Dynamic Placement Algorithm for Multiple Classes of Mobile Base Stations in Public Safety Networks

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Abstract. As new mobile base stations (mBSs) have been constantly developed with various capacities, mobile coverage, and mobility models, the level of heterogeneity in public safety networks (PSNs) has been increasing. Since disasters and emergencies require the ad hoc PSN deployments, dynamic mBS placement and movement algorithm is one of the most important decisions to provide the critical communication channels for first responders (FRs). In this paper, we propose a heterogeneous mBS placement algorithm in an ad hoc public safety network. We define different classes of mobile base stations that have varying performance characteristics and consider three different FRs mobility models. Our proposed algorithm applies the modern clustering technique to deal with the characteristics of different kinds of mBSs.

Keywords: Mobile base station placement · Adhoc public safety networks · 5G · LTE

1 Introduction

As Public Safety Networks (PSNs) continue to get more and more coverage, many different classes of mobile base station (mBS) and deployment models are emerging [1–3]. Each of the hardware and deployment models has its own advantages disadvantages. The challenge has quickly shifted from merely meeting the network demand to being able to do that in a cost effective way.

Connectivity and coverage among user equipments (UEs) of some or all first responders (FRs) are the most basic requirements in many PSNs. When the FRs arrive at a disaster site, such as scene of a fire, volcanic eruption, terrorist attack, etc., a PSN must be dynamically deployed to meet the needs of different FRs. Many different deployment mechanisms exist for deploying the base stations. These include, but are not limited to, drones, truck bases, hot air balloons, and being manually established at a location in order to handle the transportation

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and installation of the mBSs. It is likely that these mechanisms will continue to evolve over time. For example, in a recent study from AT&T, the concept of the 'Flying Cow' or 'Cell on Wings' used in the extreme hazardous scenario serving the FRs is presented. Therefore, we study the mBSs placement problem from a deployment mechanism independent perspective and generalize these different mechanisms as various classes of transportation models that have their associated movement costs.

The rest of this paper is organized as follows. Section 2 discusses the related work and our contributions. Section 3 outlines the system model and problem statement, e.g. the mBS classes introduction, the UE mobility models, the channel model and the performance metrics. Section 4 describes the proposed method for continuous optimal mobile base station placement solution. Section 5 presents the empirical results regarding the performance of the proposed algorithm, and the comparison to the baseline model. Finally, Sect. 6 summarizes the paper and outlines ideas for future research.

2 Related Work

In this section, we review the recent mBS placement research relevant to cellular networks and at last our contributions are summarized.

In our previous work [4], we proposed algorithms for single class of mBS placement with limited UE mobility models. However, due to different service requirements in PSN scenarios [1] and the advantages of heterogeneous network architecture [5], multiple classes of mBSs have been developed, e.g., the Vehicle Network System (VNS), Cell on Light Truck (CoLT), Cell on Wheels (COW) and System on Wheels (SOW) [6]. The performance of the heterogeneous mBSs of Aerial LTE Base Stations (AeNB) and Portable Land Mobile Unit (PLMU) for PSN communication have been researched in [7]. In this work, our proposed algorithm is designed for dynamic placement of multiple classes of mBSs.

Due to the flexibility and mobility of drones, a growing amount of research has been focused on its applications in cellular network or PSN [8–10]. The channel modeling between drones and UEs in urban setting has been addressed in [11] where a realistic path loss and shadow fading model has been proposed. We apply the same channel model in our work. In [12,13], the energy restricted model for drones has been used. We use the Flying CoW model from AT&T [14] which has unlimited power supply with a thin tether. The dynamic limitation of drones has been considered and analyzed in [15]. But due to the fast development of drones, we apply more flexible restrictions on its dynamic limitation.

UEs in PSN scenarios are often referred as FRs. The studies on mobility models of FRs are very limited. A general study of network performance impact of UE mobility model has been addressed in [16]. In our work, we consider three UE mobility models, including Random Way Point Model (RWP) [15] and two PSN application related models. Generally, the placement of mobile base stations are NP-hard problem [12], where several approaches including greedy, numerical and game theory based are studied in [12,15,17]. We solve this problem with clustering technique.

