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Measurement based threat aware drone base station deployment

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Abstract: Unmanned aerial vehicles are gaining importance with many civilian and military applications. Especially the surveillance, search/rescue and military operations may have to be carried out in extremely constrained environments. In such scenarios, drone base stations (DBSs) have to provide communication services to the people at the ground. The ground users may have no access to the global positioning system (GPS), therefore their locations have to be estimated using alternative techniques. Besides there may be threats in the environments, such as shooters. In this work, we address the problem of optimal DBS deployment under aforementioned constraints. We propose a novel DBS deployment algorithm that uses estimated positions of ground users and threats. The proposed algorithm is based on receiver signal strength (RSS) based maximum likelihood (ML) estimate of user locations and K-means clustering supported heuristic that takes into account the positions of threats. Numerical results show that proposed algorithm performs close to the computation intensive near-optimal algorithm and strikes a good trade-off between the number of unserved users and the probability of DBSs not being hit.

Key words: Drone base stations, tactical networks, metaheuristic, urban warfare

1. Introduction

The world's population is becoming more and more urbanized each year. As stated in the United Nation's report, 30% of world's population was urban in 1930 and it is projected that 66% of world's population will be urbanized by 2050 [1]. The urbanization process brings some potential threats to the peace of society. The demand for limited resources such as water, energy and food creates pressure to the system. This may result in the increase of unrest and violence in society and require military interventions in order to provide stability in densely populated regions. However, current military doctrines do not sufficiently recognize the challenges of conducting operations in urban environments [2]. Considering the necessity of urban warfare in future conflicts, NATO examines the impact of urban operations on the military and seeks to identify possible gaps in training, requirements and capabilities.

There are key factors, which make the operation in urban battlefield challenging. Intelligence collection is difficult and most of the time human intelligence [3] is needed regarding the activities of adversaries. The presence of civilians in the operation area necessitates precision fire to prevent loss of civilian life. As the urban operations are ground-intensive, maneuver warfare tactics are very difficult to apply. Last but not least challenge is the provisioning of a reliable communication network for allied forces [3, 4].

Establishing and maintaining a wireless battlefield communication network is a challenging task. Terrestrial communication suffers from non-line-of-sight (NLoS) and deployment of relays or base stations poses

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difficulties, along with the security risks. In addition to this, mobility of friendly forces on the battlefield continuously affects the network coverage performance, hence the repositioning of communication equipments is required. However, as the ground intensive urban combat restricts the area for deployment, the equipments may not be placed at the appropriate locations [3]. Furthermore, the selection of the suitable position requires the location information of the soldiers. However, the presence of widely available and inexpensive global positioning system (GPS) jammers may prevent the sharing of position information. In order to mitigate the effects of GPS jamming, researchers focus on the development of anti-jamming GPS system equipped with antenna arrays and advanced signal processing algorithms such as beamforming and spatial filtering [5]. However, design of an anti-jamming GPS device that meets strict size, weight,power and cost (SWaP-C) requirements and equipping all soldiers deployed in the field with these devices are challenging tasks to accomplish.

Drone base station (DBS) based communication and soldier position estimation offers inherent solutions to the aforementioned problems. First, high altitude DBS deployment reduces the probability of NLoS transmission and line-of-sight (LoS) condition dominates the channel between the DBS and the user [6]. Second, GPS of a drone is more robust to GPS jamming applied from the ground as the antenna has an unobstructed view of the sky, which ensures good signal reception and provides, to some extent, spatial filtering of jamming signals [5]. Hence, with the help of localization techniques and usage of drones as reference points estimating the locations of soldiers becomes possible [7]. In particular, received signal strength (RSS) based localization, which does not require hardware modification of drone is an attractive method for this application. Final advantage of the DBS use is related to the handling of soldiers' mobility. DBS is able to fly to the new position in order to maximize coverage when the soldiers move from one location to another.

As there are threats to soldiers in the ground, there are threats to DBSs in the air as well. The authors in [3, 8] report that the urban warfare is primarily conducted with small arms such as sniper rifles or machine guns. In this respect, we identify that small arm equipped enemy who is trained to shoot down DBS, which we call drone shooter thereafter, pose a significant risk in maintaining DBS-based communication service in the urban warfare. Therefore, DBS placement decision should be made considering the coverage and drone safety requirements with respect to an operation undertaken. This phenomenon complicates the already difficult problem of DBSs deployment [9].

In this work, we examine the scenario of urban warfare and its challenges from the perspective of wireless communication networks. We propose a novel DBS deployment algorithm, which employs both low-cost RSS-based technique to estimate soldier positions in the urban environment and utilize k-means clustering supported heuristic algorithm which takes into account the presence of drone shooters. We consider air-to-ground Gaussian mixture path loss model [6] and derive the maximum likelihood (ML) estimation of the angles between DBSs and soldiers, that enables position estimates of soldiers. For the same scenario, we investigate a near-optimal upper bound for coverage using a computationally intensive particle swarm optimization (PSO) method. Finally, the discussion is provided regarding the deployment decision under two conflicting objectives, namely, minimum number of soldiers unserved and maximum probability of DBSs not being hit. To the best of our knowledge, this is the first article which investigates the DBSs placement problem considering the requirements of urban warfare.

