Optimizing Drone Deployment for Cellular Communication Coverage During Crowded Events

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***Abstract*—In case of unexpected or temporary events, cellular networks can become quickly saturated. A promising solution is using unmanned aerial vehicles (UAVs), known as drones, as flying base stations. In this article, we address the issue of anomalous behaviour within cellular networks that occurs during crowded events. The proposed approach consists of two parts: the detection of overloaded cells using machine learning algorithm (LSTM – Long Short-Term Memory) and the deployment of drone-Bss to assist the cellular network by providing wireless coverage. Initially, we use the LSTM algorithm to analyze the impact of extra-data on the network and then detect the peaks of users demands. Then, we formulate an optimization problem for maximizing the number of users to serve when deploying drones taking into account the energy constraints. The proposed approach is validated using real dataset extracted from the CDR of Milan. Simulation results show that the use of drones can satisfy the QoS requirements of the network.**

***Index Terms*—Optimization, Drone-BS Deployment, Anomaly Detection, Machine Learning, Crowd Monitoring.**

I. Introduction

The tremendous number of smartphones, tablets, laptops and the popularization of the use of social media passing through 4G generates an enormous amount of data that may be gathered and managed by cellular networks. During mass events, extra data are uploaded. During a protest for example, photos and videos are uploaded to social media and during a marathon event, additional eHealth data are loaded to the network. In these scenarios, the extra data may overload the network and cause some anomalies that require autonomic and pro-active tools. Indeed, smart mechanisms must be integrated into the architecture and may be based on machine learning techniques that have the power of exploiting the plethora of data generated by cellular networks.

The cellular operators are confronting a major challenge due to the high number of applications using cellular connectivity and how to ensure ubiquitous connectivity for several devices and users in a flexible, reliable, and secure manner while improving the load on network resources. Another influential issue for network operators is to identify sudden and local anomalous behavior inside the network, whether it is an explicit peak of users demands (happening during mass events like a protest), which requires smart tools to ensure network elasticity and service survivability.

One of the proposed solutions is the use of drones or Unmanned Aerial Vehicles (UAVs), also known as drones, as flying base stations [1]. Drones are characterized by mobility, flexibility, and adaptive altitude. They are expected to provide diverse civilian, commercial, and governmental services. Although drone-cell technology is a promising solution to buck up and support cellular network, it needs an optimized method to deploy drones.

In literature, we find different works focusing on anomaly detection and optimized drone-cell deployment. [2] proposes an unsupervised clustering technique for fault detection and diagnostics in a cellular network based on key performance indicators (KPIs). The input data includes call blocking and signal quality measurements, but it does not provide online anomalies detection. [3] explores the problem of congestion and proposes a framework for congestion management in a drone-cells network. In [4], authors present an UAV-based IoT platform and introduce the case of UAV-based crowd surveillance applying facial recognition tools. They developed a testbed using a built-in UAV along with a real-life LTE network. A Support Vector Regression machine learning method was utilized in [5] to define an online anomaly detection tool. In [6]a comparison for anomaly detection using SVR and two other algorithms named Multi-Layer Perceptron and Multi-Layer Perceptron with Weight Decay was proposed. Alsharo[7] proposed an energy management framework for cellular heterogeneous networks assisted by solar powered drone small cells. They formulated an integer linear programming problem in order to minimize the total energy consumption of the networks over a time-slotted period while maintaining the network coverage and connectivity. Authors also proposed a wireless relay selection scheme involving multiple mobile Unmanned Aerial Vehicles (UAVs) to support communicating ground users in [8]. The goal is to optimize the transmit power levels and trajectories of the relaying UAVs in order to maximize the data rate transmission of the ground users which are suffering from the absence of direct link.

