slot, such coefficient are known by means of estimations based on the periodical exchange of CSI.

In each slot, we also introduce the variables $x_{n,s}$, $x_{n,v}$, $x_{n,u}$, which take values between 0 and 1. They represent the fraction of the user traffic which is sent to BS s (resp, u, v). Therefore we have, $\forall n$,

$$\sum_s x_{n,s} + \sum_v x_{n,v} + \sum_u x_{n,u} = 1 \tag{1}$$

We assume that each class of base stations has a maximum number of users it can serve, denoted with M^S (resp. M^V, M^U). This implies that

$$\sum_n x_{n,s} \leq M^S \ \ \forall s \tag{2}$$

$$\sum_n x_{n,v} \leq M^V \ \ \forall v \tag{3}$$

$$\sum_n x_{n,u} \leq M^U \ \ \forall u \tag{4}$$

The mean loss rate experienced by the n-th user in a given slot can therefore be expressed as

$$\Pi_n = \sum_u x_{n,u}\pi_{n,u} + \sum_v x_{n,v}\pi_{n,v} + \sum_s x_{n,s}\pi_{n,s} \tag{5}$$

Moreover, with $\epsilon_{n,u}$, $\epsilon_{n,v}$ and $\epsilon_{n,s}$ we indicate the mean amount of energy consumed by the device during the given slot when associated to the base station belonging to one of the three classes. Hence the mean amount of energy consumed by the device can be expressed as

$$E_i = \sum_u x_{n,u}\epsilon_{n,u} + \sum_v x_{n,v}\epsilon_{n,v} + \sum_s x_{n,s}\epsilon_{n,s} \tag{6}$$

While the experienced loss rate depends on the environmental conditions (such as network congestion, mutual RF technologies interference and so on) at run time and the possible failures caused by the disaster, the device energy consumption due to the specific communication technology mainly depends on the adopted technology.

3 Formulation of the optimization problem

In this section, we formalize the problem of optimal user association in the considered scenario, in order to determine in each time slot the most energy efficient user association strategy. We consider a single time slot, and we consider the problem of determining, $\forall n$, the variables $x_{n,s}$, $x_{n,v}$, $x_{n,u}$, that minimize the experiences loss rate and the cost function which accounts for the total energy consumed at the devices during the given time slot. Let $\mathbf{X}^{UAV}$, $\mathbf{X}^{BS}$ and $\mathbf{X}^{U}$ denote the arrays for the variables associated to the three classes of base stations during the given time slot.

Problem 1 (Optimal user association in a time slot).

$$\min_{\mathbf{X}^{UAV},\mathbf{X}^{BS},\mathbf{X}^{U}} \quad \sum_n \mathit{\Pi}_n + E_n \tag{7}$$

Subject to:

$$Equation\ (1),\ (2),\ (3),\ (4),\ (5),\ (6)$$

$$\forall n, s, u, v$$

$$0 \leq x_{n,s}, x_{n,v}, x_{n,u}, \leq 1 \tag{8}$$

$$\tag{9}$$

Problem 1 is a linear programming problem, and hence it can be solved optimally. However, a centralized approach in which a single coordination function collects the estimations of packet loss ratios for the whole network and computes the optimal user association does not scale, as it would require the collection and exchange of a substantial amount of delay sensitive control traffic among the devices in the system. Moreover, such a centralized coordination function should dispose of substantial storage and computing resources, which are not always available in a disaster scenario.

In addition, given the mobility of users and of part of the BS, the transmissive conditions (and hence the coefficients π) change over time. As a result, the duration of each time slot should be small enough to capture these variations and adapt accordingly the user association. However, the solution of problem 1 may change drastically from a slot to the other due to fading. An ideal system who would configure user association according to the solutions of Problem 1 in each time slot would be forced to continuously adjust the selected strategy. As changes in user association bear costs in terms of control information and of time required to implement them, such a strategy would not be viable in realistic settings.

4 A distributed approach to optimal user association

Given the aforementioned issues, in this section we propose a distributed heuristic to solving Problem 1, based on a game theoretic approach. Our approach determines in each time slot the optimal user association configuration without the need of a centralized coordination.