Recently, DBS deployment has attracted many researchers. There are diverse use cases for the utilization of DBSs and it is considered as an important component in beyond-5G networks [10]. In our previous work, we studied fairness-aware multiple DBSs deployment and analyzed the use of the efficient clustering algorithms for determining the positions of a number of DBSs in a 3-dimensional (3D) space in order to achieve maximum log-sum data rate. The work in [11] derives the optimal deployment altitude of a single DBS to maximize coverage with minimum transmit power. In [12], the backhaul capacity-aware 3D placement of a DBS is considered. The authors propose two placement approaches, one maximizes user coverage and the other maximizes the total user data rate. [13] studies the placement of a single DBS to maximize network revenue that is defined as the number of users covered. The authors in [14] employ PSO technique to find the number of DBSs required and their positions to minimize the number of uncovered users. In [15], a polynomial time algorithm aiming to minimize number of DBSs needed to cover users is proposed. Here, the problem formulation does not consider interference amongst DBSs. The DBSs deployment based on circle packing theory is studied in [16] and [17]. In the former work, the positions of DBSs are determined to maximize total coverage with minimum transmission power and in the latter, DBSs are placed to maximizes the number of covered users with different quality of service requirements. In [18], clustering algorithms are used to position the unmanned aerial vehicle (UAV) mounted picocells in a two-tier network. There is also some discussion regarding the effect of user positioning error on the received signal strength for users serviced by the UAV picocells. However, the presence of NLoS link and interference amongst base stations are ignored. In addition, the assumed user positioning errors are not sufficient to investigate network performance in the GPS denied urban environments.

RSS-based positioning technique is very attractive for DBS-based soldier positioning application because it provides a low cost and easy-to-implement solution. RSS-based positioning does not require antenna arrays employed in angle based localization technique [19]. Furthermore, it does not require precise time synchronization that is needed in time-based localization approaches [20]. The use of drones for positioning is studied in [21] and [22]. The author in [21] considers a single flying drone equipped with GPS and particle filtering algorithm to design RSS-based positioning. In [7], drone based positioning using RSS samples is studied for urban environment. The authors derive Cramer-Rao lower bound for the estimated distance as a function of the elevation angle and the drone to node distance. However, more realistic Gaussian mixture channel model is not considered and formulation of ML estimator is not provided.

The rest of the paper is organized as follows. In Section 2, we present the system model. In Section 3, the DBSs deployment algorithm which considers the requirements of urban warfare is presented. In Section 4, we present numerical simulations and discuss the trade-offs and performance. Finally, in Section 5 we summarize our work and discuss the future work.

2. System model and assumptions

We focus on a downlink transmission system, where DBSs provide service to the soldiers in urban terrain as shown in Figure 1. Using the definitions given in [23], we identify that there are two major zones in urban battlefield, theater of operation (TOO) and theater of war (TOW). In our work, friendly force soldiers are distributed in the TOO according to the structured group mobility model (SGMM) which is used for modelling task oriented node positioning [24, 25]. Drone shooters are distributed uniformly in the TOW. However, to be more realistic it is assumed that each soldier has a protected zone around himself, where drone shooters are not positioned. The users and drone shooters are assumed to be stationary and the deployment problem is solved for this fixed topology.

Due to GPS jamming, we consider that soldiers have no access to GPS service, whereas DBSs utilize GPS service to locate themselves. We consider both friendly forces and drone shooters are positioned on ground, not on rooftops or in buildings. Deploying drone shooters on the rooftops are not feasible as they can be easily detected by surveillance drones and become an open target. On the other hand, buildings may limit

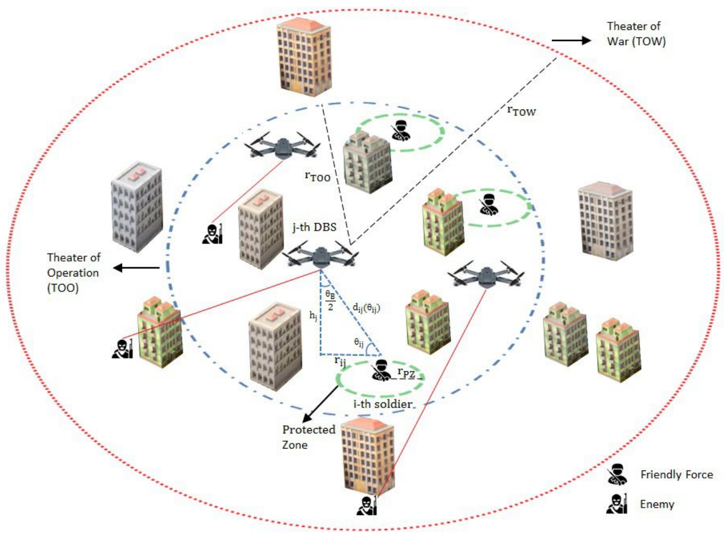

Figure 1. System model

the shooter's mobility and field of view. DBSs are assumed to be located at a fixed altitude and have same transmission power. We also assume that a separate frequency band is allocated for the communication among DBSs and enough capacity is provided.

DBS deployment consists of two phases. In the first phase, DBSs fly to the fixed points assigned to each of them to form an equilateral triangle on the TOO. At the corners of triangle, DBSs collect short pilot signals emitted from the radios of soldiers. We assume that all pilot signals reach to DBSs. In the second phase, the RSS of pilot signals are used to estimate soldier positions and deployment algorithm determines the final positions of DBSs. It is assumed that soldiers are stationary and each soldier is served by a single DBS. We consider Time Division Multiple Access (TDMA) for multiple access. In this scheme, each DBS assigns equal fraction of time slots to each soldier. We consider that each user is connected to DBS achieving largest Signal to Noise Ratio (SNR).