Most of the suggested anomaly detection solutions have been assessed using simulated data to detect the anomalies, which may influence the real performance and require time especially when the networks become denser. Within this context, we propose a self-organized anomaly detection scheme using Long Short-Term Memory (LSTM) machine-learning algorithm to forecast the normal behavior of the network. This solution is applied to a pre-analyzed semi-synthetic data set of cellular data in the context of a mass event in Milan city. The LSTM algorithm is applied to calculate the normal load of the network and then define the minimum and the maximum acceptable threshold values. The proposed approach compares then the collected real data to the predicted values and generates alerts if the measured real time data exceeds the thresholds. After that, the platform executes the 3-D drones-BS deployment scheme aiming to collect data in overloaded cells. We formulated an optimization problem aiming to support the network's capacity and taking into account the energy constraint of drones.

The rest of the paper is structured as follows; in Section II the anomaly detection method for abnormal events caused by protest event data is detailed. In section III, we present the drone-cell assisted deployment approach and we detail the optimization model. Simulation parameters and a comprehensive analysis for the impact of the extra data on the network is presented in section V. Finally, section VI concludes the paper.

II. Dynamic Anomaly Detection

A. Data Set

The (CDRs) Call Detail Records used in this study is published as a part of the Big Data Challenge launched by Telecom Italia in 2014 [9]. The CDRs contains information like Calls, SMS, and Internet activity of a customer that are captured by the Telecom companies. The used dataset is a description of data of the city of Milan which is divided into 10,000 squares of size a 235m x 235m. The subscribers' communications activities are detailed in the dataset. The cell ID presents the geographical location. The activity occurrence time, the country code, incoming and outgoing calls, received and sent text messages and data usage (Internet) are available in the dataset. The proposed data is in time slots of 10 minutes. 6 cells are controlled during a protest in the center of Milan city. During the protest, we study the impact of photos and videos data uploaded on social media.

B. Network Load Prediction and Anomaly Detection

LSTM-based Prediction Model: Different works investigated the Recurrent Neural Network (RNN) to deal with forecasting time series in several areas. RNN is a class of Artificial Neural Network (ANN). Even they provide good results treating time series, they suffer from the vanishing gradient. For our study, we used the Long Short Term Memory(LSTM) algorithm for network load prediction. The LSTM was firstly proposed in 1997 by Hochreiter and Schmidhuber [10] for language modeling to solve the vanishing problem.

Long Short-Term Memory is a recurrent neural network formed of three layers: Input Layer, Hidden Layer, and Output Layer [11]. It includes special blocks, each block contains special multiplicative units called gates. A typical memory block is composed of three gates. The incoming data are going to be treated by the input gate so it could add information.

The Information that is no longer required for the LSTM understanding are going to be removed by the forget gate. The useful information are going to be selected by the output gate from the current cell, state and showed out as an output. Let's consider the following formulation, $X = (x_1, ..., x_t)$, be the input sequence, $Y = (y_1, ..., y_t)$ the output vector sequence and hidden state of memory cell, $K = (\kappa_1, \ldots, \kappa_t)$.

$$\kappa_t = K(W_{\kappa x} x_t + W_{\kappa\kappa} h_{t-1} + b_\kappa) \tag{1}$$

$$p_t = W_{\kappa y} y_{t-1} + b_y \tag{2}$$

Where:
$W_{\kappa x}$ corresponds to the weight between the input and hidden layer parameters, $W_{\kappa y}$ corresponds to the weight between hidden and output layer parameters, $W_{\kappa\kappa}$ corresponds to the weight between hidden layers, b_κ and b_y symbolizes the bias vectors for the output and hidden layers. K is a nonlinear activation functions.
To apply LSTM in the proposed scheme, we first predict the normal daily load on each cell by training the LSTM model with the history and measured network load dataset. In this model, we stack 3 LSTM layers: the first layer considers one input, the second layer is hidden and contains 4 LSTM blocks, and finally the third layer is the output layer and generates a single prediction value. his model is trained for 3000 epochs and used a batch size of 1.