Distributed optimization by means of game theory consists of defining local decision strategies for the individual nodes, called players, based on their local knowledge acquired by neighbors, so as to ensure that the resulting global behavior satisfies a given global objective. In our case, we have a set of n players ($i.e.$, the user devices) that simultaneously select some of the three available communications means to which access to the network, at the cost of the lowest energy consumption possible. We consider a set of players $P := c_1, c_2, \cdots, c_n$ of finite size $n \geq 2$. Formally, the strategy set for each player $c \in P$ is defined as $S^c = Y$, such that a strategy of a player is the selection of a set of the possible connections towards some UAVs, base stations or neighboring nodes $\overline{s}^c \subset Y$. In what follows we assume that, for each class of BS, each user associates to the BS which delivers the strongest received signal. In our game, the strategy of a player is given by an integer number belonging to the interval $[1, 7]$, which are all the possible selection combinations ($i.e.$, 1 stands for base station only, 2 for UAVs only, 3 for neighboring nodes only, 4 to 6 only two modes out of the three possible, while the last one encompasses all the three modes. Based on the adopted strategy, indicates as s_j, a proper action is conducted by the j-th player, namely o_j, among the set of allowed actions $O_j(s_j)$. Specifically, these actions are represented by the variable $x_{n,s}$, $x_{n,v}$, $x_{n,u}$ and their constraint expressed in Equation 1. Therefore, the output of the player is a selection of UAVs, base stations and nodes, usable by the communication means indicated by the strategy.

Combining the strategy sets of all the players, namely $S = S^{c_1} \times S^{c_2} \times \cdots \times S^{c_p}$, a strategy profile $s \in S$ implies a certain payoff to each player c, namely $\varPhi^c(s)$, which are aggregated in the so-called profile of payoffs denoted as ϕ. The payoff is the gain achievable by a player to use a given communications means instead of the other possible ones, specifically, in our game, a player c receives a gain, namely α, for experiencing a good communication quality, *i.e.*, the reciprocal of the loss pattern reduced of the cost to send the messages by using such a communication means:

$$\varPhi^c(s) = \alpha(o(s)) - E(o(s)) = 1 - \varPi(o(s)) - E(o(s)). \tag{10}$$

where $o(s)$ is the function that given a strategy properly returns the variable $x_{n,s}$, $x_{n,v}$, $x_{n,u}$ set according to the selected BS, UAV and user device, while the two functions for the loss pattern and the energy consumption are normalised by considering the highest value so that their return is within the interval $[0, 1]$. The scope of the game is to determine the best strategy profile that implies the maximum payoff for all the players.

$$s^* \in arg \max_{s \in S} \frac{1}{N} \sum_{i \in L} \varPhi^c(s_i). \tag{11}$$

In our game, players are selfish, *i.e.*, there is no direct communication between the players, and each one only cares to maximize its own profit or to minimize its own costs without considering the state of the other players (with the eventuality of damaging them, even if it is not intentional). Then, the game is defined non-cooperative, and its normal form is given by $\varGamma = (P, S, \pi)$, with the objective of maximizing the payoff for all the players. One of the most studied aspects of such class of games is the existence of Nash Equilibria (NE), *i.e.*, given a certain strategy $s \in S$, it is not profitable for a player to select a different node than the one in the current strategy profile since moving to a neighbor node will not change or even reduce the achievable payoff, so a player has no incentive to change strategy:

$$\exists s \in S : \forall c \in P, \forall x \in Y, \pi^c(s^c, s^{-c}) \geq \pi^c(x, s^{-c}) \quad \rightarrow s \text{ is a NE.} \tag{12}$$

The demonstration of the existence of such equilibria is a known NP-hard problem and is resolved by means of theorems by making proper assumptions of the characteristics of certain elements of the game. A well known result of the research in non-cooperative games is that if the strategies are mixed, then the existence of at least one Nash Equilibium is guaranteed. A pure strategic game consists in a player always picking the strategy of highest quality (i.e., the one with highest payoff), while a mixed strategic game encompasses players that has a probability associated to the selection of the strategy of highest quality (meaning that there may be cases where the player does not take that strategy but one with lower payoff).