In this paper, we address the above-mentioned challenges. Our contributions can be summarized as follows:

- We extend the work of mBS deployment with multiple classes of base stations to meet the most critical requirements in PSN scenarios. Different classes of mBSs are associated with corresponding coverage weights, recalculation frequency and relocation threshold.
- Our proposed algorithm applies the modern clustering technique. It solves the base station placement problem from the view of the central control instead of non-cooperative method, which is more suitable in PSN scenarios since most FRs and base stations are deployed with the central control.
- Besides the commonly used RWP model, we also develop two mobility models for PSN scenarios to represent the special characteristics for FRs since they are usually deployed in groups and often have specific working areas.

3 System Model and Problem Statement

In this section, we present the system model and discuss the different mobile base station classes, mobility and channel models and also the quantitative performance metrics that can be used to assess the performance of different solutions.

3.1 Mobile Base Station Classes

Various kinds of mBSs have been developed recently to meet the critical requirement of PSN scenarios. For example, the Emergency Drop Kit from AT&T shows the ability for rapid connectivity during emergencies in rural areas, as well as areas which may be temporarily out of communications [18]. It is designed for a short-term solution until the dedicated deployment arrives. The aerial base stations, especially drone-based ones get a lot of attention and development in recent research. AT&T has proposed their all-weather drone base station (Flying CoW) [14] in 2018 for coverage in extreme conditions. A thin tether is connected between the drone and ground terminal for unlimited power supply and high speed data connection. CoW and SoW have long been used as temporary communication solutions with different capacities due to their flexible mobility and fast deployment. In this paper, we model three kinds of mBSs as in Table 1. Our proposed dynamic placement algorithm can be easily extended for more classes of mBSs.

Table 1. Mobile base station classes

mBS	Drone	CoW	SoW
Capacity	Low	Medium	High
Recalculation frequency	High	Medium	Low
Relocation threshold	Low	Medium	High

3.2 UE Mobility Model

The performance impacts of UE mobility models for ad hoc networks and cellular networks have been analyzed in [16,19]. In this paper, we consider three UE mobility models including the RWP model which has been widely used for general UE mobility modeling. In RWP model, each UE independently selects a random destination inside the Region of Interest (ROI) and moves in a straight trajectory with a constant speed. After reaching the destination, UE pauses for a while before the next move.

In the other two models, more public safety features have been considered. Since most FRs are deployed as a group, in first model, UEs are firstly classified as leaders and non-leaders of the groups. The initial grouping association happens based on UE's role as a leader or following the closest leader. The leaders follow the RWP model and their group members follow the leaders. Figure 1 illustrates this situation. In the second model, a number of Points of Interest(POI) have been initialized in ROI and all the UEs move randomly approaching or around the closest POI depending on the distance between UE and POI, which are shown in Fig. 2. Similar event-driven and role-based (EDRB) mobility models are studied in [20,21]. We acknowledge the more accurate FRs mobility modeling, the better algorithm being able to design and this will be one direction for our future work.

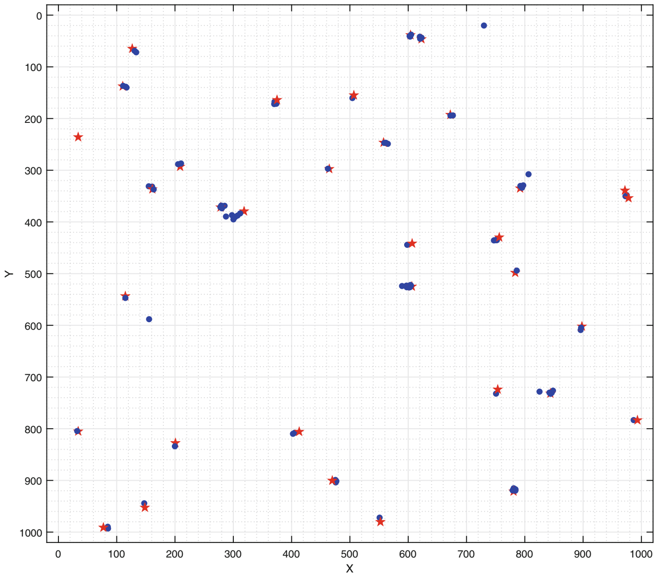

Fig. 1. UE mobility model with leaders in red star (Color figure online)

