Charging Station Placement in Unmanned Aerial Vehicle Aided Opportunistic Networks

Salih Safa Bacanli†, Enas Elgeldawi‡, and Damla Turgut†
†Department of Computer Science, University of Central Florida
‡Department of Computer Science, Faculty of Science, Minia University
{sbacanli, turgut}@cs.ucf.edu, enas.elgeldawi@mu.edu.eg

***Abstract*—Unmanned aerial vehicles (UAVs) are widely used in many application areas within opportunistic networks. In this paper, we investigate the charging station placement problem in the application scenario with ten UAVs deployed in an opportunistic network environment. We have used a real-world dataset that contains human mobility traces from North Carolina State University. The UAVs cruise on the network with spiral shapes and distribute messages to the nodes on the ground. The charging station locations are generated with random, Density-based spatial clustering of applications with noise (DBSCAN) and k-means clustering approaches. The evaluation results indicate that the k-means algorithm with three clusters outperformed the other two methods in terms of the success rates and the message delay.**

I. Introduction

Unmanned aerial vehicles (UAVs) are used in civilian, military, and other types of different applications. The UAVs used in the military are generally large in size and have longer cruise time with a single charge. In contrast, the UAVs used in civilian applications are much smaller, have shorter cruise time, and require full charging after cruising around 20 to 45 minutes. This limited battery life creates challenges when it comes to civilian applications.

In our application scenario, the UAVs cruise around an area where the mobile nodes on the ground communicate in a peer-to-peer manner, in an opportunistic network. The ground nodes create messages, and these messages are distributed between nodes through the assistance of the UAVs. The UAVs require charging every 45 minutes flight time, and they land on the charging stations for recharging and then take off again when set.

One of the challenges is the scanning pattern problem for UAVs. Since the flight time is short, inspecting the entire map with a single UAV may not always be possible even though a few studies use one UAV for examining the whole map [1], [2]. In that case, a scanning method or a pattern aimed at scanning small parts of the map should be developed.

Another challenge is the appropriate placement of the charging stations for the scanning pattern. Placing the charging stations too close to each other may impact UAVs' ability to scan different parts on the map. On the other hand, keeping the charging stations far away from each other may create fragmented locations on the map. The UAVs need to be in the proximity of a charging station so they can return to it once they drain their batteries.

Additional challenges occur due to the nature of the opportunistic network environment. An appropriate packet routing strategy, which can result in high success rates and low message delays, for the UAV and the nodes on the ground are essential. The connectivity between different nodes can change from time to time due to nature of connectivity within the opportunistic networks.

We have simulated an opportunistic network environment with different charging station places and various numbers of charging stations for the UAVs. We have used spiral shapes as the scanning pattern followed by UAVs on the environment.

The contributions of this study can be summarized as follows:

- We have defined an application scenario where commercially available UAVs are leveraged in an opportunistic environment. The simulation study is conducted using a real-world dataset.
- For our application scenario, we proposed a charging station placement solution based on a spiral-based scanning technique for the UAVs. The proposed routing strategy between the UAVs and the nodes on the ground makes minimal information exchange. No location information or encounter history are exchanged, resulting in more lightweight communication architecture. We can include additional UAVs in the system without modifying the data processing architecture.

The remainder of the paper is organized as follows. In Section II, we have compared the literature with our work. A detailed description of the application scenario within the opportunistic environment is given in Section III. Our proposed approach is presented in Section IV. The performance evaluation results are discussed in Section V while the paper concludes in Section VI.

II. Related Work

Many routing strategies have been developed over the years [3], [4]. For opportunistic networks, one of the most well-known approaches is epidemic routing [5]. Besides epidemic, spray and wait [6], PROPHET [7], and State-based Campus Routing (SCR) [8] are the other few examples of opportunistic routing strategies.

Wang et al. [9] have proposed improvements to the PROPHET. Bacanli et al. [8] designed an opportunistic network message flooding strategy in a campus environment and used an encounter dataset to create SCR without any UAVs. Bacanli and Turgut [1], [10] further extended their work to incorporate additional military standard UAVs, which do not use charging stations to scan the whole environment.

Tseng et al. [11] modeled the energy consumption of drones through various flight scenarios and investigated the flight path planning along with the recharging optimization to ensure the drones complete their tour as planned. Yu et al. [12] aim to minimize the time of deliveries by the UAVs, and they leverage stationary as well as mobile recharging stations (e.g., unmanned ground vehicles). Bourass et al. [13] developed a scheme to determine the optimal itineraries for electric vehicles to reach their destination, aiming to minimize the recharging wait time of these electric vehicles. Gong et al. [14] examined a scenario where a UAV collects data from a set of sensors on a straight line with a minimum flight time objective.

