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Adel Mounir Said, Michel Marot, Hossam Afifi, Ahmed E. Kamal, Hassine  
Moungla, Gatien Roujanski

► **To cite this version:**

Adel Mounir Said, Michel Marot, Hossam Afifi, Ahmed E. Kamal, Hassine Moungla, et al.. Models for real/non-realtime traffic QoS in UAV assisted cellular networks. IEEE International Conference on Communications (ICC), IEEE, May 2023, Rome, Italy. hal-04196514

**HAL Id: hal-04196514**

**<https://hal.science/hal-04196514>**

Submitted on 6 Sep 2023

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# Models for Real/Non-Realtime Traffic QoS in UAV Assisted Cellular Networks

Adel Mounir Said  
Switching Department  
National Telecommunication Institute (NTI)  
Cairo, Egypt  
adel.mounir@nti.sci.eg

Michel Marot  
SAMOVAR - Telecom SudParis  
Institut Polytechnique de Paris  
Palaiseau, France  
michel.marot@telecom-sudparis.eu

Hossam Afifi  
SAMOVAR - Telecom SudParis  
Institut Polytechnique de Paris  
Palaiseau, France  
hossam.afifi@telecom-sudparis.eu

Ahmed E. Kamal  
Electrical and Computer Engineering Department  
Iowa State University  
Ames, USA  
kamal@iastate.edu

Hassine Mouncla  
LIPADE  
Université Paris Cité  
Paris, France  
hassine.mouncla@u-paris.fr

Gatien Roujanski  
Telecom SudParis  
Institut Polytechnique de Paris  
Palaiseau, France  
gatien.roujanski@telecom-sudparis.eu

**Abstract**—Two models are proposed to optimize unmanned aerial vehicles (UAVs) traffic offloading in cellular networks. The first model optimizes the realtime traffic service, while delaying non-realtime traffic in the cell buffers (BS and the currently serving drone). Delayed traffic is then transmitted later when free resources are available and has a maximum service delay limit. The proposed model provides a heuristic solution to minimize the losses in non-realtime traffic based on the maximum delay and the size of the cell buffers. The second model completes the work by providing an optimal Integer Linear Programming solution to minimize the number of needed UAV assuming no data loss and buffering availability. It is also parameterized with the same delay limits as the first model.

The performance of the proposed models is studied using the call detail record (CDR) dataset of the city of Milan cellular network provided by Telecom Italia. The two models showed great QoS performance based on the maximum delay of non-realtime traffic and cell buffer size compared to models that do not include the buffering and the delay limits.

**Index Terms**—Realtime traffic, QoS, unmanned aerial vehicle, offloading, machine learning, placement optimization

## I. INTRODUCTION

UAVs (Drones) can be exploited for communications, and can serve as a flying base station (BS) to temporarily cover a specific location [1] and help in offloading traffic. In addition, it can be used to increase the cell bandwidth (BW) when there is high traffic due to an event (anomaly) [2], [3].

On the other hand, since users' traffic can be classified based on its time dependence, cellular resources must be utilized in an efficient manner. Accordingly, while cellular resources used to send realtime traffic, non-realtime traffic will be buffered waiting for free resources to be sent. Even non-realtime traffic has a maximum delay or it will be discarded. Therefore, we need to optimize the needed number of drones and its buffer to serve realtime traffic and reduce non-realtime traffic loss.

In this contribution, we aim to solve optimization problems when deploying UAVs that can deal with both realtime and non realtime traffic. We first design two models: one heuristic

and one optimal to model our deployment case. We then show that buffering non-realtime traffic in cells having periods of anomalies brings improvements in reducing required UAVs while maintaining same quality of service. So, the first model aims at minimizing the non-realtime traffic losses for a certain buffer size of both BS and UAVs. It provides a heuristic solution for such problems. The second model is integer linear programming (ILP) based and gives the minimum number of drones required assuming the buffer size is fixed of the BS integrated with the drones' buffer and a time limit on non-realtime traffic assuming there is no losses in this data. The results of both solutions are compared to the perfect prediction and long-term memory (LSTM) prediction as will be shown in the performance section.

