Energy-Efficient User Clustering for UAV-Enabled Wireless Networks Using EM Algorithm

Salim Janji  
Poznan University of Technology  
Poznan, Poland  
salim.janji@doctorate.put.poznan.pl

Adrian Kliks  
Poznan University of Technology  
Poznan, Poland  
adrian.kliks@put.poznan.pl

Abstract

Unmanned Aerial Vehicles (UAVs) can be used to provide wireless connectivity to support the existing infrastructure in hot-spots or replace it in cases of destruction. UAV-enabled wireless provides several advantages in network performance due to drone small cells (DSCs) mobility despite the limited onboard energy. However, the problem of resource allocation has added complexity. In this paper, we propose an energy-efficient user clustering mechanism based on Gaussian mixture models (GMM) using a modified Expected-Maximization (EM) algorithm. The algorithm is intended to provide the initial user clustering and drone deployment upon which additional mechanisms can be employed to further enhance the system performance. The proposed algorithm improves the energy efficiency of the system by 25% and link reliability by 18.3% compared to other baseline methods.

I. INTRODUCTION

Drone small cells (DSCs) have gained popularity in recent years as a solution to wireless communication problems such as lack of fixed infrastructure (e.g. due to natural disasters) or the need for temporal capacity increase (e.g. to manage traffic in a mass-event). If properly deployed, and despite its inherent limitations, UAV-enabled wireless can leverage the performance of the network due to increased probability for line-of-sight (LOS) connectivity and reduced total path loss. Furthermore, due to their mobility, the location of the BS can adapt to the changes in ground user distribution to improve the total throughput of the system. DSCs can also be a cost-effective substitute for building expensive cellular towers and infrastructure where the need for such infrastructure is limited in terms of time or capacity [1], or be deployed along with existing infrastructure in heterogeneous cellular networks [2].

Nonetheless, utilizing UAVs for serving ground users in a given area has its limitations. Limited onboard energy restricts the deployment duration and transmit power thereby limiting the communication range. Furthermore, in the case of multiple DSCs, severe co-channel interference can substantially degrade users’ link qualities [3]. Therefore, the problem of 3D deployment and user allocation is a complex one when taking into consideration factors such as power minimization and interference mitigation. DSCs locations should minimize the path loss and maximize signal-to-interference-plus-noise-ratio (SINR) along with serving the highest possible number of users. Additionally, DSCs should be aware of each other to avoid inter-UAV collisions [1].

The topic of DSCs deployment optimization gained a lot of focus in recent years [4-10]. The problem is commonly approached by optimizing a subset of all inherent aspects (e.g. locations or number of drones vs. coverage, transmit power vs. interference, etc.) without taking into account other factors such as initial deployment and user clustering. In this paper, we target the problem of power minimization, interference mitigation, DSC localization, and user clustering jointly along with deciding a minimum required number of drones to serve a given user set with known locations. Our centralized algorithm is based on Gaussian Mixture Models (GMM) and we call it Drone Users Clustering Expectation Maximization (DUCEM) algorithm. We believe it could also serve as an initial clustering step before applying further heuristic mechanisms to further improve system performance. That is, its results are more optimal than other clustering algorithms (e.g. K-means).

The paper continues as follows. Section II briefly summarizes related research found in the literature. The system model and optimization problem formulation are given in Section III. We introduce EM algorithm in IV and present our modified version for DSCs clustering in Section V. Section VI introduces random waypoint mobility (RWM) model and reference point mobility group (RPGM) model that are used for user mobility simulation. We also describe K-means algorithm which is chosen as the baseline with which we compare our algorithm’s performance and present the results. Finally, in Section VII we give our final remarks and conclusion.
II. RELATED WORK