Won [15] proposed UBAT, a heuristic framework based on the ant colony optimization to solve the charging station deployment problem for UAVs. Ribeiro et al. [16] presented a new optimization model based on mixed-integer linear programming that addresses UAV routing and charging station planning for belt conveyor inspection used in the mining industry. The aim was to define the appropriate number of UAVs for monitoring the system.

Amaro, Ángeles and Juárez [17] provided a theoretical framework for a single drone used in animal monitoring application scenarios in which one of the proposed data collection schemes in cluster-based wireless sensor networks is based on UAVs. In this scheme, the UAV only visits the clusterhead for data collection since all the cluster members forward their sensed data to their clusterhead, resulting in reduced flight time and energy usage.

III. Application Scenario

In our application scenario, the nodes communicate with each other as well as with the UAVs. The UAVs communicate whenever they encounter each other. The nodes on the ground are part of an opportunistic network, and the UAVs help the network achieve low message delays and high success rates.

The nodes refer to people walking with their smartphones connected through WiFi, and they create text messages every 60 minutes. Three hours after the initial creation of the message, the nodes stop receiving messages due to the 3 hours message lifetime. Both UAVs and the nodes on the ground use IEEE 802.11 WiFi protocol. The maximum connectivity distance is 250 meters, which is appropriate for the IEEE 802.11 standard. The UAVs, however, are only responsible for distributing the messages through the network.

The charging station size is a circle with a 1m diameter. The UAV stays at the charging station for 30 seconds. Since charging a battery will take much longer than 30 seconds, we assume that the drained battery will be replaced with a fully charged one in 30 seconds.

The UAVs make random spiral scans on the environment at 100m altitudes. We assume that the UAV's maximum speed is 20m/s and has 30 minutes cruising time with a single charge. The UAV's specifications follow the commercial drone, DJI Mavic 2 Pro Drone [18]. The UAVs' scanning strategy is autonomous, and they ensure to have sufficient battery power to reach any charging station before their battery is depleted.

The proposed system can broadcast messages through the campus area with the UAVs considering a university campus where the dataset is collected.

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IV. Proposed approach

Regardless of the charging location generation technique, each charging location has at least one UAV at the start. After the UAV takes off, it goes to a random location and scans the environment with a random spiral radius. The spiral radius is the maximum distance between the center of the spiral and the limiting distance. If the distance between the UAV and the center of the spiral goes outside of the mapped environment or if the UAV reaches the maximum spiral distance, the UAV stops and goes to another random location to make another spiral scan. If the UAV is cruising away from the closest charging station and barely has enough battery to make a return trip to that station, the flight plan is immediately canceled, and the UAV is redirected to the closest charging location. Once the UAV reaches the charging station, it waits on the charging station for 30 seconds for battery replacement and then takes off for a new spiral scanning.

The spiral pattern for the spiral scan is selected since inspecting a small area is possible by adjusting a(density) and R(maximum radius) parameters of the spiral (see Figure1). In the spiral pattern we use, Archimedes spiral, the density of the spiral (a) stays constant, unlike Fibonacci(Golden) spiral where the density(a) increases. The density of the spiral is the distance between two consecutive arcs. The maximum radius of the spiral is the distance between the center of the spiral and the largest arc. For our application case, the density parameter(a) is set to 200. The maximum communication distance between nodes and a UAV is around 223 meters. In that case, if the spiral density is 200 meters, at least two encounters can occur with a stable node on the ground since the maximum radius of the spiral is 400 meters.

UAVs do not request any location information from the nodes or the other UAVs. The packet exchange between the nodes and UAVs is minimal so that an encounter time between them can be sufficient to make packet exchange communication efficient. The UAVs have a GPS or a location sensor as they travel around locations that are determined dynamically. As a result, the UAVs can be added or removed from the environment for maintenance or other purposes.