The paper is organized according to the following sections; related work is surveyed in section II. In section III, the problem statement is described. Section IV is dedicated for the performance evaluation. Paper is finalized by section V that presents the conclusion and future work.

## II. RELATED WORK

The work of [4] proposed the proactive deployment of drones to offset the overload of unplanned events in 5G networks. The authors proposed using the prediction and control model to solve the deployment of drones in an efficient manner. Also, propose to use the Software Defined Network (SDN) to easily integrate/reintegrate the drones with the network by reconfiguring the SDN.

Then, the work of [5] proposed an optimization model for deploying drones at active sites in the cellular network in a proactive mode. The parameters of the model are designed to increase coverage while reducing the communication load between drones. This work is based on the creation of a connection diagram, a street graph, and a density function. Even the problem statement is not the same, typical leaks of the clear model and reference results.

Another two papers [3] and [6] targeted the same problem statement of proposing the use of drones to overcome unplanned events in the cellular network. The first work suggested using long-term memory (LSTM) to detect unplanned events and to satisfy the additional BW required in cells. Another work, improving the deployment of drones in the network using LSTM as well. Both operations do not differentiate the type of traffic based on time.

Several works proposed improving the placement of the drones in the cellular network. In [7], authors of focused on optimizing the placement of the drones in cells using mixed-integer non-convex program in order to maximize coverage. While in 2021, the published work of [8] and [9]. The first work optimizes drones positions in 3D based on realtime measurements to make continuous dynamic adjustments for load based management. While the other work study the effect of the drones positions in terms of altitude and horizontal and incentive selection on the network performance.

The work of [10] studied the effect of the use of drones in the 5G cellular network in terms of capacity, quality, robustness, and correlation stability between the used drones and the ground station. In [11] proposed the use of D2D to alleviate the failure of vehicular communication.

The main contribution of these papers is the proposal to use drones in the cellular network to enhance the coverage, while others propose an optimal model for the position of the drones. These contributions didn't mention the use of drones to overcome the rapid increase of BW demands in the specific cells during unplanned events except the work of [4], [3], and [6]. But these mentioned works didn't take into consideration the different traffic types based on the time.

### III. MODEL I: MINIMIZING DATA LOSS

#### A. Assumptions

- $D_t^p$ : the demand at  $t$  of priority traffic. It is realtime up to a certain extent: it must be served within a time window  $\tau$ . Before to be served, it is put in a queue considered as infinite (since the corresponding traffic is delivered within  $\tau$  and since we assume the system is dimensionned correctly, that is the bandwidth capacity  $C$  is sufficient to serve the priority traffic only, a buffer size of  $C\tau$  is sufficient to store priority traffic excess).
- $D_t^{np}$ : non-realtime traffic demand at  $t$ . It is always put in a FIFO dedicated queue, the maximum size of which being  $B$ .
- $X_t^p$ : queue size of the priority buffer;
- $X_t^{np}$ : queue size of the non priority buffer;
- $S_t^p$ : the amount of data served at  $t$  for the priority traffic;
- $S_t^{np}$ : the amount of data served at  $t$  for the non priority traffic;
- $\delta_t^p = \begin{cases} -S_t^p & \text{if } X_t^p > 0 \\ 0 & \text{otherwise} \end{cases}$  ;
- $\delta_t^{np} = \begin{cases} -S_t^{np} & \text{if } X_t^{np} > 0 \\ 0 & \text{otherwise} \end{cases}$  .