The application of DSC has been investigated so far in various contexts. In particular, the authors in [4] developed a machine learning scheme for predicting the number of required drones for load balancing in small cells based on historical data. In [5], DSCs sequential placement is optimized to reduce the total number of drones and achieve maximum coverage. However, interference was not taken into account. The authors in [6] considered optimal deployment of two DSCs taking into consideration coverage and interference. In [7], the authors proposed an interference mitigation scheme using affinity propagation which reduces the power of interfering drones and clusters the users using K-means algorithm without targeting the initial user clustering and allocation problem. In [8], the authors mitigate DSC interference in LTE hetNets by applying 3GPP Release-10 enhanced inter-cell interference coordination (eICIC), and optimize UAV deployment using a genetic algorithm (GA). In [2], the authors optimize the transmit power and altitude of each DSC operating in a heterogeneous LTE network comprised of macro base stations, mmWave small base stations, and DSCs operating in the microwave band. The proposed algorithm determines subcarrier allocation using the Hungarian optimization method without targeting the problem of user-cell association. Using game theory, the authors in [9] formulated the problem in a mean-field game framework where the altitude of DSCs is controlled to improve total SINR. In [10], a solution based on Particle Swarm Optimization (PSO) algorithm was derived that maximizes coverage while maintaining link quality.

In general, the mechanisms reported in the literature do not jointly consider the following dynamic issues of DSCs deployment:

- number of required drones for a given area
- interference mitigation between DSCs
- limited energy of DSCs.

Our work presents a heuristic mechanism that tries to address all of the aforementioned aspects of DSCs deployment.

III. PROBLEM FORMULATION

Fig. 1 presents the considered scheme where $U$ ground users are randomly distributed and served by the set of $M$ drones, $M$. We consider a 3D Cartesian coordinates system in which each user $u$ is located at $x_u = (x_u, y_u)$. The location of the $j$th drone is denoted by $F_j = (x_j, y_j, h_j)$, where $h_j$ denotes the flying attitude, and $j \in M$. In our system, we consider that all active drones are flying at the same fixed height $h = 10$ m. As discussed in [11], 10 m is the optimal height for positioning a typical small cell antenna. Lower values cause possible coverage issues, and higher ones increase interference with neighbouring cells. Next, we assume drone $j \in \{1, \ldots, M\}$ can transmit at a specified power $P_{T_j} \leq P_{\text{max}}$, and $P_{\text{max}}$ is the maximum transmit power of the DSC. In consequence, it will serve all $U_j \leq U$ users within its coverage area. As will be explained later in Section V, $P_{T_j}$ is directly proportional to $\Sigma_j$, the covariance value of the Gaussian distribution associated with drone $j$.

![Fig. 1. Scenario of users served by DSCs.](image)

As the drones are flying over a certain area, it is rational to assume that a LOS link exists between drones and users [12]. Thus, we evaluate the free-space path loss model in our analysis. The distance between each drone and ground user is given by:

$$d_{j,u} = \sqrt{(x_j - x_u)^2 + (y_j - y_u)^2 + h^2},$$  

and the channel gain from drone $m$ to user $u$ can be defined as:

$$H_{j,u} = \alpha_0 d_{j,u}^{-\lambda},$$
Here, $\lambda$ is the path loss exponent and $\sigma_0^2$ is the channel power at reference distance $d_0 = 1$ m. In consequence, the signal-to-noise ratio (SNR) between user $u$ and serving drone $j$ is then given by:

$$\text{SNR}_{j,u} = \frac{P_{T_j} H_{j,u}}{\sigma_0^2}$$

(3)

where $\sigma_0^2$ is the power of additive white Gaussian noise (AWGN) at the receiver. For modeling the interference from other DSCs, the signal-to-interference-plus-noise ratio (SINR) of user $u$ served by DSC $j$, $\Gamma_{u,j}$, is given by:

$$\Gamma_{u,j} = \frac{P_{T_j} H_{j,u}}{\sigma_0^2 + \sum_{i \neq j} P_{T_i} H_{i,u}}$$

(4)

In consequence, the theoretical capacity limit can be derived based on Shannon’s formula as

$$R_{\text{total}} = \sum_{j=1}^{M} \sum_{u=1}^{U} W(j,u) B \log_2(1 + \Gamma_{u,j})$$

(5)

where $W(j,u) = 1$ if user $u$ is served by drone $j$ and 0 otherwise, and $B$ is the allocated bandwidth per user channel.