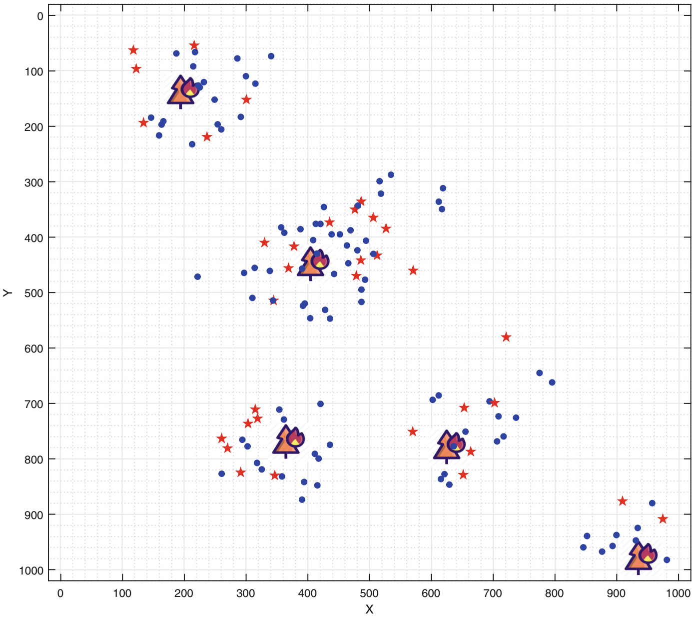

Fig. 2. Screen-shot of UE mobility model with 5 points of interest

3.3 Channel Model

The channel model we adopted is well studied in [11]. The path loss consists of two parts: Line of Sight (LoS) transmission and Non-line of Sight (NLoS). The path loss of the LoS and NLoS links in dB is given respectively by

$$L_{path} = 20log(\frac{4\pi f_c d}{c}) + \eta_{path}$$

where the string *path* can stand for LoS or NLoS, f_c is the carrier frequency, d is the distance between UE and base station, c is the speed of light, and η_{path} is the average additional losses. The probability of the occurrence of a LoS connection is given by:

$$P_{LoS} = \frac{1}{1 + \alpha e^{-\beta(\theta - \alpha)}}$$

where θ is the elevation angle from base station to UE or $\arctan(h/d)$, h is the height of base station, α and β are environment-dependent constants. Consequently, the probability of a NLoS connection is $P_{NLoS} = 1 - P_{LoS}$. Finally, the probabilistic mean path loss is given by

$$L = L_{LoS}P_{LoS} + L_{NLoS}P_{NLoS}$$

To simplify the problem, we assume all the mobile base stations from the same class have the same operational height and transmitting power. The interference from neighboring mBSs under a specific threshold will be neglected.

3.4 Performance Metrics

In this part, we discuss the performance metrics to evaluate our proposed algorithm compared to a baseline static placement method where the same set of mobile base stations are regularly placed in the ROI. The average SINR of all UEs based on the channel and communication model of a specific mobile base stations placement will be the main performance consideration. In order to evaluate the UE at the cell edge, the 5th percentile of SINR will be studied [10]. Since the main objective of base station (BS) placement is to reduce the distance between UE and BS, the UE-to-BS distance will also be addressed. For most drone-based placement problem, the collision avoidance scheme should be investigated, but our proposed clustering algorithm can automatically solve this problem.

4 Heterogeneous Mobile Base Station Placement Algorithm

In this paper, we propose a dynamic placement algorithm for heterogeneous mBSs that employs a variant of K-means++ clustering technique to deal with the characteristics of different kinds of mBSs. The dynamic placement algorithm consists of two parts, static placement of mBS for a specific UE distribution, and the periodical recalculation with mBSs moving threshold. The first part deals with the static situation and the second part makes the process dynamic. In the rest of this section, we describe them separately. To represent the mBS features from Table 1 in the algorithm, for each mBS, we assign three parameters: Capacity Weights C_w, Recalculation Period R_p in seconds and Relocation Threshold R_t in meters.

4.1 Clustering for Static UEs

In our previous work [4], K-means and its variant algorithms have been used for UE clustering by the single class of mBS. The K-means++ algorithm is an improvement with better initialization [22]. We modify the K-means++ with respects of different cluster size to represent the various capacities of mBS classes. The K-means clustering process is a series of UE-mBS association and mBS relocation to the centroid of its associated UEs iteratively. The mBS's capacity C_w will influence the UE association at each iteration by the weighted distance between UE and mBS. Algorithm 1 shows this process.

We show an example of the clustering in Fig. 3. The black dots represent the UEs in the ROI and in this case, total of 8 mBSs are deployed: one SoW (orange truck), two CoW (green car) and five drones (azure drone). The clustering edges are presented by the blue lines. With higher configured capacity weight of SoW, the coverage of the SoW in this example is the biggest. On the other hand, drones and CoW cover with small and medium capacities respectively. The location of mBS is determined by the centroid of its associated UEs.