Our goal is ( $T$  being the operation duration):

$$\min_{S_t^p, S_t^{np}} \sum_{t=0}^T \max [D_t^{np} - (B - X_t^{np}), 0]$$

$$s.c. \quad \forall t, X_{t+1}^p < \sum_{k=0}^{\tau} S_{t+k}^p \quad (1)$$

$$\forall t, X_{t+1}^p = D_t^p - \delta_t^p + X_t^p \quad (2)$$

$$\forall t, X_{t+1}^{np} = \min [B, D_t^{np} - \delta_t^{np} + X_t^{np}] \quad (3)$$

$$\forall t, S_t^p + S_t^{np} \leq C. \quad (4)$$

The constraint (1) means that the priority demand at  $t$  must be served at least in the next  $\tau$  time units (remember the queues are FIFO). The constraints (2) and (3) model the classic FIFO queue processes. The last constraint (4) represents the fact that the sum of the services at time  $t$  cannot exceed the total bandwidth capacity.

#### B. Heuristic

As a solution of the above problem, we propose a heuristic based on a prediction of the priority demand:  $P_t^{t+i}$  is the prediction at time  $t$  of the amount of bandwidth demand at time  $t+i$  for the priority traffic. The parameters  $\xi$  and  $\varepsilon$  are respectively a fixed time horizon for the prediction and a bandwidth security parameter to "absorb" predictions errors: we keep a bandwidth margin to be sure to have sufficient bandwidth reserved for the priority traffic in case of prediction underestimation and thus not assigning all the remaining bandwidth to the non priority traffic. The overall idea is that since the priority traffic will be sent in the  $\tau$  future time slots, we can delay it a little bit to empty as much as possible the non priority traffic.

At each time  $t$ , if  $X_t^p + D_t^p + \sum_{k=1}^{\xi} P_t^{t+k} < C\varepsilon$ , and if  $X_t^{(np)} > 0$ , then serve the priority class up to  $S_t^p = \frac{X_t^p + D_t^p + \sum_{k=1}^{\xi} P_t^{t+k}}{\xi} + \varepsilon$  and the non priority class up to  $S_t^{np} = C - S_t^p$ .

The performance criteria to observe are the loss rate of non priority traffic and the response time of the priority one.

This algorithm must be compared with the best effort one without prediction: the traffics are served in best effort fashion where the priority traffic is first served, and then the non priority one if possible.

#### C. LSTM Prediction Model

Long Short-Term Memory is used in time series prediction problems which is one of the difficult predictive modeling type problems. LSTM is a Recurrent Neural Network (RNN) that is trained using BackPropagation (BP) through time. Therefore, it fits the problem of predicting time series of cells traffic. It has three layers. Input layer, hidden layer, and output layer. Each layer consists of memory blocks which have the same function as neurons with a smarter component that makes it more efficient than the classic neurons. These memory blocks

contain three types of gates; Forget, input and output gates. These blocks gates use the sigmoid activation units to control their triggering, state change and the information flow through its conditional block.

We implemented our model in Python using the Keras library. The model was trained by 67% of the data set, and 33% used for testing. Figure 1 shows the prediction of cell traffic where the predictive training set has orange color and the predictive test set has green color and blue color represents the real data set. The results of the is measured in terms of route mean square error (RMSE).

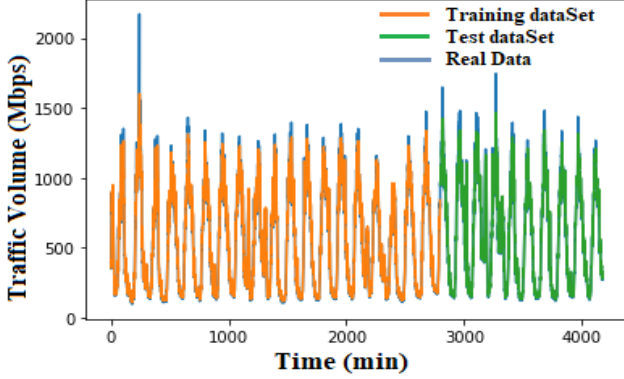


Figure 1: LSTM traffic prediction

#### IV. MODEL II: MINIMIZING NEEDED DRONES

##### A. Definitions

- $T$ : duration of time frame in terms of slots.
- $\Delta$ : slot duration.
- $\tau$ : maximum delay of non-realtime traffic in terms of slots.
- $BS_{BW}$ : BS bandwidth.
- $R_t^C$ : predicted bandwidth requirements from critical traffic to be served during slot  $t$ .
- $R_t^D$ : predicted bandwidth requirements of non-realtime traffic that has reached its time limit in slot  $t$
- $S_t^D$ : amount of  $R_t^D$  served in previous slots
- $n_t$ : number of UAVs that must be dispatched in slot  $t$
- $N$ : total number of UAVs
- $U_{BW}$ : bandwidth provided by a UAV
- $\zeta_t^D$ : binary variable which is 1 if and only if the  $R_t^D$  is served completely before slot  $t$