In typical application of game theory, the payoff functions of the players are assumed to be well known and externally given, and based on such a set of functions it is possible to drive each player output and determine the existence of Nash Equilibria. Moreover, as the game is non-cooperative, it is possible that a set of players decide to exploit the same communication means, possibly causing congestion. To this aim, in Equation 10, we add a contribution measuring the goodness of the selection with respect to the other players, by inserting a form of cooperation. Such a contribution is not fixed a priori, but it is dynamically computed based on the feedback provided by the other players. Such a feedback is -1 is the considered strategy is followed by the player returning the feedback, i other wise. So at the time a player decide to pursue a strategy, it broadcast such a decision to its reachable peers, receiving back feedback to estimate the goodness of the decision in the next iteration of the game.

In this case, the resolution of our game is not possible through the typical means provided by the game theory to deal with non-cooperative games. In this work we drawn from the theory of distributed strategic learning [9], where each player can learn from the received feedback for their outputs so as to create a payoff value and to determine if a given strategy yields the best response. Specifically, the resolution of our game requires a Reinforcement Learning (RL) scheme [10], where the players interacts with the other nodes and receives some feedback which represent the consequences of their actions and which depend on the state of the system and the actions of the other players. By using such feedback, each player learns to select or not a certain strategy based on its consequences. Strategies leading to to high payoffs in a certain situation will be preferred whenever the same situation recurs, while those strategies leading to lower payoffs will be avoided.

In order to tackle this problem, in this paper we apply the COmbined fully DIstributed PAyoff and Strategy-RL (CODIPAS-RL) [9], a learning scheme derived from strategy and payoff (Q-learning) Reinforcement Learning. CODIPAS-RL is an exploration strategy characterized by a high effectiveness in finding the best response dynamics in a game.

Let us denote with $y_{j,t}(s_j)$ the probabilities of the j-th player to choose s_j at time t, and $y_{j,t} = [y_{j,t}(s_j)]_{s_j \in A_j} \in Y_j$ be the mixed strategy of the j-th player. Moreover, we indicate with $r_{j,t}$ the perceived payoff at the time t, made of the two contributions of the loss rate and consumed energy aggregated with the estimation of the strategies based on the received feedbacks. CODIPAS works as follows:

- At time slot $t = 0$, each player chooses a strategy s and from it derives an action o. Then, it received a series of feedbacks for its action and builds a numerical value of its payoff. The payoff is properly initialized to $r_{j,0}$, given from the initial estimation of the loss rate and the energy consumption without the third contribution we envisioned to avoid congestion phenomenon.
- At time slot $t > 0$, each player has an estimation of its payoffs, namely $r_{j,t}$, chooses a strategy $x_{j,t+1}$ for the next time slot, which is a function only of the previous strategy $x_{j,t}$, the estimated payoff $r_{j,t}$ and the target value for the payoff function.
- The game moves to t+1.

Such a scheme is combined with proper payoff and strategy learning, leading to CODIPAS-RL:

$$\begin{cases} y_{j,t+1} = f_j(\lambda_{j,t}, o_{j,t}, r_{j,t}, \hat{r}_{j,t}, x_{j,t}) \\ \hat{r}_{j,t+1} = g_j(\nu_{j,t}, o_{j,t}, r_{j,t}, y_{j,t}, \hat{r}_{j,t}), \end{cases} \quad j \in [1, N], t \geq 0, o_{j,t} \in O_j(s_j). \tag{13}$$