Algorithm 1. Static UE Clustering with Different Mobile Base Station Capacities

```
Initial mBSs placement;
iter = 1;
while iter < MAX_ITER do
    for i = 0; i < N_B; i = i + 1 do
        num_UE = 0;
        X = 0;
        Y = 0;
        for j = 0; j < N_U; j = j + 1 do
            if U_j ∈ B_i then
                num_UE = num_UE + 1 ;
                X = X + U_j.x ;
                Y = Y + U_j.y ;
            end
        end
        B_i.x = X ÷ num_UE ;
        B_i.y = Y ÷ num_UE ;
    end
    Affiliate UE to mBS in the following loops;
    for j = 0; j < N_U; j = j + 1 do
        min_dist = Inf;
        for i = 0; i < N_B; i = i + 1 do
            dist = sqrt((U_j.x − B_i.x)^2 + (U_j.y − B_i.y)^2);
            dist_w = dist ÷ B_i.C_w;
            if dist_w < min_dist then
                min_dist = dist_w ;
                U_j.B_id = i ;
            end
        end
    end
    iter = iter + 1 ;
end
```

4.2 Periodic Recalculation for Dynamic UEs

The UE clustering is for the static situation, and we make this re-cluster periodically to adapt to UEs' mobility. The frequency of this recalculation and distance to trigger mBSs' movement depend on the characteristics of mBS classes. For example, the cost of drone's movement should be much less than CoW or SoW, thus the recalculation frequency $(1/R_p)$ of drones should be much higher and the distance threshold (R_t) for movement should be much smaller than CoW and SoW. This process is illustrated in Fig. 4.

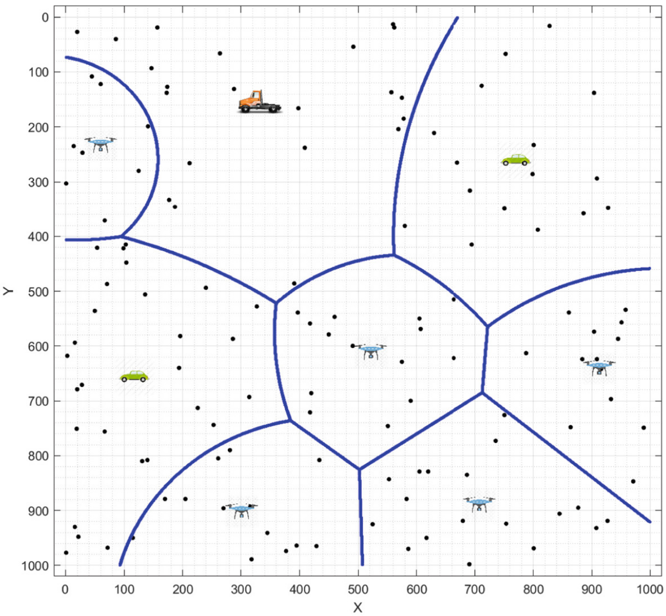

Fig. 3. Static placement of 3 mBS classes: one SoW (truck), two CoW (car) and five drones (Color figure online)

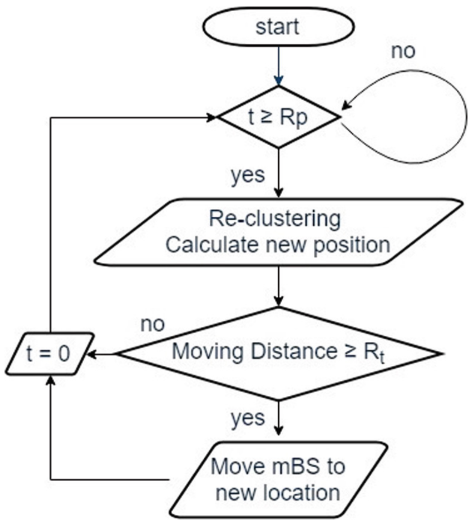

Fig. 4. Flow chart of periodical recalculation of mBS

5 Simulation and Discussion

We implement the dynamic placement algorithm for mBSs in MATLAB. The simulation related parameters for different kinds of mBS are listed in Table 2. We compare our algorithm with the baseline method which is the regular and stationary placement of the same set of mBS. Four mobility models are considered. Random walk V1 selects a new random destination and then UE moves in the straight line. Random walk V2 is direction oriented, which means a new direction within a range from current direction is selected and then UE moves in that direction. The simulation results converge with little variance after 600 simulation time intervals (STI) in our configuration. So for each case, we run the simulation of 1000 STI and the result is averaged over 10 repetitions. We choose four deployments to present different combinations of heterogeneous mBS which is summarized in Table 3. The number of UE in all the simulation is set to 100 and the number of points of interest is set to 5.