Focusing only on data communications, the total maximum power consumed by drones can be given by:

$$P_{\text{total}} = \sum_{i=1}^{M} P_{T_i}$$

(6)

where we have neglected propulsion energy as it is irrelevant to our problem. Thus, the energy efficiency of the whole system is defined as follows:

$$EE = \frac{R_{\text{total}}}{P_{\text{total}}}$$

(7)

It is assumed that the transmitted power of each drone can be continuously varied up to a limit $P_{\text{max}}$. Also, the maximum number of users served by each drone is also limited to $U_{\text{max}}$. Furthermore, each user is guaranteed a minimum SNR value of $\text{SNR}_T$. The optimization problem is then formulated as:

$$\max_{P_{T_j}, P_{j}, U_j} EE = \max_{P_{T_j}, P_{j}, U_j} \frac{R_{\text{total}}}{P_{\text{total}}}$$

s.t.

a) $\text{SNR}_{j,u} \geq \text{SNR}_T \quad \forall u \in U$

b) $U_j \leq U_{\text{max}} \quad \forall j \in M$

c) $P_{T_j} \leq P_{\text{max}} \quad \forall j \in M$.

Next Sections present our heuristic approach to solving this problem.

### IV. Expected-Maximization Algorithm

Expectation Maximization (EM) algorithm is based on Gaussian Mixture Models (GMMs) where it is assumed that the set of samples is drawn from a “mixture” of Gaussian distributions [13]. A GMM can be defined as:

$$\pi(x; \theta) = \sum_{j=1}^{M} P(j) N(x; \mu_j, \Sigma_j),$$

(9)

where the parameters $\theta = \{P, \mu, \Sigma\}$ include mixing proportions, means of Gaussian components, and covariances respectively, and $N(x; \mu_j, \Sigma_j)$ represents the $j$-th Gaussian distribution.

The EM algorithm learns the parameters $\theta$ given a set of sample points, $X_t$, and number of mixtures, $M$ (As will be explained later, M denotes the number of drones). It consists of two steps (estimation step, called E-step, and maximization step, called M-step) performed iteratively:

1) (E-step) Evaluate the posterior assignment probabilities given by:

$$p^{(l)}(j|t) = p(j|\mathbf{x}_t, \theta^{(l)}) = \frac{P^{(l)}(j) N \left( \mathbf{x}_t; \mu_j^{(l)}, \Sigma_j^{(l)} \right)}{\sum_{j'=1}^{M} P^{(l)}(j') N \left( \mathbf{x}_t; \mu_j^{(l)}, \Sigma_{j'}^{(l)} \right)}$$

$$P^{(l)}(j) N \left( \mathbf{x}_t; \mu_j^{(l)}, \Sigma_j^{(l)} \right)$$

$$= \frac{P^{(l)}(j) N \left( \mathbf{x}_t; \mu_j^{(l)}, \Sigma_j^{(l)} \right)}{P(\mathbf{x}_t; \theta^{(l)})}$$

(10)
where \((l)\) denotes iteration number, and \(x_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix}\) is the sample \(t = \{1, \ldots, n\}\) where \(n\) is the number of samples.

2) (M-step) Update parameters according to:

\[
p^{(l+1)}(j) = \frac{\hat{n}(j)}{n}, \quad \text{where} \quad \hat{n}(j) = \sum_{t=1}^{n} p^{(l)}(j|t). \\
\mu_j^{(l+1)} = \frac{1}{\hat{n}(j)} \sum_{t=1}^{n} p^{(l)}(j|t)x_t. \\
\Sigma_j^{(l+1)} = \frac{1}{\hat{n}} \sum_{t=1}^{n} p^{(l)}(j|t) \left( x_t - \mu_j^{(l+1)} \right) \left( x_t - \mu_j^{(l+1)} \right)^T.
\]

As can be observed, the E-step obtains the posterior probabilities that denote the probability of having the sample observed \(x_t\) being drawn from the \(j\)-th Gaussian component. In the M-step, the parameters of each component \(j\) are updated to increase the total likelihood of the GMM. It is worth noting that the EM algorithm is guaranteed to converge to a local optimal solution [13].