The function f_j determine the update of the strategy at the next time slot and defines the strategy learning pattern of the j-th player, where $\lambda_{j,t}$ is its strategy learning rate that may vary from player to player and/or during the learning process. The variable $r_{j,t}$ contains the feedbacks received by each contacted nodes, while $\hat{r}_{j,t}$ is the estimation of the payoff function. The function g_j updates the estimation of the payoff function for the j-th player, by specifying the payoff learning pattern and is characterized by a given speed named as $\nu_{j,t}$, which may be different than the speed of the strategy learning function. We assume that the learning rates are taken identical for all the players and equal to $\lambda_{j,t}$ = 0.1 and $\nu_{j,t}$ = 0.6, respectively. In this work we have adopted the Boltzmann-Gibbs based CODIPAS-RL, since it outperforms the standard RL algorithms, and has been proved the convergence of the algorithm toward a pure strategy Nash equilibrium with sufficiently small learning rates [9]. Specifically, let us define the Boltzmann-Gibbs distribution as a strategy mapping $\widetilde{\beta}_{j,\epsilon} : \mathbb{R}^{|S_i|} \rightarrow \mathbb{R}^{|S_i|}$ known as the soft-max function and formulated as follows:

$$\widetilde{\beta}_{j,\epsilon}(\hat{r}_{j,t})(s_j) = \frac{e^{\frac{1}{\epsilon_j}\hat{r}_{j,t}(s_j)}}{\sum\limits_{s'_j \in S^j} e^{\frac{1}{\epsilon_j}\hat{r}_{j,t}(s'_j)}}, \quad s_j \in S^j, j \in [1, N] \tag{14}$$

In such an equation, s'_j may be interpret as any possible strategy for the j-th player which is different to s_j, and the parameter ϵ_j for the j-th player may be identical to the one of the other players, or may be different, and its reciprocal can be interpreted as the rationality level of the player. When $\epsilon \rightarrow 0$, such a strategy mapping returns the strategy characterized by the maximum value for the estimated payoff $\hat{r}_{j,t+1}$; therefore we assume $\epsilon = 0.1$. Based on such a distribution, we can formulate the f and g functions of the learning pattern in Equation 13 as follows:

$$\begin{cases} y_{j,t+1} = (1 - \lambda_{j,t})y_{j,t} + \lambda_{j,t}\widetilde{\beta}_{j,\epsilon}(\hat{r}_{j,t}) \\ \hat{r}_{j,t+1}(s_j) = \hat{r}_{j,t}(s_j) + \nu_{j,t}\mathbb{1}_{\{o_{j,t+1} \in O_j(s_j)\}} \\ (r_{j,t+1} - \hat{r}_{j,t}(s_j)), \end{cases} \quad j \in [1, N], t \geq 0, o_{j,t} \in O_j(s_j). \tag{15}$$

The function $\mathbb{1}_{\{o_{j,t+1} \in O_j(s_j)\}}$ indicates the active strategy of the player and assumes 0 if the action $o_{j,t}$ has not been played by the j-th player at time t, 1 otherwise, so as to update only the component corresponding to the action that has been played. In Equation 15, the learning of the payoff and the strategy are coupled and updated together: the feedback of an action at the time instance t is used to update the payoff estimation, and such an estimation is used to determine the strategy. The stable solution of such an equation can be assumed as an equilibrium for a modified game, where the payoff function of our game is perturbed with an extra entropy contribution indicating its dependency on the loss pattern applied by the network dynamics and the actions of other players.

5 Numerical evaluation

We have implemented a Java application that randomly deploy BS, user devices and UAV within a Cartesian space, where each of them has a couple of coordinates. Initially the application determine for each user device the closest BS and UAV based on the Euclidian distance among a user device to all the deployed BS and UAV and select those with the lowest distance. We have assigned as energy consumption three values 0.25, 0.5 and 0.75, respectively to the ad-hoc connection towards another user device, to UAV and to BS. We assume that the communication between the user device and the UAV is not based on cellular technology, as with the BS, but by using WiFi, in an ad-hoc manner. As for the device-to-device communication a low rate and efficient communication mean as Bluetooth can be exploited, with UAV this is not the optimal decision, so a more powerful RF technology as WiFi may be used. It is also true that a UAV can be equipped with a cellular antenna making it looks like a moving BS, so in that case the cost value for the energy consumption is equal to the one of BS. Each element has a very low loss rate initially, equal to 0.1, as wireless communications always drop packets due to interference and other issues. So that at the beginning all the user device only is associated to the nearest BS. At a time T_D, the disaster occurs and the loss rate of BS increases as a consequence of the occurred failure. We do not assume the complete destruction of a BS, but only its lossy behaviour. The destruction of BS can be modelled by using a Poisson point process with a thinning operation [27]. With a given probability π_D each BS of N is tagged as compromised and the respective loss rate assumes a given values within a certain interval ($e.g.$, from 0.2 to 0.5). After running the game and computing the payoff for each possible strategy, we have fixed a starting probability equal to 0.9 (we want a slight varability in the winning strategy selection) that the player picks up the strategy with the highest gain.