The positions of drone shooters are assumed to be obtained via Human Intelligence (HUMINT) network [26] or by soldiers who are trained to visually estimate target locations [27] and report to DBSs. Because soldiers report the positions relative to their locations, the same error margin is applied to real positions of drone shooters. The probability of DBSs not being hit is calculated when they reach their final operational positions for providing service to soldiers.

We denote soldiers, DBSs and drone shooters by the sets $\mathcal{U} = \{1, ..., U\}$, $\mathcal{D} = \{1, ..., D\}$ and $\mathcal{T} = \{1, ..., T\}$, respectively. The position of the ith soldier, (x_i^u, y_i^u) and lth drone shooter, (x_l^t, y_l^t), are estimated and denoted by $(\widehat{x_i^u}, \widehat{y_i^u})$ and $(\widehat{x_l^t}, \widehat{y_l^t})$, respectively, where $i \in \mathcal{U}$ and $l \in \mathcal{T}$. We denote the 3D position of the jth DBS by (x_j^d, y_j^d, h_j^d) where $j \in \mathcal{D}$.

2.1. Path loss model

We adopt the Gaussian mixture path loss model proposed in [6], whose simplified version is widely used by the researchers for the analysis of DBS placement problems [12–14]. It is important to note that we apply a realistic excess path loss model, which is dependent on the operating frequency, environment and elevation angle between the DBS and the soldier. The path loss between the ith soldier and jth DBS in the LoS and NLoS cases are formulated as,

$$PL^{ij}_{LoS}(\theta_{ij}) = 10\gamma \log\left(\frac{4\pi d_{ij}(\theta_{ij}) f_c}{c}\right) + \eta_{LoS}(\theta_{ij}), \tag{1}$$

$$PL^{ij}_{NLoS}(\theta_{ij}) = 10\gamma \log\left(\frac{4\pi d_{ij}(\theta_{ij}) f_c}{c}\right) + \eta_{NLoS}(\theta_{ij}), \tag{2}$$

where γ is the path loss exponent, f_c is the operating frequency, c is the speed of light, $d_{ij}(\theta_{ij}) = \frac{h_j}{\sin(\theta_{ij})}$ and $\theta_{ij} = \arctan\frac{h_j}{r_{ij}}$ are the distance and elevation angle between the soldier i and DBS j, respectively where h_j is the altitude of the jth DBS and r_{ij} equal to $\sqrt{(x^d_j - x^u_i)^2 + (y^d_j - y^u_i)^2}$ is the horizontal distance between ith soldier and the jth DBS. $\eta_{LoS}(\theta_{ij})$ and $\eta_{NLoS}(\theta_{ij})$ are the excess path loss components (in dB) of the LoS and NLoS links, respectively.

In [6], the excess path loss samples, which are obtained by a ray tracing simulation, are organized in terms of the elevation angle. For simplicity, the authors propose to use Gaussian distribution for $\eta_{LoS}(\theta_{ij})$ and $\eta_{LoS}(\theta_{ij})$ as follows,

$$\eta_{LoS}(\theta_{ij}) \sim \mathcal{N}(\mu_{LoS}, \sigma^2_{LoS}(\theta_{ij})), \tag{3}$$

$$\eta_{NLoS}(\theta_{ij}) \sim \mathcal{N}(\mu_{NLoS}, \sigma^2_{NLoS}(\theta_{ij})), \tag{4}$$

where μ_{LoS} and μ_{NLoS} are the mean excessive losses and σ_{LoS} and σ_{NLoS} are the standard deviations of the LoS and NLoS links, respectively. The elevation angle dependent standard deviations of the LoS and NLoS links are formulated as,

$$\sigma_{LoS}(\theta_{ij}) = \alpha_1 \exp(-\beta_1 \theta_{ij}), \tag{5}$$

$$\sigma_{NLoS}(\theta_{ij}) = \alpha_2 \exp(-\beta_2 \theta_{ij}), \tag{6}$$

where pairs (α_1, β_1) and (α_2, β_2) are frequency and environment dependent parameters for the LoS and NLoS links, respectively.

The authors in [28] derive a closed form expression for the probability of LoS,

$$p^{ij}_{LoS}(\theta_{ij}) = \frac{1}{1 + a\exp(-b(\theta_{ij} - a))}, \tag{7}$$

where a and b are environment dependent constants, p^{ij}_{LoS} is the probability of LoS between ith soldier and jth DBS. The probability of NLoS for the same pair, p^{ij}_{NLoS}, is calculated as $1 - p^{ij}_{LoS}(\theta_{ij})$.

Finally, the elevation angle-dependent mean path loss is formulated as:

$$\overline{PL}_{ij}(\theta_{ij}) = PL^{ij}_{LoS}(\theta_{ij}) p^{ij}_{LoS}(\theta_{ij}) + PL^{ij}_{NLoS}(\theta_{ij})(1 - p^{ij}_{LoS}(\theta_{ij})). \tag{8}$$

2.2. Modeling soldier distribution

In the urban warfare, small teams are assigned to operations at the tactical level. They operate and move in groups to accomplish a given task [29]. The SGMM is used to model node positioning which helps researchers to analyze military networks in a more realistic way [24, 25]. In our work, we consider a snapshot of a network where a number of soldier groups are distributed in the TOO, which is a cell with radius r_{TOO}. In this model, first group leaders are distributed uniformly in the TOO. Then, soldiers are positioned in reference to their group leaders. Figure 2 shows the placement of the ith soldier with respect to the group leader k. The distance, d_i^k, and angle, a_i^k, between the soldier i and group leader k are selected from a Gaussian and uniform distribution, respectively. In our previous work, we investigated the performance of networks where users are uniformly and non-uniformly distributed [9]. In case of non-uniform user distribution, the interference becomes more challenging to handle when user groups are in close proximity.