V. DRONE USERS CLUSTERING EXPECTED MAXIMIZATION ALGORITHM (DUCEM)

In this paper, we propose using a modified EM algorithm to tackle the problem of DSCs placement and user clustering along with considering the system energy efficiency.

The set of sample points, \(X\), is taken to be the set of users distributed on the ground to be served by DSCs. Furthermore, \(\mu_j\) indicates the \(j\)-th DSC location in the 2D \(x, y\) Cartesian plane, and \(\Sigma_j\) is associated with the transmission power \(P_{T_j}\) of drone \(j\) (i.e. the values of each covariance matrix are proportional to the transmission power of each DSC). The posterior probabilities \(p(j|t)\) bear no mapping to parameters in the real system but serve in determining the power and location of each DSC as evident in equations (12) and (13).

The reasoning behind our choice is that by examining equations (10-13) we observe that each sample point \(x_t\) (i.e. location of user \(t\)) contributes to the parameters of all components (drones). The magnitude of this contribution is determined by the posterior probability given in equation (10). Thus, the contribution of \(x_t\) to DSC \(j\) parameters decreases as \(p(k|t)\) increases. This is evident from (10) as \(N(x; \mu_k, \Sigma_k)\) increases, \(p(j|t)\) decreases. This translates into the observation that user \(t\), if served by DSC \(k\), would contribute less to parameters updates of DSC \(j\) in (11-13). Therefore, because of EM algorithm dynamics, it can be associated with the practical problem of DSC users clustering where each user requires to be served by one DSC. Our DUCEM algorithm introduces several modifications to the standard EM to suit our considered problem:

1) Each covariance matrix \(\Sigma_{jM \times M}\), is a diagonal matrix with equal diagonal values to map the DSCs circular coverage of ground users to a circular distribution of samples around means (power is transmitted equally through each axis around the DSC). By removing this constraint, coverage of DSCs will take a non-circular form (i.e. using beamforming). This will be a topic of our future work.

2) The diagonal values of \(\Sigma_j\), denoted as \(\Sigma_j\), are limited to a maximum value \(\Sigma_{\text{max}}\) to resemble the real case scenario of limited transmit power of drones \(P_{\text{max}}\). This limits the number of sample points \(x_t\) to be associated with component \(j\).

3) \(\Sigma_j\) is only allowed to increase while \(U_j \leq U_{\text{max}}\). This ensures that the number of users served by DSC \(j\) is bounded by \(U_{\text{max}}\).

4) The change of \(\Sigma_j\) per DUCEM iteration is limited by a maximum value of \(d\Sigma_{\text{max}}\). This reduces overlapping between clusters and reduces the chance for a cluster to be completely contained in another one. Not limiting \(d\Sigma_{\text{max}}\) allows abrupt big jumps in \(\Sigma_j\) initial updates where sample points far from \(\mu_j\) substantially affect the update in (13) because the corresponding posterior probability is large (other components have not yet contributed to the denominator in (10)).

Fig. 2 shows the difference between setting a maximum \(d\Sigma_{\text{max}}\) for a certain set of sample points and \(M = 4\). As observed, limiting \(\Sigma_j\) change in equation (13) reduces overall overlapping. Clearly, this improves interference between DSCs. To summarize, the update in equation (13) is limited by \(\Sigma_j^{(l+1)} - \Sigma_j^{(l)} \leq d\Sigma_{\text{max}}\), and \(\Sigma_j^{(l+1)} \leq \Sigma_{\text{max}}\).