Dynamic Network Anomaly Detection: During the protest, in the center of Milan, the amount of uploaded data (photos, videos) to social media could cause sudden congestion to the cellular network and then decrease its quality of service. The prediction model is applied to calculate the normal load of each terrestrial base station as a function of the time. Based on this prediction model, we define the minimum (Min) and the maximum (Max) acceptable threshold values. The real-time collected data generated by users' demand is then compared to these predicted values (Min-Max). Anomalous time-interval is detected if measured real time data is lower or higher than the appropriate tolerance thresholds. Hence, the terrestrial base stations may fail to handle all connected users because of the congestion within the cell and conduct to a malfunction in the infrastructure. For this reason, we are proposing an automatic plateform that allows network operators to detect anomalous network cells and launches the deployment of drones with a mission of data collecting in overloaded cells. The objective is to improve the quality of service (QoS) of the network.

III. Optimized 3-D Deployment of UAVs

In this section, we formulate an optimization problem of 3-D drone-cells deployment aiming to serve the maximum number of users with the minimum consumption of energy.

A. System Model

This section presents the system model and states the studied problem. We consider a cellular network assisted by a set of dynamic drones, denoted $D = \{D_1, D_2, \dots, D_k\}$. Drone-Bs (DBSs) act as flying base-stations to back up the network and cover the overloaded cells. The symbols and notations used in the paper are summarized in Table II.

a) Network Model: In this study, the proposed network model is centralized and composed of a coordinator base station, charging stations and a set of drones (Figure 1). We consider an urban area of interest to deploy DBSs. In Figure 1, we distinguish three overloaded areas to be covered by DBSs which can serve users in multiple cells. we consider an uplink transmission that can be used for data collection (uploading photos, videos).

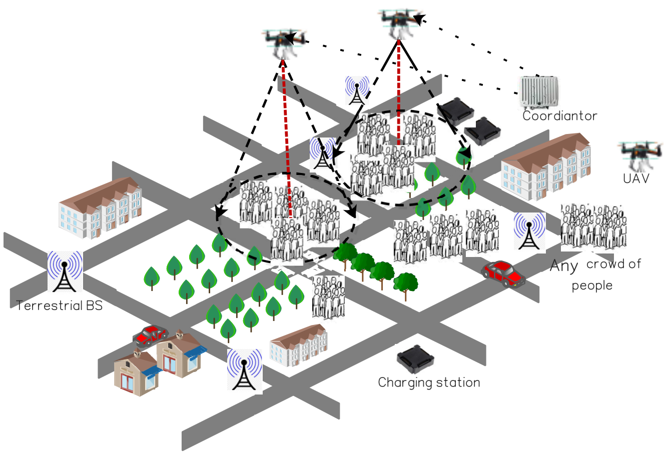


Figure 1: Drone-assisted Network Model in crowded events.

The coordinator executes the prediction algorithm and then locates the set of cells that should be assisted, denoted by $S = \{S_1, S_2, \dots, S_n\}$. The set of charging stations is presented by $C = \{C_1, C_2, \dots, C_c\}$. The management of the drone-cells deployment is based on the global objective function defined hereafter.

Initially, all drones are located at the charging stations. Based on the decision of the coordinator, they move to a constant altitude h in the designated cells to serve ground outdoor users. They return back to the charging station at the end of the mission or when their batteries are depicted. In fact, the state-of-charge (SoC) should be greater than $\underline{W} Joules$, which presents the residual energy for the drone to return to the charging station. We define $\overline{W}$ as the maximum energy level of the drone.

Let a given DBS $k \in D$ be located in the 3-D Cartesian space at (x_k, y_k, h) where the altitude h should not be lower than H_{min}. The Euclidean distance between DBS d and point $p = (X_p, Y_p, Z_p)$ is given by the following equation:

$$\delta_{k,p} = \sqrt{(x_k - X_p)^2 + (y_k - Y_p)^2 + (h - Z_p)^2} \tag{3}$$

We note that the size of the area to be covered is a function of the altitude of the drone, which affects the number of users served by the drone-BS.