##### B. Optimization Problem Formulation

###### Objective Function

Minimize the total number of used UAVs.

$$\text{Minimize } \sum_{t=1}^T n_t$$

##### Constraints

$$BS_{BW} \cdot \Delta + n_t \cdot U_{BW} \cdot \Delta - R_t^C - (R_t^D - S_t^D) \geq 0 \quad (5)$$

We must use a number of UAVs in slot  $t$ ,  $n_t$ , to serve the remaining non-realtime traffic with a deadline in slot  $t$ . This remaining non-realtime traffic is  $R_t^D - S_t^D$  since part of this traffic,  $S_t^D$ , may have been served in earlier slots.

$$\sum_{i=t+1}^{t+\tau} S_i^D \leq BS_{BW} \cdot \Delta + n_t \cdot U_{BW} \cdot \Delta - (R_t^C - R_t^D + S_t^D) \quad (6)$$

This means that any remaining bandwidth from the BS and the UAVs can be used to serve non-realtime traffic with future due dates.

We need to give priority in service for  $R_i^D$  over  $R_j^D$  for  $i < j$ , that is,  $S_i^D$  must take place before  $S_j^D$ , for  $i < j$ . This is implemented in two parts:

- 1)  $\zeta_t^D$  is 1 if  $S_t^D = R_t^D$ , and is 0 if  $S_t^D < R_t^D$ , i.e.,  $\zeta_t^D = 1$  means that  $R_t^D$  was completely served in earlier slots.

$$\zeta_t^D \leq \frac{S_t^D}{R_t^D} \quad (7)$$

Notice that if  $S_t^D < R_t^D$  then  $\zeta_t^D = 0$ . But, when  $S_t^D = R_t^D$  then  $0 \leq \zeta_t^D \leq 1$ . However, since the optimization problem tries to minimize the sum of  $n_t$ , then it will try to maximize  $\zeta_t^D$  in order to allow non-realtime traffic to be served early if there is sufficient bandwidth (without using additional UAVs), hence reducing the number of UAVs that might be needed in the future. The above equation is nonlinear. In order to linearize it, we rewrite it as

$$\zeta_t^D \cdot R_t^D \leq S_t^D \quad (8)$$

Then, we define  $V_t^D = \zeta_t^D \cdot R_t^D$ , and we rewrite the equation again as

$$V_t^D \leq S_t^D \quad (9)$$

which is a linear equation.  $V_t^D$  can be evaluated using the following set of linear equations:

$$V_t^D \leq \zeta_t^D \cdot K \quad (10)$$

$$V_t^D \geq 0 \quad (11)$$

$$V_t^D \leq R_t^D \quad (12)$$

$$V_t^D \geq K \cdot \zeta_t^D - K + R_t^D \quad (13)$$

where  $K$  is a very large number.

2)

$$S_{t+1}^D \leq \zeta_t^D \cdot K \quad (14)$$

Also,  $K$  is a very large number. This means that if  $R_t^D$  is not totally served early, then  $R_{t+1}^D$  can be served early at all. Only if  $R_t^D$  is served early, then  $R_{t+1}^D$  can be served early, partially or totally.

$$0 \leq S_t^D \leq R_t^D \quad (15)$$

$$n_t \geq 0 \quad (16)$$

$$n_t \leq N \quad (17)$$

## V. PERFORMANCE EVALUATION

In this section, the performance of the two proposed models is validated. We used a communications dataset consisting of two months of call data records (CDR) for voice calls, Internet data and SMS. This data set is provided by Telecom Italia in Milan [12]. In our simulation, we select one of the most crowded cells (cell id=5060) in the city center of Milan city. The simulation results is obtained using Python version 3.8.