5) Each user is associated to the cluster with smallest value of Standardized Euclidean Distance (SED) given by:

\[
SED_{j,u} = \sqrt{\frac{((x_j - x_u)^2 + (y_j - y_u)^2 + h^2)}{\Sigma_j}}.
\]

Users allocations are given by the matrix \(W_{M \times U}\) where \(W(j, u) = 1\) if the \(u\)-th user is associated with drone \(j\) and 0 otherwise.

6) Each DSC is centered at the mean location of its served users.
7) The algorithm begins with \( m = 1 \) as the initial number of drones (components) and adds another drone while a solution that satisfies the requirements of the maximum number of users or link reliability is not yet found.

8) At each iteration, the total system EE is obtained. The setting that yields maximum EE \( (\theta_{opt} = \{\mu_1, \Sigma_1, \ldots, \mu_M, \Sigma_M\}) \) is saved and is chosen as the final solution. EM algorithm converges when the maximum change, \( \max d\theta \), of any of the parameters \( \mu_j \) and \( \Sigma_j \) after iteration \( i \) is limited by \( \varepsilon_1 \). Also, a new DSC is added when the number of DSCs is not enough to find a solution that satisfies the maximum number of users and maximum power constraints. Finally, \( \varepsilon_2 \) ensures that no new drones are added until EM updates are close to convergence.

![Fig. 2. Comparison of clustering overlap for a given set of test points with different \( d\Sigma_{max} \) values.](image)

Algorithm 1 shows the pseudocode for the DUCEM scheme. The algorithm takes as an input the drones maximum power \( P_{max} \), maximum number of users per cluster \( U_{max} \), and the locations of users \( X \). The location and transmitting power of each drone are initialized arbitrarily around the considered area. Furthermore, two thresholds are set: \( \varepsilon_1 \) which determines the minimum change in drone parameters \( (\mu, \Sigma) \) after which convergence is reached, and \( \varepsilon_2 \) which sets the threshold of parameter change below which a new drone would be added if no solution that satisfies power and capacity requirements is yet found. On each iteration the posterior probabilities are obtained and each drone parameters, \( \theta \), are updated. Users are then assigned to
the drone with lowest resulting SED given by (14). The drones 2D locations are then recalculated as the centers of assigned users clusters in step 6. The power of each drone is then obtained by satisfying the SNR requirement. As long as no solution satisfying the constraints is found the algorithm reiterates. If the maximum change per parameters (step 29) is below \( \varepsilon_2 \), a new drone is added. The algorithm stops if the change in parameters is below \( \varepsilon_1 \) and a solution is found. It then returns the settings that result in the highest energy efficiency score (steps 23 - 27).

Algorithm 1 Drone Users Clustering Expectation Maximization

**Input:** \( X, U_{\text{max}}, P_{\text{max}} \)

**Output:** \( M, \theta_{\text{opt}} = \{P, \mu, \Sigma\}, P_T \forall j \in M, W_{\text{opt}}^M \times U \)

**Initialization:** Initialize \( \theta = \{P^{(0)}, \mu^{(0)}, \Sigma^{(0)}\}, i = 0, \max EE = 0, \varepsilon_2 < \varepsilon_1 \)

**LOOP Process**

1: while \((\max d\theta > \varepsilon_1 \) or \( \text{SolutionFound} = 0 \)) do
2: Obtain posterior probabilities \( p(j|t) \forall j \in M \)
3: Obtain \( \Sigma_{j_{\text{new}}} \) according to (11) and (12) \( \forall j \in M \)
4: Allocate users to DSC with minimum SED given in (14) and obtain \( W^i \)
5: for \( j \in M \) do
6: if \( (U_j \leq U_{\text{max}} \) or \( \Sigma_{j_{\text{new}} < \Sigma_j} \) then
7: Update \( \Sigma_j = \Sigma_{j_{\text{new}}} \)
8: end if
9: end for
10: if \((\max d\theta < \varepsilon_2 \) and \( \text{SolutionFound} = 0 \)) then
11: Add new DSC: \( M = M + 1 \)
12: Go to step 2
13: end if
14: SolutionFound = 1
15: if \((U_j \geq U_{\text{max}} \) or \( P_j > P_{\text{max}} \)) \( \forall j \in M \) then
16: SolutionFound = 0
17: end if
18: if \( \text{SolutionFound} = 1 \) then
19: Obtain EE
20: if \( EE > \max EE \) then
21: \( \max EE = EE^i \)
22: \( \theta_{\text{opt}} = \theta^i \)
23: \( W_{\text{opt}} = W^i \)
24: end if
25: end if
26: maxd\theta = \max\{\max_j (\mu_j^i - \mu_j^{i-1}, \Sigma_j^i - \Sigma_j^{i-1})\}
27: i = i + 1
28: end while
29: return \( m, \theta_{\text{opt}} = \{P, \mu, \Sigma\}, P_T \forall j \in M, W_{\text{opt}} \)