Table I: Notations and Descriptions

Notation	*Description*
$D = \{D_1, D_2, \dots, D_k\}$	The set of drones
$S = \{S_1, S_2, \dots, S_n\}$	The set of congested cells
$C = \{C_1, C_2, \dots, C_c\}$	The set of charging stations
$\overline{W}$	The maximum energy level of DBS
$\underline{W}$	The lowest energy level of DBS
T	The drone service time
h	The constant altitude of DBS
(x_k, y_k, z_k)	The 3-D geographical coordinates
V	The constant speed of the drone
ψ	The total length of the trajectory of the drone
q_i	The displacement of the drone
P_{hov}	The hovering power level of the drone
P_{har}	The hardware power level of the drone
η_{LoS} and η_{NLoS}	The average propagation loss LoS and $NLoS$, respectively
Γ_{LoS} and Γ_{NLoS}	The path loss of LoS and $NLoS$, respectively
m_d	The mass of the drone
V_{max}	The maximum speed of the drone
G	The earth gravity
ν_p	The number of the drone's propellers
R_p	The radius of the drone's propellers
P_0, P_i	The drone hardware power at full speed and in idle mode, respectively
ς	the speed of light
$W_d(T, \psi)$	The energy consumption of the drone
$\delta_{d,i}$	The distance between a drone d and user i
N_{max}	The maximum number of available drones

b) Air-to-Ground Channel Model: The Air-to-Ground channel is characterized by its higher chance of line-of-sight (LoS) connectivity. Indeed, we consider a path loss model including both transmissions: Line-of-Sight (LoS) and Non-Line-of-Sight ($NLoS$). The probability of having a LoS connection between a drone and covered users depends on the elevation angle of the transmission link. The LoS probability can be expressed by [7]:

$$P_{LoS} = \frac{1}{1 + \alpha \times \exp(-\beta[\theta - \alpha])} \tag{4}$$

where α and β are constant values that depend on the environment (rural, urban, dense urban, etc). θ is the elevation angle between the DBS and a given ground user. If h is the DBS's altitude and d the horizontal distance between the DBS and the user, then θ is expressed in degrees as:

$$\theta = \frac{180}{\pi} arctan(\frac{h}{d}) \tag{5}$$

Consequently, the probability for the aerial base station to ground user links to have a $NLoS$ is given by the following equation:

$$P_{NLoS} = 1 - P_{LoS} \tag{6}$$

According to equation 4, the LoS probability increases as the elevation angle θ increases.

B. Drone Power Model

Reducing the energy consumption is a major challenge specially when using drones in public safety and UAV-assisted Cellular Networks. Indeed, DBS consumes energy in data collection (the communication energy) and in-flying (the propulsion energy) [12]. The communication energy is related to the signal processing and signal transmission while the propulsion energy refers to the mechanical energy consumption for movement and hovering. Typically, the energy consumption caused by wireless transmission is neglected compared to the propulsion energy and is ignored in the proposed model. Furthermore, the energy consumption of the DBS depends on the role and the mission of the DBS, the flying path and weather conditions.

We denote by P_{hov} and P_{har} the hovering and hardware power levels, respectively. The flying power can be expressed as [7]:

$$P_F^d = P_{hov} + P_{har} = \sqrt{\frac{(m_d G)^3}{2\pi R_p^2 \nu_p \rho}} + \frac{P_0 - P_i}{V_{max}} V_d + P_i \tag{7}$$

Where V_d and m_d are the constant speed and the mass of the drone respectively. V_{max} is the maximum speed, ρ is the air density and G is the earth gravity. ν_p and R_p represent the number and the radius of the drone's propellers, respectively.

We differentiate two statues for the drones: serving or idle. In fact, P_0 and P_i are the hardware power levels when the drone is flying in full speed and when the drone is in the idle mode.

IV. Problem Formulation

In this section, we formulate the optimization problem with two objectives: maximize the service time of the drones, and maximize the number of covered users in overloaded cells.

A. *Maximizing the DBs service time*

Since drones only receive data in the uplink direction, and since receiver's power consumption is very small, the communication energy consumption is ignored in the proposed model. Hence, we only formulate the energy consumed in flying. This metric helps to minimize the number of deployed drones.