The distributions of the voice calls, Internet and sms are shown in Fig.2.

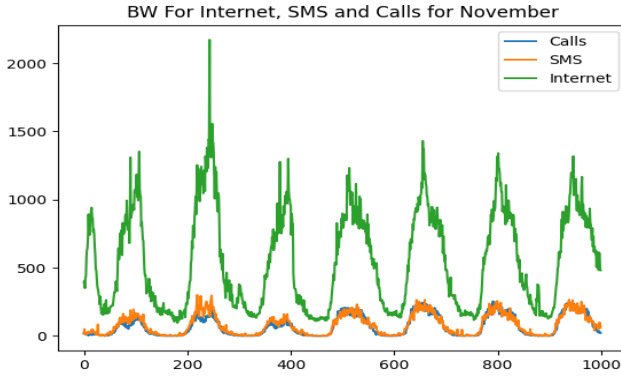


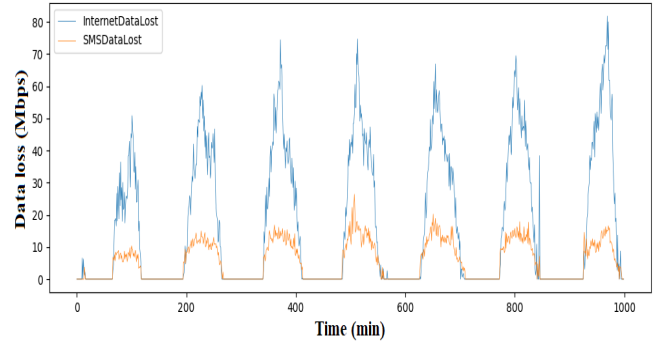
Figure 2: Traffic distribution of November

The performance of the first proposed model of objective minimizing non-realtime data loss is studied. The performance is studied for the cases of no prediction, perfect prediction and prediction using LSTM. We call the BS's BW and the drone BW the cell BW. We consider the cell BW is 1, 2, 3 of the average. Furthermore, due to the limited paper space, we will not provide all figures for unpredictability, perfect prediction, and prediction using LSTM.

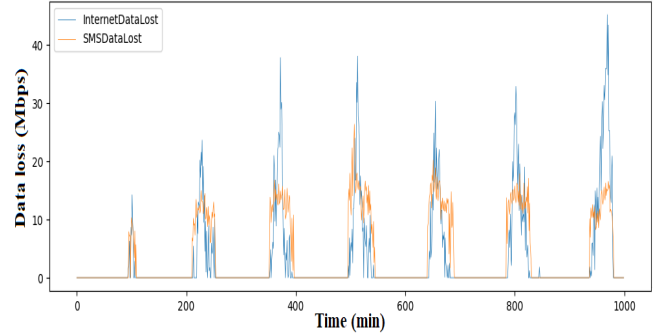
### A. Model 1: Heuristic

In this subsection, the performance of Model 1 will be illustrated in the following scenarios.

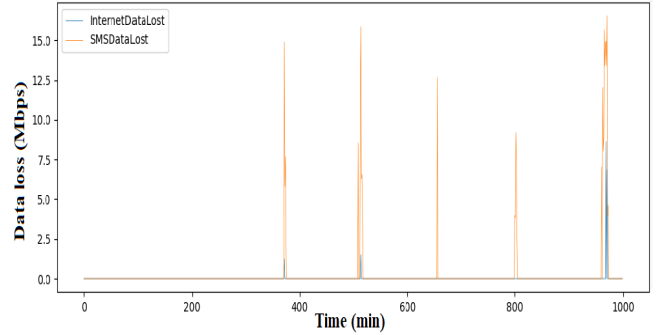
Scenario 1: The effect of cell BW on non-realtime data loss is studied in case of no prediction and a buffer size of constant value = 1. As shown in Fig. 3, As the cell's BW increases, the ability to send more traffic increases and thus data loss decreases. Cell BW has the same effect on non-realtime data for perfect and LSTM predictions but its figures are not shown due to limited space.



