# Unmanned Aerial Vehicle Allocation and Deep Learning based Content Caching in Wireless Network

**Seok Won Kang**
*Department of Computer Science and Engineering*
Kyung Hee University
17104, Republic of Korea
dudtntdud@khu.ac.kr

**Kyi Thar**
*Department of Computer Science and Engineering*
Kyung Hee University
17104, Republic of Korea
kyithar@networking.khu.ac.kr

**Choong Seon Hong**
*Department of Computer Science and Engineering*
Kyung Hee University
17104, Republic of Korea
cshong@khu.ac.kr

*Abstract*— **Data traffic is increasing with the increasing number of smart devices. Also, base stations in some regions are suddenly overloaded only for a certain period (i.e., an amusement park on holiday). Thus, to handle this issue, we need to deploy more base stations, small-cell base stations. But those are not economical solutions. Hence, in this paper, we utilized Unmanned Aerial Vehicles (UAVs) as temporary small-cell base-stations to solve the aforementioned problems. In this work, we proposed a cluster-based UAVs deployment scheme to reduce data traffic (such as video traffic) as well as service delays for the users and improve the coverage of base stations. First, we formed the user groups according to the distance of users with the help of the K-means clustering algorithm. Second, we find the optimal location to allocate the UAVs in each cluster. Third, we proposed a Long Short-Term Memory based caching scheme to cache popular contents on UAVs. Finally, the simulation results show that our proposed scheme outperforms than the other in terms of accessing delay and cache hit ratio.**

***Keywords—Unmanned Aerial Vehicle (UAV), Content Caching, LSTM, K-Means Clustering***

## I. INTRODUCTION

According to Cisco's forecast, smart devices will grow to 50 billion by 2020 [1]. Thus, with the increasing number of smart devices, the data traffic (such as online video traffic) on the communication network will also be increased. Additionally, base stations in some areas are suddenly overloaded only for a certain period (i.e., an amusement park on holiday). Moreover, deploying more base-stations and small-cell base-station in the overloaded areas is not an economical solution. In this situation, we can utilize the Unmanned Air Vehicles (UAVs) as temporary small-cell base station because UAVs can be fast and easily deployed over the overloaded areas. Furthermore, caching the popular contents on the UAVs is another feasible solution to reduce data traffic over the overloaded areas. Thus, in this paper, we utilize the UAVs as temporary small-cell base stations to solve the aforementioned problems.

Currently, several kinds of research are underway to utilize UAVs as the base stations and to solve the UAVs deployment problems. There are various studies on the optimal placement of UAVs. The paper [2][3] used reinforcement learning (Q-learning) and K-means algorithms to allocate the UAVs but they do not consider content's content caching and content's popularity prediction. The authors in paper [4] only consider a caching scheme to cache popular content on UAVs. In the paper[5], the authors presented an algorithm for managing distributed UAV ports to minimize energy consumption and ensure cooperation between UAVs. Also, deep learning such as Eco-State Networks (ESNs) is used to optimize the content and location to be cached in UAV-BS to enhance the quality of experience (QoE). However, the challenging issues of utilizing deep learning into various tasks remains open. The first issue is to pick up the best-suited neural network architecture among the numerous kinds of deep learning architectures, such as Feed-forward Neural Networks. The second issue is to efficiently optimize the hyperparameters (e.g., number of hidden layers, neurons, etc.) of the chosen neural network.

In this paper, first, we proposed a UAV allocation algorithm to improve the user's quality of services. Second, we proposed the content's popularity prediction scheme to improve the cache hit at the UAVs as well as to reduce the latency to download the video contents from the server. For the simulation purpose, we utilized the content usage dataset from [7]. Based on the dataset, we analyze the user's request patterns of each cluster to find out the impotent features to predict the content's popularity scores. Then, we trained the prediction model at the datacenter and then the optimized trained model will be deployed at the UAVs. Then, the UAVs will reactively cache the contents based on the prediction results. Our contributions are summarized as follows:

- We proposed a UAVs allocation algorithm based on the K-Means clustering method.
- We proposed a Long-Short Term Memory (LSTM) based content's popularity prediction scheme to support the intelligent caching at the UAVs.
- We analyze the dataset [7] to find out the important features to train the LSTM.

The overview system model is discussed in Section II. In the Section III, simulation is conducted based on the system model, and performance evaluation is shown in section IV.