Table 2. Simulation parameters for mBS

mBS classes	Drone	CoW	SoW
Capacity weight	1	1.5	2
Recalculation period (10 s)	1	30	90
Relocation threshold (meters)	1	30	50
Height (meters)	30	10	10
Transmit power (watts)	20	30	40

Table 3. Four deployments

	Deployment 1	Deployment 2	Deployment 3	Deployment 4
Drone	5	10	0	0
CoW	2	0	5	0
SoW	1	0	0	3

5.1 Comparison with Baseline Algorithm

We compare the performance of the proposed dynamic heterogeneous mBS placement algorithm with the baseline algorithm in Random Walk V2 model in Sect. 3.2 and deployment 1 in Table 3. The three CDF in Fig. 5 show the SINR, 5th percentile SINR and UE to mBS distance of the two compared algorithms. Generally speaking, the proposed algorithm outperform the baseline one in all the three factors, especially in the 5th percentile SINR.

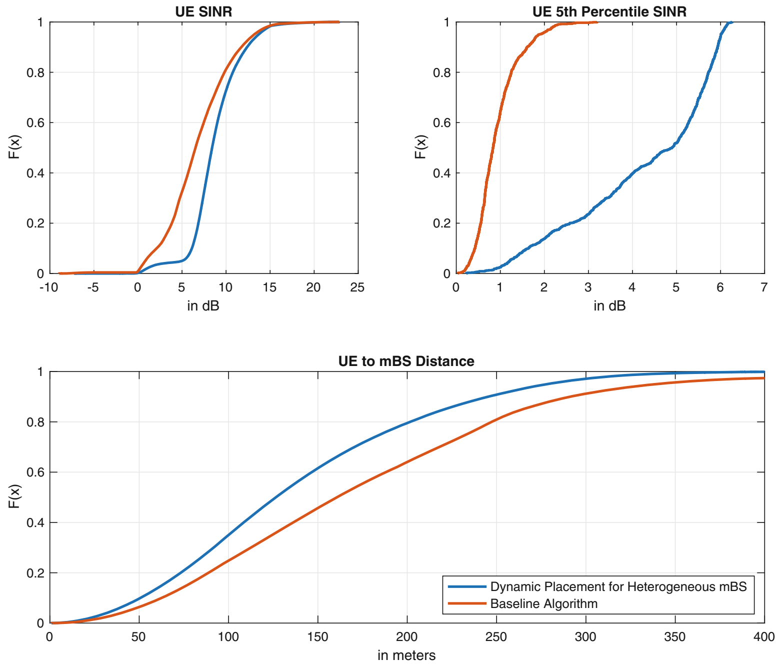

Fig. 5. Performance CDF comparison with baseline algorithm in random walk V2 model with deployment 1

5.2 UE SINR

In Fig. 6, the UE average SINR is compared for different deployments and UE mobility models. In the dimension of UE mobility models, two random walks and the following leader are very similar with slightly better SINR in following leader model. But in the POI model, the first two deployments are much worse than the other two deployments. With the deployments with only CoW or SoW POI provides better performance than the other two models. Because CoW and SoW with much better capacities can be deployed near the POI before UE placements, POI mobility model achieves high performance with Deployment 3 and 4. The second deployment with only drones performs worst in all four mobility models because drones have relatively weak transmission capacity and their moving flexibility is not advantageous when the interesting point location is already defined.

5.3 5th Percentile UE SINR

In order to consider UEs at the cell edge or the worst case in SINR, the 5th percentage SINR of different scenarios is shown in Fig. 7. Similar conclusion can be drawn for the much worse SINR in the first two deployments with drones from the former simulation results. Two observations can be found here: the 5th