Given ψ the length of the trajectory of the drone, the required energy consumption for traveling with the constant speed, V, is expressed in Eq. 8:

$$\mathrm{W}_d(T,\psi) = P_F^d \sum_{i=0}^{\psi_d} \frac{q_{d,i}}{V}$$
$$= [\sqrt{\frac{(m_d G)^3}{2\pi R_p^2 \nu_p \rho}} + \frac{P_0 - P_i}{V_{max}} V_d + P_i] \sum_{i=0}^{\psi} \frac{q_{d,i}}{V_{d,i}}; \quad \forall d \in D (8)$$

where the trajectory of the drone is expressed as the sum of all displacement between charging stations and cells ($q_{d,i}$. We assume that if the drone is in a static position, then it consumes only the power in idle mode when collecting data. However, when it is flying, it will consume the hardware power.

The optimization problem minimizing the total energy consumption for a drone $d \in D$ is given as:

$$P(1) : \underset{T,\psi_d}{Minimize} \; (\max(W_d(T, \psi_d))) \tag{9}$$

Subject to:

$$\underline{W} \leq \overline{W} - W_d(T, \psi); \tag{10}$$

$$\psi_d = \sum_{i=0}^{T} q_d(i) \tag{11}$$

Constraint (10) ensures that the designated drone has sufficient energy to return to the charging station. W_0 is the initial energy level of the drone. Constraint (11) indicates that the total length of the trajectory of the DBS is the sum of different displacement during the service time, denoted q_d.

B. *Objective 2: The maximum cell coverage*

The coverage of the drone-cell is identified by the maximum number of covered users. In fact, the size of the area to be covered change as a function of the altitude of the drone. A user is covered by the drone if the link satisfies its QoS requirement. The path loss for the LoS and $NLoS$ links in dB is given respectively by [13]:

$$\Gamma_{LoS}[dB] = 20\log_{10}(\frac{4\pi f_c \delta_{d,i}}{\varsigma}) + \eta_{LoS} \tag{12}$$

$$\Gamma_{NLoS}[dB] = 20\log_{10}(\frac{4\pi f_c \delta_{d,i}}{\varsigma}) + \eta_{NLoS} \tag{13}$$

Where ς is the speed of light, $\delta_{d,i}$ is the distance between a drone and a given user i and f_c is the carrier frequency. The values of η_{LoS} and η_{NLoS} depend on the environment and present the additional loss to the free space propagation for LoS and $NLoS$ connection, respectively.

The probabilistic mean path loss is given by:

$$PL = P_{LoS}\Gamma_{LoS} + P_{NLoS}\Gamma_{NLoS} \tag{14}$$

Considering σ as the path-loss corresponding to the QoS requirement. Hence, a given user i is served by the drone-BS, if $PL \leq \sigma_{QoS}$.

As shown in Figure 1, the coverage region for each drone is assumed to be a circular disk with radius R_d and center $O_d = (x_d, y_d)$. The user υ is covered by the drone if it is located in the circular disk. Let $\upsilon_i^d \in \{0, 1\}$ a binary variable that indicates whether a user is served by the drone or not. $\upsilon_i^d = 1$ iff user υ_i is served by the drone d located in (x_i, y_i). This condition can be written as:

$$\upsilon_i \sqrt{(x_d - x_i)^2 + (y_d - y_i)^2} \leq R_d \tag{15}$$

Depending on the QoS for all users, the best region to be served by the drone-BS is identified by offloading the maximum set of users denoted U. The optimization problem can be formulated as follows:

$$P(2) : \underset{h,\{\upsilon\},x_d,y_d}{\text{maximize}} \sum_{d\in D} \sum_{i\in U} \upsilon_i \tag{16}$$

Subject to:

$$\upsilon_i \leq 1 + \frac{R_d^2 - (x_d - x_i)^2 - (y_d - y_i)^2}{M}; \; \forall i \in U \tag{17}$$

$$\begin{aligned} &X_l \le x_d \le X_m, \\ &Y_l \le y_d \le Y_m, \\ &PL \le \sigma_{QoS} \end{aligned} \tag{18}$$

$$\upsilon_i^d \in \{0,1\}, \forall i \in U \tag{19}$$

$$\sum_{d \in D} \upsilon_i^d \le 1 \tag{20}$$

$$N_d^c \le N_{max} \tag{21}$$

where X_l, Y_l, H_L, X_m, Y_m, present respectively the minimum and maximum allowed values for x_d and y_d of the drone-BS. These values are defined by the coordinator and depend on the overloaded cell. N_{max} is the maximum number of available drones. M is a very large constant defined in order to verify the condition in Eq. (15). In fact, if the RHS(Right Hand Side) is ≤ 1, then υ_i^d may be either 0. If $RHS \ge 1$ then υ_i^d must be 0 or 1.