(a) Cell BW = 1, Buffer Size = 1



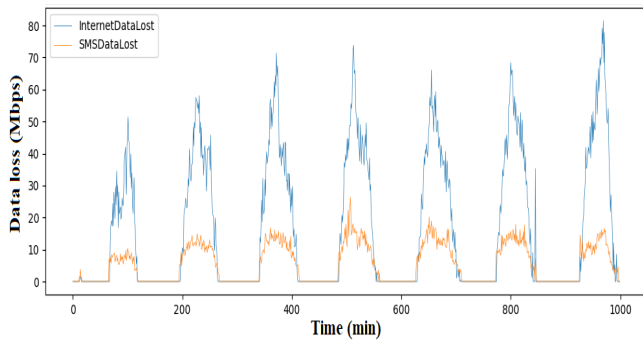
(b) Cell BW = 2, Buffer Size = 1



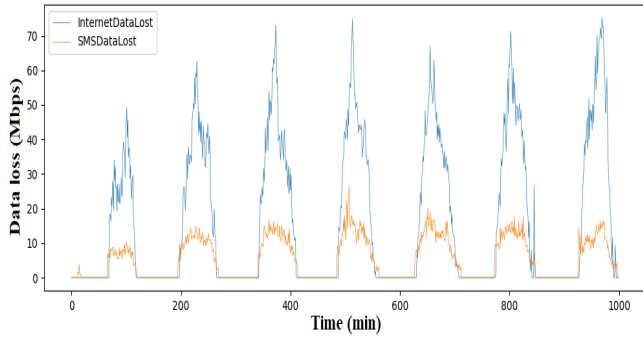
(c) Cell BW = 3, Buffer Size = 1

Figure 3: The effect of cell BW on the non-realtime data losses

Scenario 2: The effect of the maximum delay of non-realtime data  $\tau$  on the data losses has been studied for perfect and LSTM predictions. The effect is shown in Fig. 4 and 5 for  $\tau$  changes from 2 to 5, for cell BW and buffer size constant value = 1. As shown in the figures, the losses of the non-realtime data decreases with the increase of  $\tau$ . It has a little effect on data losses as cell BW and buffer size are constant.