We use three different techniques to determine the charging station locations. In the first approach, we choose the charging stations' locations as random points on the map. In the second approach, we determine the locations by the k-means clustering on the dataset. K-means clustering algorithm takes the number of clusters to be created and returns the cluster center locations of the created clusters. These centers

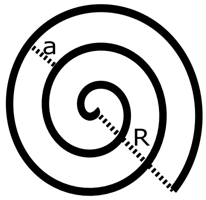


Fig. 1: Archimedes spiral with density a and maximum radius as R.

act as the charging locations. The last approach covers the case where Density-based spatial clustering of applications with noise (DBSCAN) is used to decide. DBSCAN is a non-parametric clustering algorithm that takes the maximum distance between clusters and the minimum number of nodes in a cluster as parameters. Based on the parameters, DBSCAN gives different numbers of cluster centers. The minimum number of nodes in a cluster is three for the DBSCAN cases.

The reason we compare the Density-based spatial clustering of applications with noise (DBSCAN) and k-means clustering techniques is that DBSCAN is a non-parametric clustering algorithm, whereas k-means is a parametric clustering algorithm.

The DBSCAN approach has been evaluated with parameters of 1000, 900, 800, and 700 meters for maximum distance between clusters. The tested parameters gave 2, 3, 4, and 5 cluster centers, respectively. k-means approach is evaluated with 2, 3, 4, and 5 cluster numbers. We choose 2, 3, 4, and 5 random locations to compare the results with the random charging location setting approach.

V. Simulation study

A. *Simulation environment and metrics*

We used an in-house simulator [1] to carry out our evaluation study. We assume that the encounter duration between the nodes is sufficiently long enough for packet exchange. Based on the nature of the opportunistic network, if the receiver does not receive a protocol message, the sender does not resend the packet. The reason is that the message may be received from another node when encountering takes place. The opportunistic wireless environment includes a 10% error rate for wireless communication.

The message delay and success rate have been used as the simulation metrics to evaluate the performance of the compared approaches. Message delay is considered the time between the message creation and the receipt of the message. The success rate is the distribution rate of the message. If a message stays in the node's buffer, then the success rate of the message is 0%. On the other hand, if the message gets distributed to every node, the success rate becomes 100%. At the end of the simulation, we calculate the message delay and the success rate for every message. We provide the statistical distributions as complementary cumulative distribution graphs for success rates and box plot graphs for message delays. An efficient approach should maintain low message delay and high success rates.

B. *Dataset*

We have used North Carolina State University (NCSU) dataset by Rhee et al. [19]. NCSU dataset contains 35 movement traces of students on the university campus for 78090 seconds (more than 21 hours). The participants were randomly selected students who took a course in the computer science department, and every week several randomly chosen students carried the GPS receivers for their regular daily activities. This scenario represents a typical example of the movement of the nodes in an opportunistic network.

The width of the simulation environment is 14629 meters by 9714 meters. The third movement trace was removed. The removed movement trace goes to the corner of the map where no node movement activity occurs. The dataset contains the traces of the nodes every 10 seconds. We have used the data points of all the nodes on the map at every 300 second time intervals while applying the clustering techniques.

C. *k-means clustering results*

Figure 2 presents the cluster centers generated by the k-means and DBSCAN clustering algorithms. When k-means generates two locations, it generates them on the diagonals of the map.

As the number of clusters increase, k-means clustering creates different centers. The cluster centers appear to be further away from each other when the number of clusters increases. DBSCAN, on the other hand, creates new cluster centers around the previous ones. For instance, three cluster centers are located close to the existing two cluster centers. The graph of the cluster centers gives an overview of the performance of the clustering techniques.

Figure 3 shows box plots of message delay distribution for 2 through 5 cluster centers generated with k-means clustering. k-means clustering technique gives low message delay for 2 clusters. The difference between the message delay medians of 2 and 3 clusters is similar; however, 4 and 5 cluster centers show an increase in the message delay.

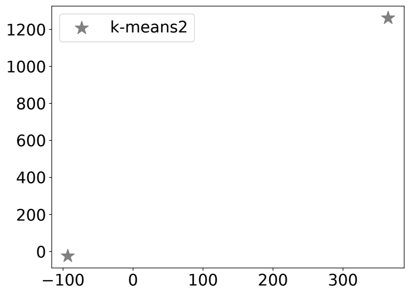
Figure 4 presents the complementary cumulative success rates graph for 2 through 5 cluster centers generated with k-means clustering. Unlike the message delay graph, the success rates give similar results for the different cluster centers.

D. *DBSCAN clustering results*

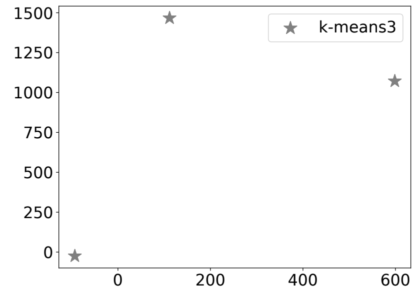
Figure 5 presents the complementary cumulative success rates graph for 2 through 5 cluster centers generated with DBSCAN clustering for maximum cluster center parameters of 1000, 900, 800, and 700 meters, respectively. In terms of success rates, DBSCAN also performs poorly.