C. *The Global Objective Function*

The global optimization problem can be expressed as:

$$\underset{h,\{\upsilon\},x_d,y_d,W_d}{\text{maximize}} \sum_{d \in D} \sum_{i \in U} \upsilon_i \tag{22}$$

Subject to: (10), (11), (17), (18), (19) and (21).

To guarantee a certain time for serving users and due to the limited energy of drones, the positions of drone-BSs should be well calculated in order to reduce the power consumption in flying which increases the activity time (T) of each drone.

The problem (22) is a mixed integer non-linear problem (MINLP) which is difficult to solve. In fact, this difficulty arises due to the coupling between the altitude (h) and the horizontal placement (x_d, y_d). Hence, we suppose that the drones move in a constant altitude and have a constant position.

D. *DBS Management scheme*

The proposed algorithm for DBS deployment is centralized and the decision is made by the coordinator that is detecting the outliers and managing the set of drones. The coordinator plays the role of network orchestrator: It is responsible in gathering the information about the network traffic, executing the LSTM prediction algorithm to detect overloaded cells and then making the right decision to deploy drones. The coordinator is selected by the network operator and can be a central node such as a macro-cell.

The framework starts by executing the prediction algorithm to identify the cells with peak users' demand. Then, the coordinator, calculates the required number of drones based on the amount of extra data. After that, it assigns DBSs to cells based on previous equations and constraints. The assignment is obtained based on the shortest path between the charging station and the congested cell. Hence, minimizing the flying distance involves reducing the energy consumption and then maximizing the service time. Figure 2 depicts a global view of the proposed framework architecture.

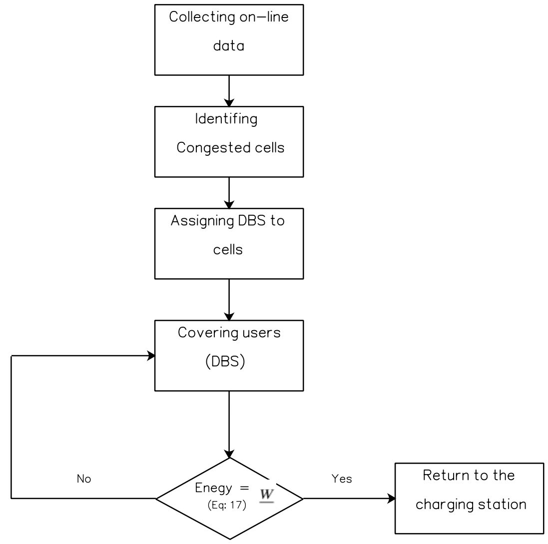


Figure 2: The proposed framework flowchart.

DBSs fly from their initial position, collect data and then return back to the charging station based on the optimized assignment defined by the coordinator. This solution tries to maximize the total QoS by avoiding the deployment of drones in cells with the highest outliers.