## II. SYSTEM MODEL

The system model is shown in Fig. 1 which includes three main parties: 1) Content Server, 2) UAV-Base Stations (UAV-BSs), and 3) User Equipment (UEs). The content server is denoted as $i$. A set of UEs can be denoted as $U =$

$\{1,2,3,..,u\}$ and Content Server stores the set of video contents $W = \{1,2,3,\dots,w\}$. Then, a set of UAV-BSs can be denoted as $B = \{1,2,3,..,b\}$. Also, UAV-BSs $b$ are attached to the cache storage and the cache storage space of each UAV-BS $b$ can be denoted as $s_b$. So the total number of cache storage space for the UAV-BSs deployed area becomes $S = \sum_{b=1}^{B} s_b$. Each UAV-BS $b$ are allocated to each user group to reduce the latency for downloading video contents as well as to improve UE's QoE. Here, we assume that one group of UEs can only connect to the assigned UAV-BS to their group. Whenever UAV-BS $b$ received the request from the UE $u$, UAV-BS $b$ checks the requested content on its local cache. If the content is not located in its local cache, the UAV-BS $b$ forwards the request to the server to download the requested content.

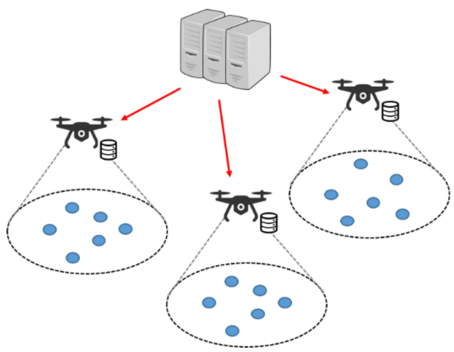

**Figure 1. System Model**

*A. UAV Allocation and Network Model*

First, we utilized the K-means clustering to from the set of UEs $U = \{1,2,3,..,u\}$ into several group of UEs $A = \{1,2,3,..,a\}$. Then, we find the centroid of each group $c_a$ to be able to allocate the UAV-BS $b$. Fig. 2 shows the variables required for UAV-BS allocation, where $d_{bu}$ is the distance between the UAV-BS $b$ and UE $u$, $R_i$ coverage area of UAV-BS $b$, H is the altitude of UAV-BS $b$ and $u_{xy}$ is the $(x,y)$ coordinate of UE $u$. The equation for obtaining the distance $r_{ij}$ between the *UE* and the *U* position on the ground is as follows :

$$r_{ij} = \|U - u_{ij}\| = \sqrt{\left(x - x_{ij}\right)^2 + \left(y - y_{ij}\right)^2}.$$

Referring to [8], this paper adopt the Air-To-Ground (ATG) channel model with the probabilities of Line of sight (Los) and Non-Line of Sight (NLoS) for a UE $u$ as follows:

$$P_{LoS}(H, r_i) = \frac{1}{1 + a exp\left(-b\left(\frac{180}{\pi}\tan^{-1}\left(\frac{H}{r_{ij}}\right) - a\right)\right)}, \quad (1)$$

$$\mathrm{P_{NLoS}}(H, r_i) = 1 - \mathrm{P_{LoS}}(H, r_i), \quad (2)$$

$$PL(dB) = 20\log_{10}\left(\frac{4\pi df}{c}\right) + P_{LoS}(H, r_i) + P_{NLoS}(H, r_i), \quad (3)$$

where $d$ represents the distance between UAV-BS $b$ and UE $u$ for the calculation of signal attenuation effect, and $c$ is the speed of light. Using the equation (1), (2) and (3) ,the signal power and signal-to-noise ratio (SNR) can be obtained as follows:

$$P_r(d) = P_t + G_t - PL - G_r - L \quad (4)$$

$$SNR = \frac{signal\ power}{noise\ power} = \frac{P_r(d)}{N} \quad (5)$$

According to the *Shannon-Hartley theorem,* the data transfer rates from UAV$_i$ to $UE_{ij}$ are as follows:

$$c_{ij}^{UAV} = B_{UAV} log_2\left(1 + SNR_{ij}^{UAV}\right) \quad (6)$$

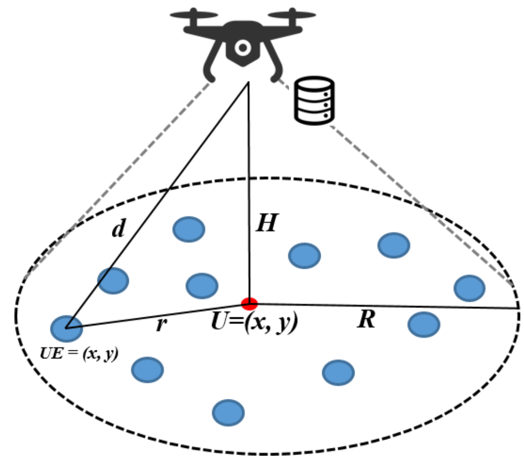


**Figure 2. UAV-BS Allocation Model**

| Parameter | Description |
|---|---|
| $f$ | Transmitter Frequency |
| $P_t$ | Base Station Transmitting Power |
| $G_t$ | Antenna Gains for the Base Station |
| $G_r$ | Antenna Gains for the User |
| $L$ | Total System Losses |
| $B$ | Bandwidth |
| $N$ | Noise Power |

**Table 1. Variables for UAV-BS Allocation**

Thus, data transfer rates between UAV-BS b and content server i becomes;

$$t_{bi}^{Server} = B_{Server} log_2(1 + SNR_{bi}^{Server}). \quad (7)$$

Then, we define data transfer rates between UAV-BS to UE as follows;

$$t_{bu}^{UAV} = \frac{a_{bu}}{c_{bu}^{UAV}},\ t_{ij}^{Server} = \frac{a_{bu}}{c_{bu}^{Server}}, \quad (8), (9)$$

where $a_{bu}$ is the size of the content to transfer from UAB-BS to UE. Using equations (6), (7), (8) and (9), the downlink delay to get the content for each UE u for content w becomes;

$$t_u^w = t_{ub}^w + t_{bi}^w(1 - x_b^w) \quad (10)$$

Where $x_b^w \in \{0,1\}$ is the cache decision variable. $x_b^u = 1$, when the content w is cached on the UAV-BS b. If the content w is not cached on the UAV-BS, $x_b^u$ becomes 0. In this case, UAV-BS b will retrieve the content from the content server $i$.

*B. Problem Formulation*

In this section, we formulate the content accessing latency minimizing problem as follows,

$$
\begin{aligned}
&\min \sum_{u=1}^{U} \sum_{w=1}^{W} t_u^w \\
\text{s.t.} \quad &\sum_{w=1}^{W} x_b^w \leq s_b, \\
&S = \sum_{b=1}^{B} s_b, \\
&x_b^w \in \{0,1\}.
\end{aligned}
$$

where first constraint limit the cache capacity of the UAV-BS $b$, second constraint limit the total cache capacity of the all UAV-BS. In this formulation, cache decision $x_b^w \in \{0,1\}$ is made based on the predicted popularity of content $w$ or predicted request count of the content $w$. We will discuss the popularity prediction in details in next section.

### *C. Content Popularity Prediction*

In this section, we discuss the content's popular prediction model to improve the cache decision of UAV-BS. Among the various type of deep learning models, we choose LSTM architecture because our inputs data are time-series data and LSTM is working well on time series data compared to normal learning method. Traditional RNNs have the advantage of being able to store data's previous state information in memory compared to regular Neural Network. LSTM takes into account not only historical information but also future conditions from time-series data. The overview LSTM architecture used in this paper is shown in Fig.3 and includes inputs layer, forward LSTM layer, backward LSTM layer, LSTM output layer, dense layer, and final output layer. The input layer is the initial point to feed the input time series information to train the model. The forward layer processes the information from the past to the future direction. The backward layer processes the information from the future to the past direction. The LSTM output layer aggregate the information from the forward layer and backward layer. The dense layer extracts the important features from the LSTM output layer. Finally, the final output layer is configured based on the prediction problem (i.e., if the problem is classification we used softmax function).

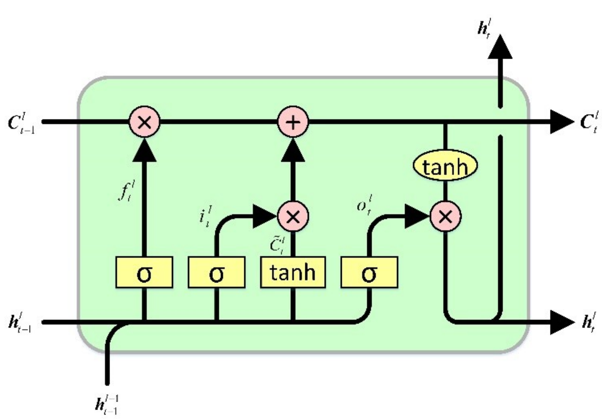


**Figure 3. LSTM architecture**

### *D. UAV-BS Allocation and Caching Algorithm*

In this section we present the UAV-BS allocation and caching algorithm. Overall, the algorithm of clustering and content caching is shown in ALG. 1.