E. *Three random cluster centers*

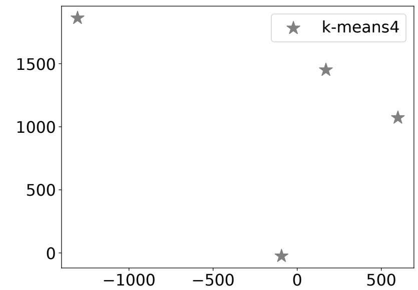
DBSCAN technique has created three cluster centers for 900 meters maximum cluster centers. In order to employ an efficient number of chargers in our application case, we suggest using 900 meters as the DBSCAN cluster parameter to acquire the number of clusters. We can then use the cluster number in the k-means clustering algorithm to determine the charging locations.



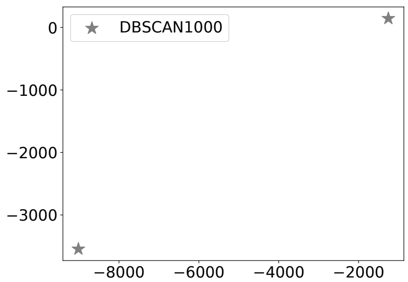
(a) Cluster centers for k-means with 2 clusters



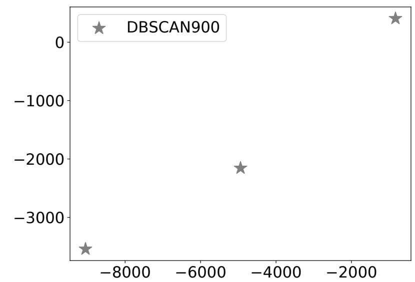
(c) Cluster centers for k-means with 3 clusters



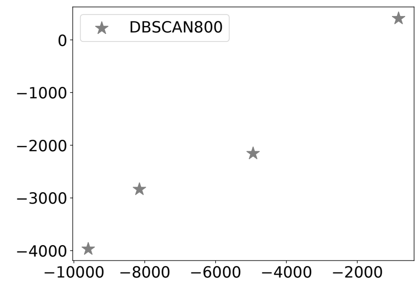
(e) Cluster centers for k-means with 4 clusters



(b) Cluster centers for DBSCAN with 1000 meter maximum cluster distance



(d) Cluster centers for DBSCAN with 900 meter maximum cluster distance



(f) Cluster centers for DBSCAN with 800 meter maximum cluster distance

Fig. 2: Cluster centers, created by k-means clustering, are shown on the map. The numbers in x- and y-axes represent the x and y coordinates of the map.

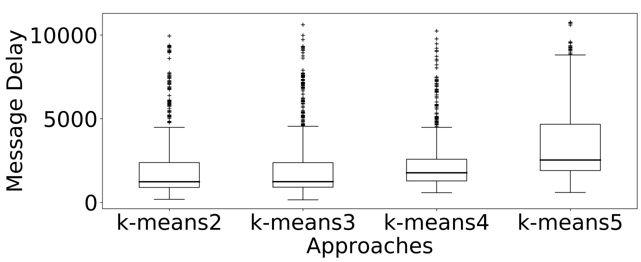


Fig. 3: Box plot distribution results of k-means clustering with numbers of different cluster centers.

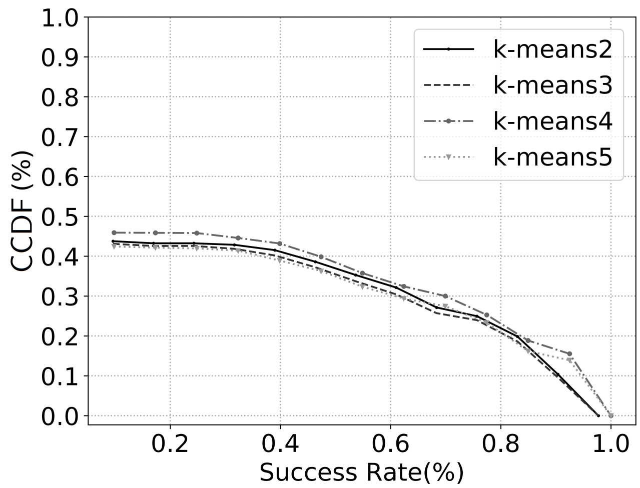


Fig. 4: k-means clustering CCDF success rates with different cluster numbers.