3. DBS deployment in urban warfare

The specific requirements of urban warfare significantly affect the DBSs deployment process. In this regard, we first derive the problem of ML estimation of soldier locations based on the RSSs. In addition, we introduce the small arm weapon model and derive the probability of DBSs not being hit anticipating the behavior of a drone shooter. Then, we present our novel deployment algorithm specifically designed for the challenges of urban warfare. In order to understand the coverage performance of our algorithm, we investigate the near-optimal deployment of DBSs by proposing 4 different optimization objectives.

3.1. Estimation of soldier locations

Here, we assume that the path loss to each drone is independent. As the drones are significantly apart, this is a reasonable assumption. The distribution of path loss is a mixture of two Gaussians (for LoS and NLoS) which is presented in [6]. The probability density function of the ith soldier's path loss vector, $\mathbf{PL_i} = [PL_{i1}, PL_{i1}, ..., PL_{iD}]$, given the location of the soldier by the elevation angles, $\theta_\mathbf{i} = [\theta_{i1}, \theta_{i1}, ..., \theta_{iD}]$,

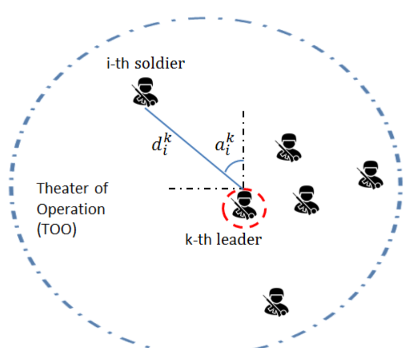

Figure 2. Placement of the ith soldier in reference to the kth group leader

are as follows:

$$f(\mathbf{PL}_i;\theta_{\mathbf{i}}) = \prod_{j=1}^{D}\left(\frac{p_{LoS}^{ij}(\theta_{ij})}{\sqrt{2\pi\sigma_{LoS}^2(\theta_{ij})}}\exp\left(-\frac{(PL_{ij}-E[PL_{LoS}^{ij}])^2}{2\sigma_{LoS}^2(\theta_{ij})}\right)+\frac{p_{NLoS}^{ij}(\theta_{ij})}{\sqrt{2\pi\sigma_{NLoS}^2(\theta_{ij})}}\exp\left(-\frac{(PL_{ij}-E[PL_{NLoS}^{ij}])^2}{2\sigma_{NLoS}^2(\theta_{ij})}\right)\right) \tag{9}$$

where $E[PL_{LoS}^{ij}]$ and $E[PL_{NLoS}^{ij}]$ are mean LoS and NLoS path losses respectively.

The log-likelihood function is

$$L(\theta_{\mathbf{i}}) = \sum_{j=1}^{D}\log\left(\frac{p_{LoS}^{ij}(\theta_{ij})}{\sqrt{2\pi\sigma_{LoS}^2(\theta_{ij})}}\exp\left(-\frac{(PL_{ij}-E[PL_{LoS}^{ij}])^2}{2\sigma_{LoS}^2(\theta_{ij})}\right)+\frac{p_{NLoS}^{ij}(\theta_{ij})}{\sqrt{2\pi\sigma_{NLoS}^2(\theta_{ij})}}\exp\left(-\frac{(PL_{ij}-E[PL_{NLoS}^{ij}])^2}{2\sigma_{NLoS}^2(\theta_{ij})}\right)\right) \tag{10}$$

Upon maximizing the log-likelihood function, we find the elevation angles of soldier i.

$$\widehat{\theta_{\mathbf{i}}} = \arg\max L(\theta_{\mathbf{i}}). \tag{11}$$

Then, the estimated location of soldier i is found by solving the multilateration problem:

$$(\widehat{x_i^u},\widehat{y_i^u}) = \arg\min_{x_i^u,y_i^u}\sum_{j=1}^{D}\left(\sqrt{(x_j^d-x_i^u)^2+(y_j^d-y_i^u)^2}-\widehat{r_{ij}}\right)^2, \forall i\in U \tag{12}$$

where $\widehat{r_{ij}}$ is the estimated distance between the ith user and jth DBS and computed using the estimated elevation angle obtained from Equation 11 as

$$\widehat{r_{ij}} = \frac{h_j}{\tan\widehat{\theta_{ij}}}. \tag{13}$$

3.2. Drone shooter model and probability of DBSs not being hit

The presence of drone shooters is one of the most challenging issues for sustaining communication service in urban warfare. Furthermore, as DBSs are shot down, the OPEX (Operational Expenditure) increases and logistic problems arise. From the communication perspective, shooting down of a single DBS significantly change the state of network and reconfiguration is needed to compensate for the service loss [30]. Therefore, it is critical to consider the security of all DBSs while determining their positions. Our proposed algorithm that we elaborate in the subsequent section takes into account the probability of DBSs not being hit as a security metric to decide the positions.