***Algorithm 1*** *UAV-BS Allocation and Caching Algorithm*

***Input*** *: i, j, w, u, UE's historical traffic data*

***Output*** *: Content cached in* $U[i].content$

```
Initialize U[i][j] using K-means clustering
Initialize popularity sorted content[i][w] using LSTM based UE's historic traffic data
for k=1 to i do
  for l=1 to w do
    if U[k].contentsize + content[i][k].size < U[k].constrain then
      U[k].content[l] ← content[i][k]
      U[k].contentsize += content[i][k].size
    else
      break
end for
```

## III. Performance Evulation

In this section we conduct the performance evaluation simulation for our proposed scheme with others. Table 2. shows that the parameters we used in our performance evaluation. For the comparison, we compared with random caching (which cache randomly), without cache (which all UEs are receive content from content server) and round robin.

**Table 2. Variable value for simulation**

| Parameter | Value |
|---|---|
| $f$ | 1.5GHz |
| $P_t$ | 10dBW |
| $G_t$ | 8dB |
| $G_r$ | 0dB |
| $L$ | 8dB |
| $B$ | 10MHz |
| $N$ | 100dBW |
| Input | IP Network Traffic Flows[7] |
| Optimizer | RMSprop |
| Batch size | 256 |

First of all, eighty (80) UEs are randomly positioned using the Poisson point process, and UAVs are allocated at the center of each UEs cluster, where the clustering done by using K-means clustering. The figure 4 shows the results of K-means clustering. For the comparative analysis of performance, if the content is not cached on UAV. In this simulation, clustering is performed according to the number of UAVs and the content server is located in the center of the coordinates. Each user requests content from a connected UAV and if the requested content is not in UAV, the content is provided by the content server.

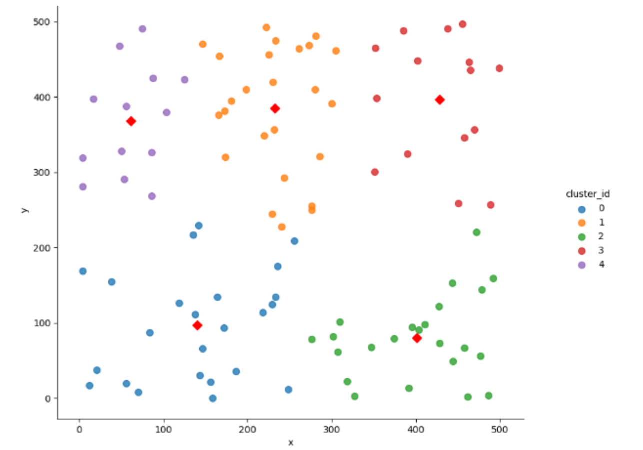


**Figure 4 K-means Clustering Result**

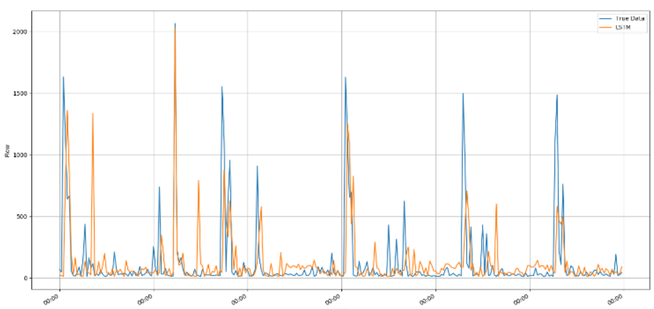

**Figure 5. Forecasting Data Traffic Usage Graph with LSTM**

Then, the total delay is compared during each user's content delivery, where the uplink for the request is not considered. Traffic data for each mobile is owned by a content server, which uses this dataset to predict content requests for each user and cache the most requested content accordingly. This simulation predicts and caches the two most requested content in UAVs, taking into account the capacity limits of UAVs. To compare the performance of the proposed caching algorithm, set the situation in which all contents are not cached and should be provided by the content server, the situation in which contents are randomly cached by UAV, and when cached by the caching algorithm proposed by this paper.