Figure 6 shows the box plots of message delay distributions for three cluster center locations generated with DBSCAN clustering, k-means clustering, and random algorithms. DBSCAN clustering generated three cluster center locations for the maximum cluster distance parameter of 900 meters. k-means outperforms both random and DBSCAN approaches in terms of message delay. DBSCAN clustering algorithm, in turn, has a lower delay than randomly generated cluster center locations.

Figure 7 presents the complementary cumulative success rates graph for 3 cluster center locations generated with DBSCAN clustering, k-means clustering, and random approaches. Randomly assigning the charging locations results in a higher success rate than the DBSCAN. k-means continues to outperform random and DBSCAN algorithms.

VI. Conclusion

In this paper, we used unmanned aerial vehicles (UAVs) to distribute messages in an opportunistic network environment that included ten UAVs with limited cruising time. We used the North Carolina State University dataset with 35 nodes on the ground, and the UAVs were randomly making spiral scans with limited battery life. They could cruise for 30 minutes and visit charging stations on the ground when their battery is too low to make another spiral scan. We have evaluated 2,

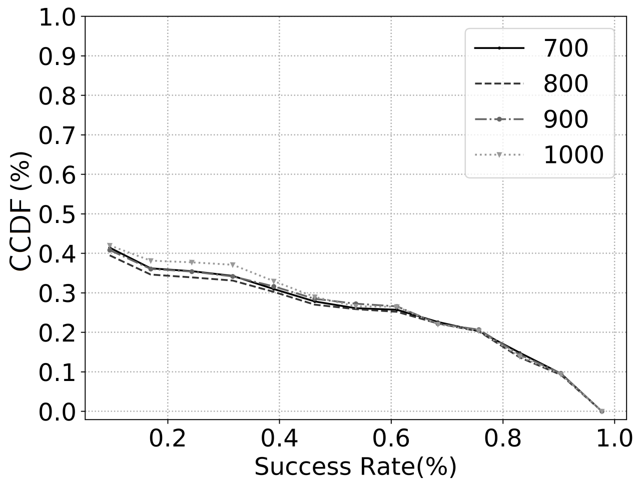


Fig. 5: DBSCAN clustering CCDF success rates with different maximum distance parameters.

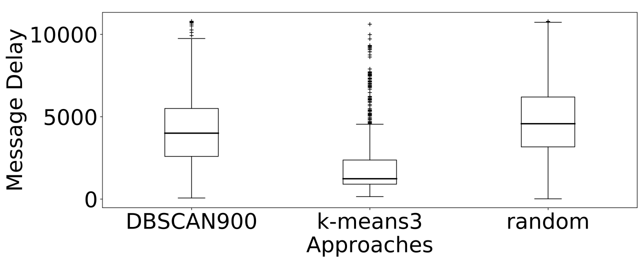


Fig. 6: Box plot distribution results of k-means, DBSCAN and random clustering with numbers of different cluster centers.

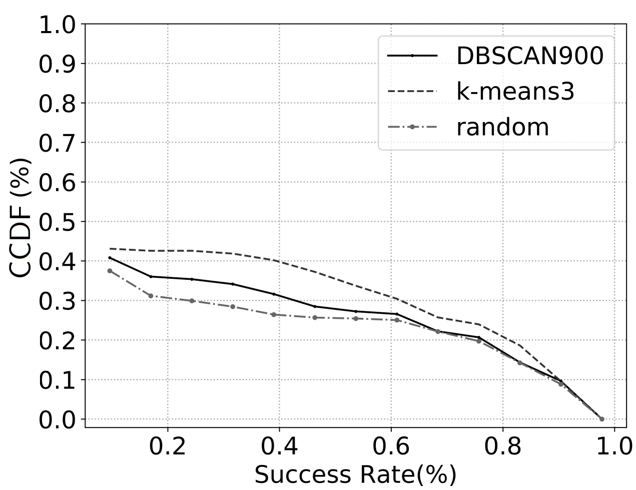


Fig. 7: CCDF success rates results of three cluster centers generated by DBSCAN, k-means and random clustering.

3, 4, and 5 charging stations with different charging station locations. The three approaches compared were random, DBSCAN, and k-mean clustering algorithms. The evaluation results show that k-means clustering outperforms the other two approaches in determining the UAVs' charging station locations.

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