While calculating the probability of DBSs not being hit, we consider each drone shooter tries to hit the nearest DBS. The probability of drone shooter seeing the nearest DBS unobstructed is calculated from (7). The probability of DBSs not being hit is calculated as $p_{noHit}=\prod_{j=1}^{D}(1-p_{hit}^j)$, where p_{hit}^j is the probability of jth DBS being hit that is expressed as $p_{hit}^j = 1-\prod_{k\in\mathcal{T}_j}(1-p_{hit}(d_{jk})p_{LoS}^{jk})$, where $\mathcal{T}_j$ is the set of drone shooters nearest to DBS j, $p_{hit}(d_{jk})$ is the probability of DBS j being hit by drone shooter k, $(k\in\mathcal{T})$, d_{jk} is the distance between the DBS j and drone shooter k, p_{LoS}^{jk} is the probability of LoS between the DBS j and drone shooter k. We assume that drone shooters are equipped with sniper rifles. The work in [31] presents the historical probability of hit values of this weapon at certain distances for stationary man-sized targets. We fit the data to the explicit mathematical formula as follows:

$$p_{hit}(d) = \begin{cases} \frac{100-5\exp(0.0028\times d)}{100}, & \text{if } d < 985m \\ \frac{210.58\exp(-0.0023\times d)}{100}, & \text{otherwise.} \end{cases} \tag{14}$$

3.3. DBS deployment based on threat aware user clustering

Here, we describe our proposed DBS deployment algorithm that sequentially executes ML estimator for soldiers' locations, k-means clustering and a heuristic which increases p_{noHit} and at the same time avoid a major degradation in the ratio of unserved soldiers, N_u. Figure 3 shows the general architecture of the proposed algorithm, which we call as Threat Aware Clustering with Estimated Positions (TACEP) thereafter. The algorithm consists of three phases. In the first phase, for each soldier, RSSs are collected and path losses between DBSs and soldier are calculated. Then, ML estimation for finding elevation angles $\widehat{\theta_{ij}}$, $\forall i \in \mathcal{U}, \forall j \in \mathcal{D}$ and multilateration for estimating user positions $\widehat{\mathbf{w_i^u}} = [\widehat{x_i^u}, \widehat{y_i^u}]$, $\forall i \in \mathcal{U}$ are applied respectively. Then the estimated soldier positions are clustered to find the positions of DBSs $\mathbf{w_j^c} = [x_j^c, y_j^c]$, $\forall j \in \mathcal{D}$. The minimum sum-of-squares clustering problem is defined as follows:

$$\begin{aligned} &\min_{\mathbf{w^c},\mathbf{A}} \sum_{i\in\mathcal{U}} \sum_{j\in\mathcal{D}} A^{ij} \|\widehat{\mathbf{w_i^u}} - \mathbf{w_j^c}\|^2 \\ &\text{subject to} \\ &\sum_{j\in D} A^{ij} = 1, \quad \forall i \in U \\ &A^{ij} \in \{0,1\}, \quad \forall i \in U, \forall j \in D \end{aligned} \tag{15}$$

where $\mathbf{w^c}$ is the positions of DBSs, A^{ij} is a binary variable and equals to 1 if ith user is associated with jth DBS. We adopt Lloyd's algorithm to solve this clustering problem. The algorithm first randomly assigns

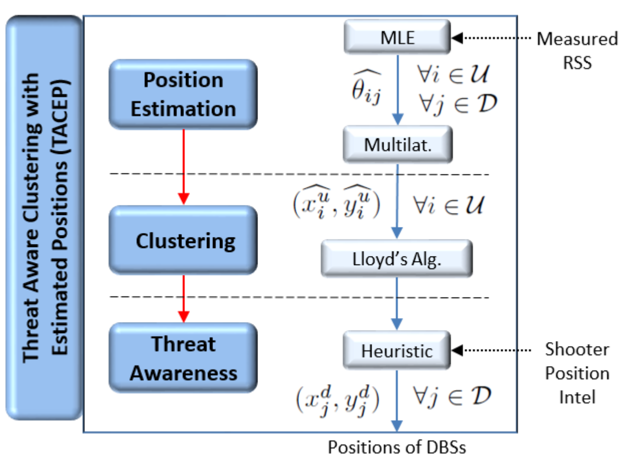

Figure 3. Algorithm architecture of TACEP

positions to the DBSs. Then, each soldier connects to the nearest DBS and the soldier groups $\mathcal{S}_1, .., \mathcal{S}_D$ are formed. The position of each DBS is found by calculating the mean of soldiers' positions connected to the DBS. The position update continues until there is no major change in the positions of DBSs. In the final step, our proposed iterative threat-aware heuristic approach is applied to find final positions of DBSs $\mathbf{w_j^d} = [x_j^d, y_j^d]$, $\forall j \in \mathcal{D}$. In this approach, first the most vulnerable DBS (the one with the highest hit probability) is found and then its new location is calculated by moving DBS by a fixed distance, d_h^{Δ}, away from the closest shooter. Next, if new p_{noHit} is larger than the previous one, the position of DBS is updated. This process continues until new p_{noHit} is not larger than the previous one. The maximum distance between the original (before applying heuristic) and new DBS position, d_h^{max}, is predetermined. If d_h^{max} is reached for a DBS and it is still the most vulnerable one, algorithm considers the second most vulnerable DBS to move.