V. Performance Evaluation

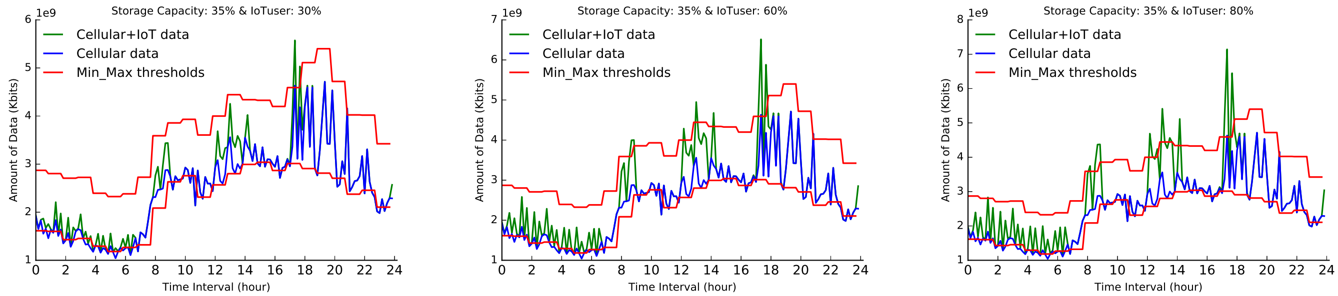
A. *Performance Metrics*

In this section, numerical results are provided to investigate the utility of using drones when anomalies are detected in cellular network. We consider real time-series dataset presented in II-A combined with semi-synthetic data generated by demands of users during the crowded event. We consider the data usage of 6 cells in the city center. We consider two types of data: Non-Real Rime (NRT) and Real-Time (RT). The NRT data is used in store-and-forward transmission mode and depends on the storage capacity of the smartphone. It is chosen to be beyond the maximal storage capacity so that it does not affect the performance of the smartphone. The RT data is uploaded immediately on social networks.

Table II illustrates the values of the remaining parameters used in the simulations for the DBS deployment. We assume a network consisting of 7 charging stations, 14 drones and six terrestrial base stations. We consider that the drones are initially charged with $\overline{W} = 6kJ$ of energy and placed at the charging station.

B. *Simulation Results*

In figures 3 and 4, we start by investigating the effect of protesting data on the cellular network. These figures present the anomalous behavior of the network for one cell from the six considered cells in the center of Milan. We study the impact of the data capacity storage and we vary the percentage of protesting data. Red curves present the range: Min and Max threshold values of normal traffic which are calculated

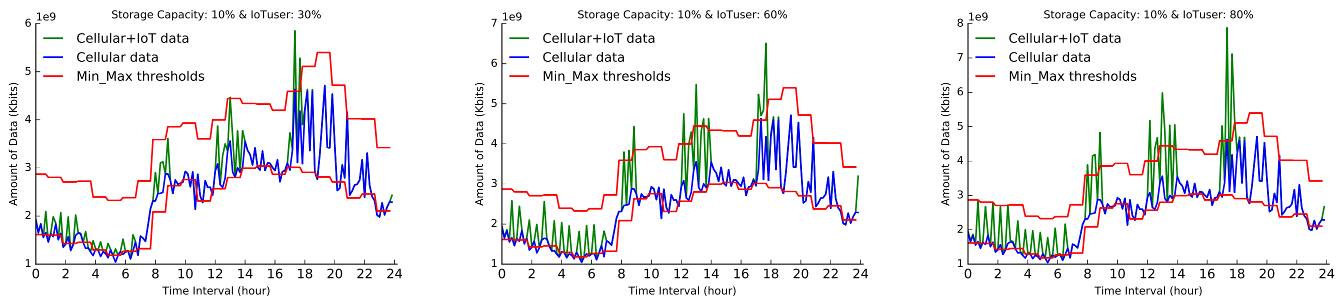


(a) Protesting data=30%

(b) Protesting data=60%

(c) Protesting data=80%

Figure 3: Network load for storage capacity = 35%.



(a) Protesting data=30%

(b) Protesting data=60%

(c) Protesting data=80%

Figure 4: Network load for storage capacity = 10%.

Table II: Simulation parameters.

Parameter	*Value*
Number of cells	6
Drone speed	15 m/s
Drone Height	10 m
Drone max battery	6KJ
Number of drones	14
Number of charging stations	7
η_{LoS}	1 dB
R_p	20 cm
Γ_{NLoS}	12 dB

based on the LSTM algorithm. Blue curves present the normal network traffic however the green curves illustrate the real time network load when adding the semi-synthetic protesting data (IoT data) which can be upload in real time on social media.