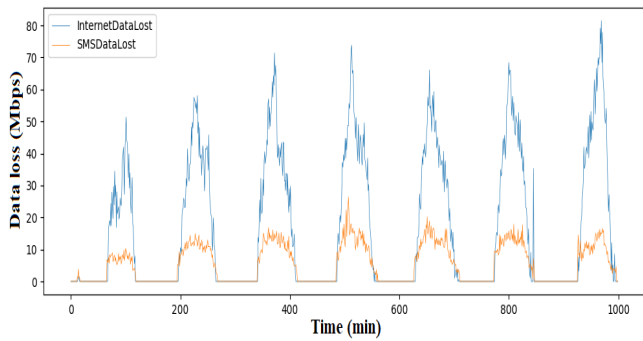


(a)  $\tau = 2$ , Cell BW = 1, Buffer Size = 1

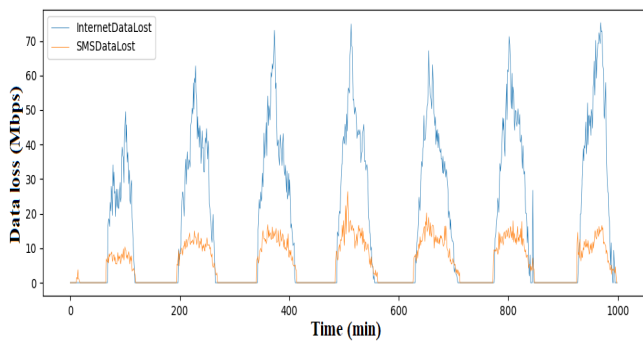


(b)  $\tau = 5$ , Cell BW = 1, Buffer Size = 1

Figure 4: Effect of  $\tau$  on the data loss of perfect prediction



(a)  $\tau = 2$ , Cell BW = 1, Buffer Size = 1

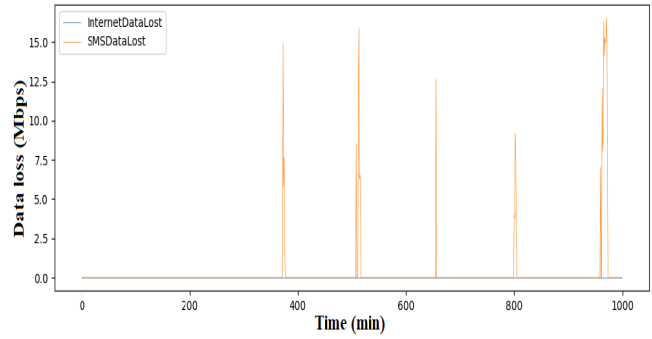


(b)  $\tau = 5$ , Cell BW = 1, Buffer Size = 1

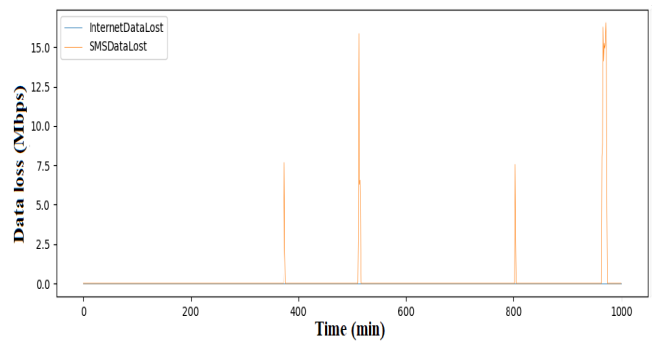
Figure 5: Effect of  $\tau$  on the data loss of LSTM prediction

Scenario3: The effect of the buffer size on the non-realtime data is studied of LSTM prediction traffic. The buffer has a

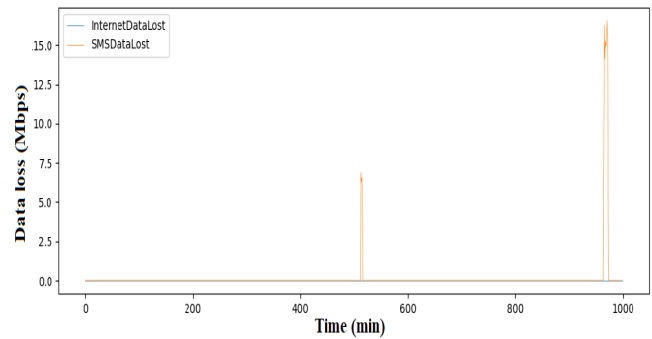
size of 1, 3, 5 and 10 of cell BW. As shown in Fig. 6, with the increase of the buffer size, the losses of the non-realtime data decreases. As expected, the buffer size has the same effect on the traffic of no predictions and perfect prediction.



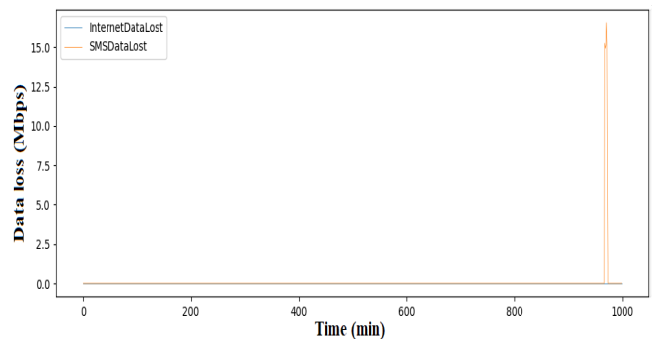
(a)  $\tau = 5$ , Cell BW = 3, Buffer Size = 1