3.4. Minimum number of unserved soldiers

The challenging nature of urban channel makes the problem of DBS deployment very hard. Randomly changing angle-dependent excess losses prevent convergence to an optimal solution for minimizing the number of soldiers unserved. However, there are methods which statistically provide better solutions than the others. In our investigation, we define 4 different objective functions to achieve a near-optimal solution for minimizing the number of unserved soldiers in the GPS-enabled environment. For each case, the positions of DBSs are obtained by maximizing the objective function and then the number of unserved soldiers, denoted as N_u, is determined. We adopt PSO algorithm for solving the problems and limit the number of iterations. Our motivation to limit the number of iterations is to consider a practical case where the computing resources are restricted as it is in the battlefield.

We assume soldier-DBS association is performed on the basis of received signal power. Let α_i be the DBS selected by the ith soldier.

$$\alpha_i = \arg\max_j R_{ij}(x_j^d, y_j^d, h_j^d), \tag{16}$$

where $R_{ij}(x_j^d, y_j^d, h_j^d)$ is the received signal power from the jth DBS at the ith soldier terminal and is calculated as:

$$R_{ij}(x_j^d, y_j^d, h_j^d) = 10^{\frac{P_T + G_{ij} - \overline{PL}_{ij}}{10}}, \tag{17}$$

where P_T is the transmission power (in dBm) of a DBS, G_{ij} is the gain of the DBS antenna and is approximated by [32].

As we indicate in Section 2, the capacity of a DBS is equally shared amongst the soldiers in the time domain. Let N_s^j, be the total number of served soldiers by the jth DBS.

$$N_s^j = \sum_{i \in U} I_i^j, \quad \forall j \in \mathcal{D}, \tag{18}$$

where binary variable I_i^j defined as:

$$I_i^j = \begin{cases} 1, & \text{if} \quad \alpha_i = j \quad \text{and} \quad DR_i(\mathbf{x}, \mathbf{y}, \mathbf{h}) > R_{TH} \\ 0, & \text{otherwise.} \end{cases} \tag{19}$$

where R_{TH} is the data rate threshold, $DR_i(\mathbf{x}, \mathbf{y}, \mathbf{h})$ is the data rate of the soldier i, $(\mathbf{x}, \mathbf{y}, \mathbf{h})$ denotes the positions of all DBSs where $\mathbf{x} = [x_1^d, .., x_D^d]$, $\mathbf{y} = [y_1^d, .., y_D^d]$, $\mathbf{h} = [h_1^d, .., h_D^d]$. $DR_i(\mathbf{x}, \mathbf{y}, \mathbf{h})$ equals to

$$\frac{W}{N_s^{\alpha_i}} \log_2 \left(1 + \frac{R_{i\alpha_i}(x_{\alpha_i}^d, y_{\alpha_i}^d, h_{\alpha_i}^d)}{N_o W + \sum\limits_{j \neq \alpha_i} R_{ij}(x_j, y_j, h_j)} \right) \tag{20}$$

Hence, the number of served soldiers can be found by $N_s = \sum_{j \in \mathcal{D}} N_s^j$ and the number of unserved soldiers equals to $N_u = N - N_s$. Given the same altitude for DBSs, the following approaches are used to find the horizontal positions of DBSs with the help of PSO algorithm. We call the algorithms given below as LinKP, LogKP, CovKP, ClogKP respectively.

3.4.1. Maximizing sum of data rates approach (LinKP)

$$\begin{gathered} \arg\max_{\mathbf{x},\mathbf{y}} \sum_{i \in \mathcal{U}} DR_i(\mathbf{x}, \mathbf{y}, \mathbf{h}) \\ \text{subject to} \\ \sqrt{x_j^2 + y_j^2} \leq r_{TOO} \qquad \forall j \in D \end{gathered} \tag{21}$$

3.4.2. Maximizing sum of log data rates approach (LogKP)

$$\begin{gathered} \arg\max_{\mathbf{x},\mathbf{y}} \sum_{i \in \mathcal{U}} \log(DR_i(\mathbf{x}, \mathbf{y}, \mathbf{h})) \\ \text{subject to the same constraint given in Eq. (21)} \end{gathered} \tag{22}$$

3.4.3. Maximizing number of served soldiers approach (CovKP)

$$\begin{gathered} \arg\max_{\mathbf{x},\mathbf{y}} \sum_{i \in \mathcal{U}} \sum_{j \in \mathcal{D}} I_i^j \\ \text{subject to the same constraint given in Eq. (21)} \end{gathered} \tag{23}$$

3.4.4. Maximizing joint coverage and sum log rate approach (CLogKP)

In each iteration of CLogKP algorithm, the particles with the largest N_s is found and then the one with the largest sum log data rate capacity is selected as the global best solution. The constraint given in Eq. (21) is applied for the positions of DBSs.

4. Simulation results

In this section, we present the performance of our proposed algorithm , named TACEP, and compare its performance with three different benchmark algorithms. These benchmark algorithms are all threat-unaware.

- The first benchmark algorithm is soldier location-unaware EQT which simply places the DBSs at the corners of an equilateral triangle over TOO.
- Second benchmark is a K-means clustering based algorithm named KCEP. It clusters soldiers based on the estimated positions and places DBSs at the centers of clusters.