VI. Simulation and Results

A. Users Mobility Model

For our simulations, we consider that users are moving within groups. This model reflects the scenario in which DSCs deployment is immediately required in mass-events (e.g. concerts, street gatherings, etc.). Other scenarios are also applicable. Each group has a leader moving according to the random waypoint mobility (RWM) model [14]. Each leader movement is determined by drawing from a memoryless stochastic process with three random variables \( D_i, T_{p,i}, \) and \( V_i \) denoting destination point at instance \( i \), pause time at the destination, and traveling speed respectively. Furthermore, each leader is surrounded by group members that are moving according to the reference point group mobility model (RPGM) [15]. According to RPGM the movement of group members can be characterized by the respective motion vector:

\[
V_i^{(g)}(t) = V_{\text{leader}}^{(g)}(t) + RM
\]  
(15)
TABLE I. SIMULATION PARAMETERS

| Parameter                                      | Value         |
|------------------------------------------------|---------------|
| DSCs altitude \( h \)                          | 10 m          |
| Path loss exponent \( \lambda \)               | 2             |
| DSCs max transmit power \( P_{\text{max}} \)   | 1 W           |
| Noise power \( \sigma_0 \)                     | -100 dBm      |
| Received power at reference distance 1 m \( \sigma_0 \) | -30 dB        |
| \( d\Sigma_{\text{max}} \)                     | 0.1           |
| Channel bandwidth \( B \)                      | 10 MHz        |
| SNR \( T \)                                   | 12 dB         |

where \( i, g \) denote the member and group numbers respectively, \( V_{\text{leader}}^g(t) \) is the motion vector of group leader \( g \) at time instant \( t \), and \( RM \) is a random vector deviated by group member \( i \) from its leader. The movement of group members can be represented by the angle and magnitude deviation between leaders and members’ motion vectors. The equations that determine the deviation at time instant \( t \) are as follows:

\[
|V_{\text{member}}(t)| = |V_{\text{leader}}(t)| + r \phi_v dV_{\text{max}} \tag{16}
\]

\[
\theta_{\text{member}}(t) = \theta_{\text{leader}}(t) + r \phi_\theta d\theta_{\text{max}} \tag{17}
\]

where \( r \in [0, 1] \) is a random number drawn from a uniform distribution at each group member movement interval, \( \phi_v \) and \( \phi_\theta \) are the speed deviation ratio and angle deviation ratio respectively, and \( dV_{\text{max}} \) and \( d\theta_{\text{max}} \) are the group members maximum speed and angle deviation respectively. Arbitrary settings of \( \phi_v, \phi_\theta, dV_{\text{max}}, \) and \( d\theta_{\text{max}} \) yield varied simulation scenarios.

B. Simulation Parameters

In our simulations we consider an area of 1200 m² for the users’ mobility model. The simulation parameters are listed in Table 1. We compare our algorithm results in terms of link reliability and energy efficiency for different values of maximum number of users per cluster \( U_{\text{max}} \). The link reliability is given by:

\[
L_{\text{rel}} = \Pr\{\Gamma_{u,j} \geq \Gamma_{Th}\}, \quad \forall j \in \mathcal{M}, \tag{18}
\]

where \( \Gamma_{u,j} \) is the SINR between user \( u \) and drone \( j \) given by (4), and \( \Gamma_{Th} \) is the SINR threshold above which the link is considered reliable.