Figure 1 shows the preliminary results obtained from our simulation. Initially the loss rate is low, equal to the initial vale of 0.1. Later on, at iteration 3, the disaster occurs and the loss rate increases to a value that is stationary when the user is kept associated to its initial BS, such a value lower due to the adaptation of our approach to multiple associations. Such a reduction is valid until a point where the loss rate is almost stationary as the loss rate do not have any changes apart to the one caused by the disaster. The transitory is due to the learning scheme, which brings the system to an equilibrium point. A similar behaviour can be seen in the energy consumption, which

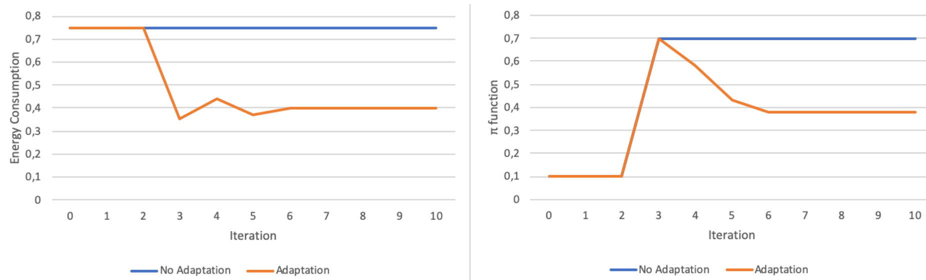

Fig. 1: Assessment results.

starts with the consumption due to the use of a BS. This is due to the case that most of the users tries to select a neighbour device or a UAV, allowing the scheme to lower the energy consumption.

6 Related work

Apart from centralized solutions, there are some distributed solutions providing mechanisms for user association. For example, in [20] the authors present a distributed algorithm considering previous paths of users in mobility and combines these data with wireless measurements to predict the upcoming connection quality of the network. Other works [21] consider an accurate model of two-dimensional and three-dimensional scenarios to determine user trajectories, when, for example some vehicles (i.e. drones) are involved. However, these works assume that mobility patterns of users are known [21], or can be guessed by training [22]. Our solution does not require previous knowledge about users behaviour.

Regarding QoS-based network selection we can find different approaches considering QoS constraints [16][17] or Quality of Experience (QoE) [12]. Some of these works are focused on a number of factors including the mobility pattern of the mobile device, the load of the candidate access network, and the preference of the candidate access network to the call request [18]. Other works [19] consider also a trade-of between users and operators preferences, such as quality of the connections or other network conditions. All these works, however, consider a single association between the user and an access point. Our approach considers, apart from the imposed QoS by executing applications, the possibility of connecting to multiple base stations.

Many of the previous works describe situations where the user terminal is associated with only one access point. The multi-RAT (Multiple Radio Access Technology) technique has emerged for heterogeneous scenarios, considering that user equipment can transmit and receive data over multiple networks [23]. Apart from these multimode terminals, multi-RAT parallel transmission from more than one AP provides a new level of complexity, as some load-balancing capabilities [24] and other network congestion prevention methods [25] must be defined, and are also found in the literature. In this work, we incorporate the use of multi-RAT transmission to the scenario where BS load levels, energy and QoS requested by users are considered.

7 Conclusions

This paper presented a solution based on game theory for the resolution of the problem of selecting among multiple communication means so as to cope with network resiliency in a post-disaster scenario. As a future work we plan to implement the proposed solution and the empirically assess the achievable quality against a centralised meta-heuristic approach based on genetic algorithms.

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