Table 1. Simulation Parameters

Parameter	Definition	Value
U	Number of Soldiers	80
D	Number of DBSs	3
T	Number of Drone Shooters	3
f_c	Carrier Frequency	$2GHz$
r_{TOW}	Radius of TOW	$1500m$
r_{TOO}	Radius of TOO	$1000m$
r_{PZ}	Radius of PZ	$50m$
d_{max}	Max. dist.	$100m$
W	Bandwidth	$20MHz$
N_0	Noise Power Spectral Density	$-170dBm/Hz$
a, b	Environmental Parameters	$9.61,\ 0.16$
η_{LoS}, η_{NLoS}	Mean Path loss	$1dB,\ 20dB$
θ_B	DBS Antenna Beamwidth	$140°$
P_T	DBS Transmission Power	$30dBm$
R_{TH}	Data Rate Threshold	$500Kbps$
d_h^{Δ}, d_h^{max}	Parameters for Heuristic	$20m,\ 100m$
N_{MC}	Monte Carlo Simulations	100

- The third benchmark algorithm is a version of CLogKP named CLogEP which we explain in this section. This serves as a lower bound on the N_u performance.

We use MATLAB as a simulation platform. The simulations are run for 100 different network topologies where the soldiers and drone shooters are distributed according to the models given in Section 2. Then, the average of N_u and p_{noHit} results, which are denoted as $\overline{N_u}$ and $\overline{p_{noHit}}$ respectively, are presented. Unless stated otherwise the parameters used in the simulations are from Table 1.

We will first determine a threat-unaware lower bound for the number of unserved users (N_u) performance. For this purpose, we will compare the 4 different objective functions for the PSO-based optimization. In Figure 4, $\overline{N_u}$ performance of 4 different optimization objectives are shown. Here, the results of the first approach, named as LinKP, show that placing DBSs to maximize the sum of data rates is inadequate for achieving the minimum $\overline{N_u}$. The second approach, LogKP, maximizes the sum of log data rates and provides significantly better performance than that of LinKP. As the soldier coverage is the main problem, CovKP is one of the most promising methods to find near-optimal results. However, we find that there is a better approach than CovKP. As the combination of CovKP and LogKP, CLogKP achieves the best performance among all approaches. In this respect, we identify CLogKP and its version named as CLogEP, which uses estimated positions of soldiers instead of real positions, as a near-optimal lower bound for the minimum $\overline{N_u}$. We provide the results of both CLogKP and CLogEP in Table 2, which shows that our proposed RSS-based ML estimator provides a good performance for estimating the soldier's positions.

$\overline{N_u}$ and $\overline{p_{noHit}}$ performance of TACEP and comparison algorithms are presented in Figure 5 and Figure 6, respectively. With respect to $\overline{N_u}$ performance of the algorithms, the worst results are obtained from EQT as expected since it does not consider the locations of soldiers. TACEP and KCEP perform very closely to each other. The performance gap between TACEP and CLogEP increases as the DBSs are placed at the higher altitudes. The reason is that as the DBSs are deployed at the higher altitudes, the interference becomes more

Table 2. Performance results for DBS altitudes 600m and 800m. The close results of CLogEP and CLogKP suggest that our proposed position estimator works efficiently.

Algorithm	$\overline{N_u}$ **(600m)**	$\overline{\rho_u}$	$\overline{p_{noHit}}$	$\overline{N_u}$ **(800m)**	$\overline{\rho_u}$	$\overline{p_{noHit}}$
TACEP	1.032	0.013	0.34	3.669	0.045	0.532
KCEP	0.872	0.010	0.279	3.204	0.040	0.485
EQT	3.784	0.047	0.29	8.811	0.110	0.465
CLogEP	0.580	0.007	0.258	1.241	0.015	0.462
CLogKP	0.418	0.005	0.244	1.094	0.013	0.459

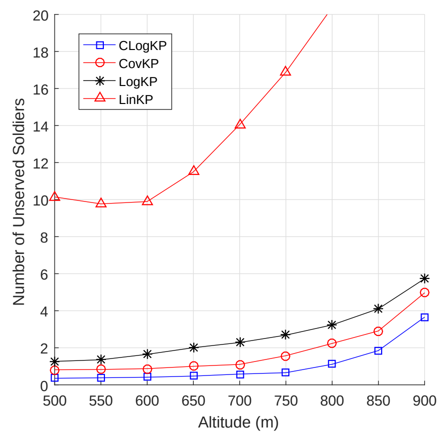

Figure 4. Number of unserved soldiers performance for different DBS altitudes. CLogKP achieves the best performance, hence it will be regarded as a lower bound on the N_u performance.

difficult to manage and requires more consideration. As presented in Figure 6, TACEP achieves the best $\overline{p_{noHit}}$ performance which is the primary objective of this algorithm. On the other hand, KCEP performs moderately well because the centers of soldier clusters are located in the relatively safe regions where shooters are present with low probability.

For the altitudes of 600m and 800m, Table 2 shows the performance of the algorithms in terms of $\overline{N_u}$, $\overline{p_{noHit}}$ and the average ratio of the number of unserved soldiers, which is denoted as $\overline{\rho_u}$ and equals to $\overline{N_u}/N$. Considering $\overline{\rho_u}$ performance at the altitude of 600m, TACEP provides more than three times better performance than that of EQT and the performance of KCEP and TACEP are very close to each other. The best performance is provided by CLogEP as expected. On the other hand, $\overline{p_{noHit}}$ performance of TACEP considerably exceeds the performance of other algorithms. TACEP outperforms ($\overline{N_u}$ near-optimal) CLogEP by 31.7% in terms of $\overline{p_{noHit}}$. This increase has a significant effect on the mission's outcome considering a DBS serves many soldiers who need to receive critical ISR information and the available number of DBSs are limited.