C. K-means Clustering

K-means clustering is a special case of EM where all components have equal covariances \( \Sigma_j \) and each point is assigned to the component with higher posterior probability \( p(j|t) \) [13]. The algorithm takes in the number of clusters and sample points \( (X, m) \) as an input. For our simulations, we employ K-means clustering with simple modifications to better suit our application. Modifications concern the realistic restriction of the maximum number of users per cluster \( U_{\text{max}} \), and maximum transmission power \( P_{\text{max}} \).

K-means clusters users with the specified restrictions of \( U_{\text{max}} \) and \( P_{\text{max}} \) that DUCEM satisfies. At each iteration, K-means algorithm is repeated 10 times with different initialization determined by Kmeans++ algorithm [13]. The algorithm is presented in Algorithm 2. As an input, K-means receives the drones maximum power \( P_{\text{max}} \), maximum number of users per cluster \( U_{\text{max}} \), and the locations of users \( X \). The algorithm begins with one drone and adds a new one (steps 6-8) if the constraints are not satisfied. Similarly to DUCEM, the transmission power for each drone is obtained by satisfying the SNR constraint (step 5) after positioning the drone at the center of the associated users (step 4). Again, the settings that yields the highest EE score is returned.
Algorithm 2 K-means Clustering

Input: $X$, $U_{\text{max}}$, $P_{\text{max}}$

Output: $\mu$, $W_{\text{opt}}$

Initialization: Initialize $M = 1$, $i = 0$, $\text{maxEE} = 0$

LOOP Process
1. while ($i < 10$) do
2. Cluster users using K-means with inputs $(X, M)$
3. for $j \in M$ do
4. $\mu_j = \text{mean} (W_{ij} X_T)$
5. calculate $P_j$ according to $\text{SNR}_T$
6. if ($U_j > U_{\text{max}}$) or ($P_j > P_{\text{max}} \forall j \in M$) then
7. Cluster users in cluster $j$ using K-means with inputs $(W_{ij} X_T, 2)$
8. Check if sub-cluster $k$ satisfies conditions in 6. If not, repeat 7 for cluster $k$
9. end if
10. end for
11. if $\text{EE} > \text{maxEE}$ then
12. $\text{maxEE} = \text{EE}^{(i)}$
13. $W_{\text{opt}} = W^i$
14. end if
15. $i = i + 1$
16. end while
17. return $\mu_j$, $W_{\text{opt}}$

D. Results

Fig. 3 shows the obtained EE for different values of $U_{\text{max}}$. On average, the EE of the system is improved by 25%. Furthermore, the achieved link reliability is obtained for two different values of $\Gamma_{Th}$. The results show that DUCEM provides, on average, 18.3% better link reliability. Fig. 4 plots $L_{\text{rel}}$ results for $U_{\text{max}} = 1500$. We observe that DUCEM results are indeed more optimal than the widely used K-means clustering mechanism. The improvement in performance is almost constant for different values of $U_{\text{max}}$. This is expected since both algorithms do not directly optimize inter-cell interference which is expected to have greater effect with increasing number of drones (i.e. decreasing value of $U_{\text{max}}$). Employing DUCEM with the mechanisms mentioned in Section II is expected to speed up convergence and achieve better results which will be the topic of our future work.

VII. Conclusion

DSCs provide a suitable solution for providing wireless coverage. However, their deployment problem requires consideration of various aspects such as co-channel interference, 3D placement, user clustering, and transmit power minimization. The problem of user clustering for DSCs has received limited attention. In this paper, a user clustering algorithm was proposed that takes into account the aforementioned aspects of the problem. The numerical results verified that the proposed algorithm enhances system performance in terms of energy efficiency and link reliability. The results of DUCEM can provide the initial clustering
Fig. 4. Link reliability ($L_{rel}$) against SINR threshold ($\Gamma_{Th}$). $U_{max} = 1500$. 

upon which further performance improving mechanisms can be implemented. To further improve the performance of DUCEM, the problem of inter-cell interference should be tackled and optimized. Other aspects to be considered and optimized for are users handover and the drone’s propulsion energy.