Considering the NRT data, we fix the storage capacity for the protesting event data to 35% and to 10% out of the total capacity storage of the smartphone. Results are presented in Figures 3 and 4, respectively. Furthermore, we vary the percentage of users' demand by considering 30% (Figures 3a, 4a), 60% (Figures 3b, 4b) and 80% (Figures3c and 4c) of network traffic. It is clear that the extra-data does not have a significant impact on the network with 30% of users' demand for both cases of storage capacity. In essence, we depict an overrated peak of data (between 5PM and 6 PM in Figures 3a and 4a). These load peaks impact the radio channel occupancy causing the anomalies. They are detected if the real-time network load is higher than the maximum value of the predicted data. When the users' demand increases to 60%, we still have the same load peak as the first scenario but with a higher amplitude. We notice an other smaller peak detected between 1PM and 2PM. This peak is more important with 10% of capacity storage. This is because, data is sent on real time to the network however in the case of Figure4b, 35% of semi-synthetic data is stored on the smartphone.

Finally, when protesting data reaches 80% of data, the cellular network is seriously impacted in both cases. Indeed, the streaming data causes three peaks (around 9 AM, 2 PM, and 6 PM) with different degree, but the most important load peak is between 5PM and 6PM where the global data traffic is nearly double compared to the ordinary network measurements. We conclude from these results that the uploaded data on social media in the protest will add an important load to the normal cellular network and it drastically impacts the network in some configurations. Moreover, The variation of storage capacity parameter can influence the amplitude of the peak. It is clear than with 10% the peak is more important than 35%. This is due to the fact that the forward time for the NRT application does not coincide with the usual network peak hour. Finally, results are also influenced by the behavior of the cell to which the user is attached. The normal cellular load peak hour can be different from a cell to another, and this is related to the load profile of each cell. The presented results are for one cell. The behaviour of other five cells is similar to the presented results but with different time and degree of peaks.

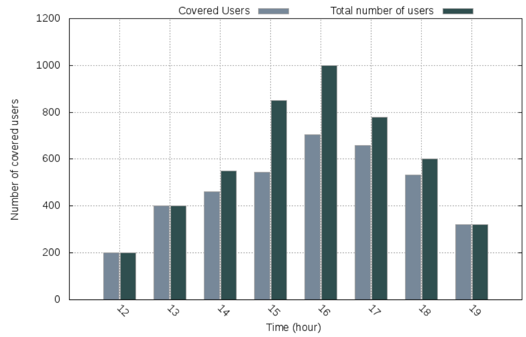


Figure 5: The number of covered users vs the total number of users

After detecting the anomalous time-intervals in each cell by executing the LSTM prediction and anomaly detection algorithm, the coordinator identifies the set of congested cells and executes the deployment scheme in order to collect data and maximize the coverage. We make a zoom on the peaks in other cells tacking into account the behaviour of each cell. We consider cells with the highest peaks of users' demand when people are protesting between 12PM and 7PM. The protests arrive to the main square of the city and then block roads. They walk on the streets of Milan city center. The maximum load is reached between 3PM and 4PM and then decreases. Figure 5 depicts the preliminary results for the optimization problem with 14 drones. It is clear that all users are fully covered before 2PM and drone-BSs collect required data. When they are out of charge, they return back to the charging stations. However, with the high peak of demands, 14 drones are not sufficient to cover all users. In essence, only between 65% and 70% of users are covered. This is because, the number of available drones is insufficient (Drones are still charging) and is lower than the requested number. After charging the batteries, drones can collect data from all cells and cover all users (at 7PM).

VI. Conclusion

In this paper, we present a dynamic network anomaly detection approach that has been validated with real dataset. Then, we developed a 3-D DBS deployment aiming to support macro-cells when data rate demand is exploded. In essence, we formulated an optimization problem where its objective is to maximize the number of users to cover in overloaded cells by finding the optimal 3-D placement of the UAVs in addition to minimizing the UAVs' energy consumption. Hence, the goal is to improve the quality of service (QoS) of the network. The proposed solution helps network operators to efficiently manage their infrastructure and allows them to implement self-organized and autonomous networks that can face the plethora of unexpected data. In the future, we will work toward performing crowd surveillance and analyzing of recorded videos.

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