At the altitude of 800m, KCEP and TACEP again perform very close to each other in terms of $\overline{\rho_u}$ performance. It is observed that CLogEP handles the network better as the altitude increases. This gain is obtained via CLogEP's interference management capability which comes with increased computational complexity. In regard to $\overline{N_u}$ performance, TACEP provides nearly 15% better performance than those of CLogEP and EQT. This result shows that the efficiency of TACEP is higher at lower altitudes.

Trade-off curve of $\overline{N_u}$ with respect to $\overline{p_{noHit}}$ performance of the algorithms are shown in Figure 7. It

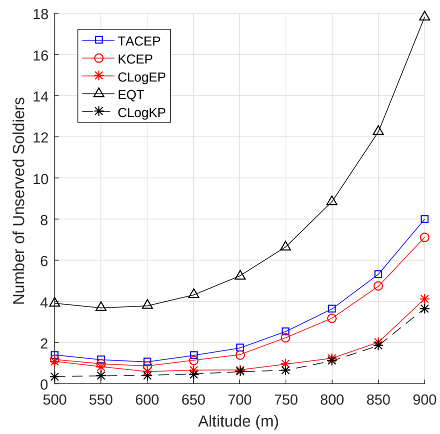

Figure 5. Number of unserved soldiers performance versus DBS altitudes. Proposed TACEP has a performance almost equal to KCEP and very close to ClogEP.

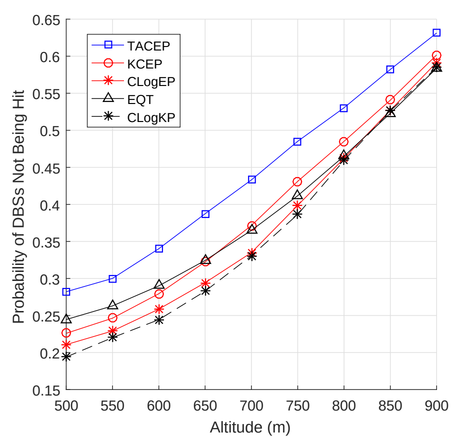

Figure 6. Probability of DBSs not being hit performance versus DBS altitudes. Proposed TACEP has a significantly better performance.

shows that the best performance is provided by CLogEP, as expected. According to these results, TACEP's improved $\overline{p_{noHit}}$ performance does not compromise the near-optimal $\overline{N_u}$ performance of CLogEP but strikes a good trade-off between $\overline{N_u}$ and $\overline{p_{noHit}}$. In addition to that, TACEP may be chosen to meet mission specific requirements such as the DBSs' deployment altitude and security.

In the final analysis, we investigate the effect of the number of drone shooters on the probability of DBSs not being hit. Figure 8 shows that TACEP provides the best performance and outperforms other algorithms by at least 30% at all altitudes. This shows the efficiency of the TACEP on handling the increasing number of drone shooters present in the theater of war.

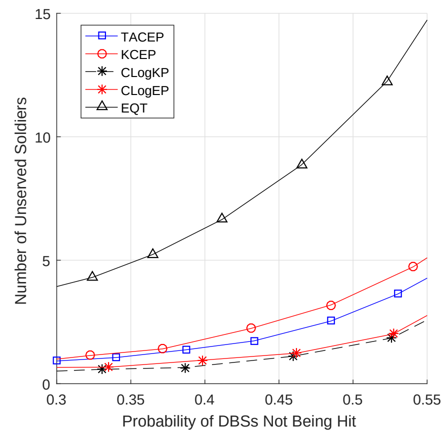

Figure 7. The number of unserved soldiers with respect to probability of DBSs not being hit. The results are obtained for the altitude range [500m-900m]. The results show that our proposed fast algorithm strikes a good trade-off.

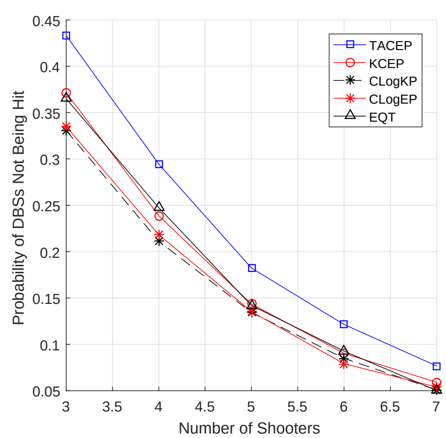

Figure 8. Probability of DBSs not being hit performance versus number of drone shooters. DBS altitude is 700m.

5. Conclusion

In this work, we have provided a comprehensive examination of the deployment of DBSs in an urban warfare scenario. In this respect, we have introduced specific challenges, namely, a GPS denied environment for the soldiers on the ground and presence of drone shooters aiming to destroy DBSs. Considering these challenges, we have proposed a fast algorithm, referred to as TACEP, to determine the positions of DBSs. Furthermore, we have proposed a PSO based algorithm in order to achieve near-optimal soldier coverage. Simulation results have shown that TACEP outperforms all other algorithms in terms of probability of DBSs not being hit. TACEP also provides a near-optimal coverage performance, when compared with a computation intensive PSO-based algorithm. Future work will consider the case of mobile soldiers and online, adaptive DBS deployment schemes.

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