(b)  $\tau = 5$ , Cell BW = 3, Buffer Size = 3



(c)  $\tau = 5$ , Cell BW = 3, Buffer Size = 5



(d)  $\tau = 5$ , Cell BW = 3, Buffer Size = 10

Figure 6: Effect of buffer on the data loss of LSTM prediction

Scenario 4: In this scenario, we consider the major influencing parameter that affects the data losses between cell BW,  $\tau$  and the size of the buffer that does not cause losses in non-realtime data. As shown in Fig. 7, the major influence parameter is the cell BW. The conclusion behind this scenario, does not mean that  $\tau$  and buffer size have no effect, on the contrary, it means that the data has a finite lifetime corresponding to its maximum delay, so increasing  $\tau$  and buffer size will not save data without resources to transmit. Therefore, increasing the buffer size will save the data temporary until reaching its maximum delay, then it will be dropped.

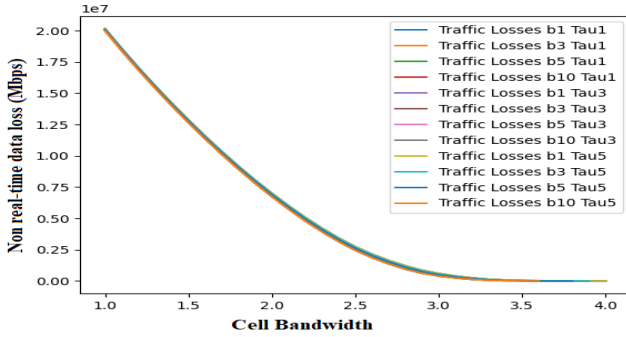


Figure 7: Cell BW for zero losses

### B. Model II: MILP

The optimization model described before is needed to determine the precise minimal number of drones for each dataset slice representing one day of realtime and non-realtime traffic. It calculates the number of drones but helps also in measuring the effect of the buffering in the reduction of requested drones. All the scenario assumes a zero loss in the total traffic. We have evaluated the model for several days in the dataset of Rome. We show in Fig. 8 the effect of allowing longer delays and hence a greater buffer in drones on the required minimal number of drones for several days in the dataset. Logically, when the  $\tau$  value is larger, hence enabling non-realtime to wait for opportunities of less realtime traffic in the future time slots, and be sent without the need of extra drones. If  $\tau$  is shorter, the non-realtime traffic has to leave early and cannot wait for eventual empty realtime traffic slots. The more sporadic the realtime traffic is, the less drones we will need.

## VI. CONCLUSION

In this work, we proposed two models for maintaining QoS of the cellular network with UAV dealing with realtime and non realtime traffic. Assuming realtime data is sent immediately, the first model proposed a heuristic solution to minimize non-realtime data losses by buffering this data to be sent when cellular resources become available. The results of this model demonstrated that non-real time data loss decreases with increasing cell BW, maximum delay  $\tau$  and cell buffer size.

The second model aims to provide an optimal ILP model by providing an optimal solution to minimize and calculate the

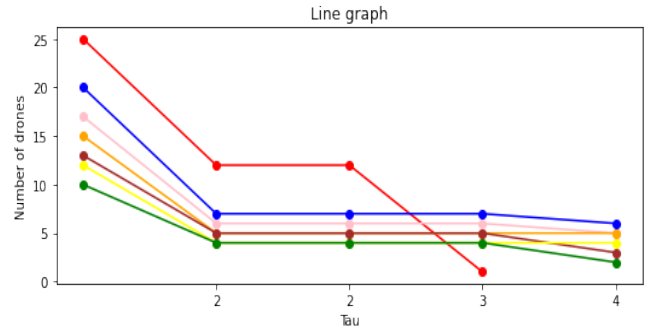


Figure 8: The effect of  $\tau$  on the number of drones

number of required UAVs. It is also based on the same mix of realtime and non realtime traffic. It includes a maximum delay variable to let non-realtime traffic be sent after a certain delay. The results show that with an increase in the maximum delay  $\tau$  of non-realtime data, the optimal number of required UAVs is reduced.

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