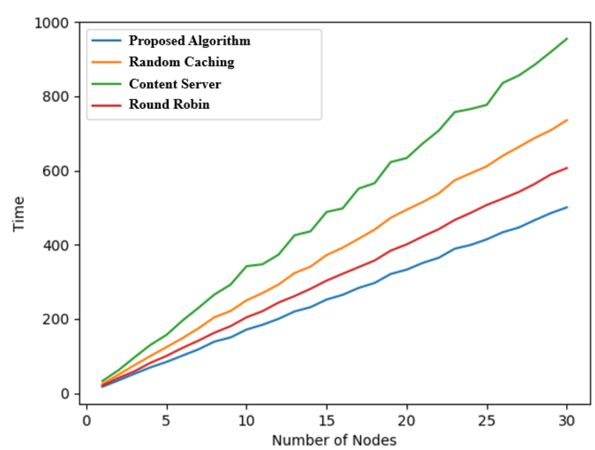


**Figure 6. Total Content Transfer Time for each algorithm**

We show the prediction results from the proposed LSTM in Fig 5 and is actually similar compare to the actual value. Figure 6 shows the sum of the delay time requests by user based on the number of users (UEs). For comparison, we used random caching, Round Robin, which cache sequentially from the content server. As shown in the graph, algorithms that analyze and cache datasets with LSTM perform better than other situations.

## IV. Conclusion

In this paper, we proposed a scheme to deploy UAVs as temporary base stations on overloaded areas. Users are clustered based on their distance and UAVs are deployed in each cluster. Then, UAVs are placed on the optimal location of the cluster and UAVs cache the popular contents by using LSTM to improve the user's QoE as well as to reduce the data traffic. In this paper, we do not tackle the energy consumption problem of UAVs. Therefore, as the future work, we will expand this work to take into account the energy efficiency of UAVs.

## ACKNOWLEDGEMENT

This work was partially supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIT) (No.2015-0-00557, Resilient/Fault-Tolerant Autonomic Networking Based on Physicality, Relationship and Service Semantic of IoT Devices), and by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea goverment(MSIT) (No.2019-0-01287, Evolvable Deep Learning Model Generation Platform for Edge Computing). *Dr. CS Hong is the corresponding author

## References

[1] Peng Zhang, Joseph K. Liu, F. Richard Yu, Mehdi Sookhak, Man Ho Au, Xiapu Luo, "A Survey on Access Control in Fog Computing", IEEE Communications Magazine, February, 2018.

[2] Liu, Xiao. Yuanwei Liu, and Yue Chen, "Reinforcement Learning in Multiple-UAV Networks: Deployment and Movement Design.", arXiv preprint arXiv:1904.05242(2019).

[3] Yumin Park, Minkyung Lee and Choong Seon Hong. "Multi-UAVs Collaboration System based on Machine Learning for Throughput Maximization", The 20th Asia-Pacific Network Operations and Management Symposium(APNOMS), Sep. 18-20, 2019, Matsue, Japan

[4] Nan Zhao, F. Richard Yu, Lisheng Fan, Yunfei Chen, Jie Tang, Arumugam Nallanathan and Victor C.M. Leung, "Caching Unmanned Aerial Vehicle-Enabled Small-Cell Neworks: Employing Energy-Efficient Methods That Store and Retrieve Popular Content

[5] Lynskey, Jared, Kyi Thar, Thant Zin Oo, and Choong Seon Hong. "Facility Location Problem Approach for Distributed Drones." Symmetry 11, no. 1 (2019): 118.

[6] Mingzhe Chen, Mohammad Mozaffari, Walid Saad, Changchuan Yin, Merouane Debbah, Choong Seon Hong, "Caching in the Sky: Proactive Deployment of Cache-Enabled Unmanned Aerial Vehicles for Optimized Quality-of-Experience," IEEE Journal on Selected Areas in Communications, Vol.35, No.5, pp. 1046-1061, May 2017

[7] Juan Sebastian Rojas Melendez, Alvaro Rendon, Juan Carlos Corrales, "Personalized Service Degradation Policies on OTT Applications Based on the Consumption Behavior of Users", International Conference on Computational Science and Its Applications 2018, pp. 543-557, July 2018

[8] Chuan-Chi Lai, Chun-Ting Chen and Li-Chun Wang, " On-Demand Density-Aware UAV Base Station 3D Placement for Arbitrarily Distributed Users With Guaranteed Data Rates," IEEE Wireless Communications Letter, Vol.8, Issue.3, pp. 913-916, Feb 2019