REFERENCES

[1] M. Mozaffari, W. Saad, M. Bennis, Y. Nam, and M. Debbah, “A tutorial on uavs for wireless networks: Applications, challenges, and open problems,” IEEE Communications Surveys Tutorials, vol. 21, no. 3, pp. 2334–2360, 2019.

[2] J. Chakareski, S. Naqvi, N. Mastronarde, J. Xu, F. Aghf, and A. Razi, “An energy efficient framework for uav-assisted millimeter wave 5g heterogeneous cellular networks,” IEEE Transactions on Green Communications and Networking, vol. 3, no. 1, pp. 37–44, 2019.

[3] H. V. Abeywickrama, Y. He, E. Dutkiewicz, B. A. Jayawickrama, and M. Mueck, “A reinforcement learning approach for fair user coverage using uav mounted base stations under energy constraints,” IEEE Open Journal of Vehicular Technology, vol. 1, pp. 67–81, 2020.

[4] J. Hu, H. Zhang, Y. Liu, X. Li, and H. Ji, “An intelligent uav deployment scheme for load balance in small cell networks using machine learning,” in 2019 IEEE Wireless Communications and Networking Conference (WCNC), 2019, pp. 1–6.

[5] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim, “Placement optimization of uav-mounted mobile base stations,” IEEE Communications Letters, vol. 21, no. 3, pp. 604–607, 2017.

[6] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Drone small cells in the clouds: Design, deployment and performance analysis,” in 2015 IEEE Global Communications Conference (GLOBECOM), 2015, pp. 1–6.

[7] Y.-S. Chao, C. Shao-Hung, and Z. Han, “An integrated affinity propagation and machine learning approach for interference management in drone base stations,” IEEE Transactions on Cognitive Communications and Networking, vol. PP, pp. 1–1, 10 2019.

[8] A. Kumbhar, I. Güvenç, S. Singh, and A. Tuncer, “Exploiting lte-advanced hettnets and feicic for uav-assisted public safety communications,” IEEE Access, vol. 6, pp. 783–796, 2018.

[9] L. Li, Z. Zhang, K. Xue, M. Wang, M. Pan, and Z. Han, “Ai-aided downlink interference control in dense interference-aware drone small cells networks,” IEEE Access, vol. 8, pp. 15 110–15 122, 2020.

[10] W. Shi, J. Li, W. Xu, H. Zhou, N. Zhang, and X. Shen, “3d drone-cell deployment optimization for drone assisted radio access networks,” in 2017 IEEE/CIC International Conference on Communications in China (ICCC), 2017, pp. 1–6.

[11] M. Ding and D. Lopez-Perez, “Please lower small cell antenna heights in 5g,” 11 2016.

[12] Q. Wu, Y. Zeng, and R. Zhang, “Joint trajectory and communication design for multi-uav enabled wireless networks,” IEEE Transactions on Wireless Communications, vol. 17, no. 3, pp. 2109–2121, 2018.

[13] R. Singh, T. Jaakkola, and A. Mohammad, “6.867 machine learning. fall 2006.” [Online]. Available: MITOpenCourseWare,https://ocw.mit.edu.

[14] C. Bettstetter, G. Resta, and P. Santi, “The node distribution of the random waypoint mobility model for wireless ad hoc networks,” IEEE Transactions on Mobile Computing, vol. 2, no. 3, pp. 257–269, 2003.

[15] J. Geetha and G. Ganapathy, “Reference point group mobility and random waypoint models in performance evaluation of manet routing protocols,” Journal of Computer Systems, Networks, and Communications, vol. 2008, 01 2009.

[16] D. Arthur and S. Vassilvitskii, “K-means++: The advantages of careful seeding,” vol. 8, 01 2007, pp. 1027–1035.