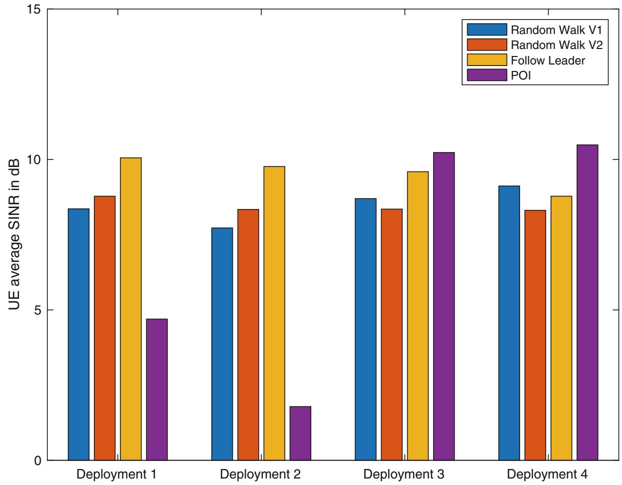

Fig. 6. UE average SINR in various deployments and mobility models

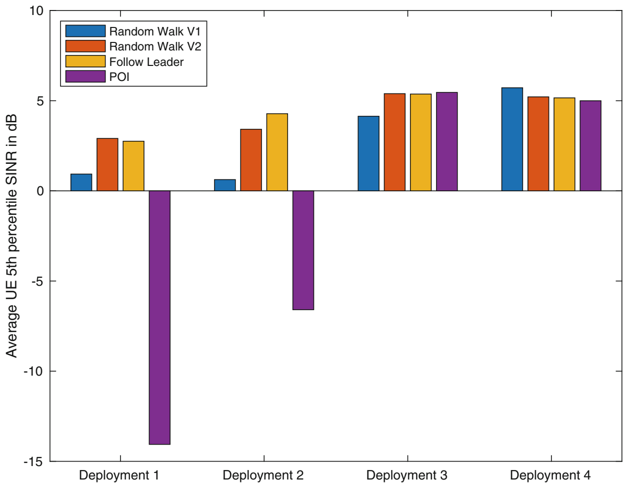

Fig. 7. Average 5th percentile SINR in various deployments and mobility models

percentile SINR in random walk V1 is much lower than in random walk V2, and the first deployment has the lowest value. The first observation is hard to explain since the two random walk models intuitively should perform similarly. But the actual simulation configurations can be the reason. The second observation can draw the conclusion that the only drone deployments can achieve higher SINR for UE at the serving edge due to the high mobility and flexibility of drones.

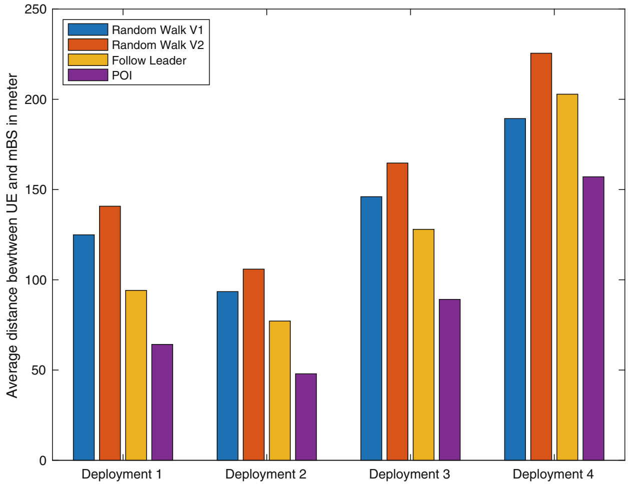

Fig. 8. Average distance between UE and mBS in various deployments and mobility models

5.4 Total mBS-to-UE Distance

Because the normal cell configuration for permanent base station optimization is usually not applicable for mBS, especially the drone-based BSs, the distance between UE and mBS is an important factor. The average UE-to-mBS distance is illustrated in Fig. 8. In the dimension of UE mobility models, the Following Leader and POI models outperform the two random walk models mainly due to the relatively more clustered UE distribution in these models. Otherwise on the dimension of deployments, the one with only drones has the least UE-to-mBS distance and the only CoW and only SoW deployments increase the distance gradually. The UE-to-mBS distance is impacted heavily by the flexibility of mBS.

5.5 Further Discussions

We compare four different deployments in the simulation. In the reality, each kind of mBS should be associated with corresponding cost in operation, which is not considered in our current work. In that case, the optimal deployment should depend on the 'budget' or the mBS' availability in each kind, and the disaster's property.

We use 1000 STI for our simulation, but in reality the disaster scenario and the communication requirements from FRs can vary hugely. For example, in the POI model, the point of interest can move due to the disaster's changing or other factors. But this is out of our consideration in the current work. The simulation result should provide a sight of basic understanding on various deployments and disaster situation.

6 Conclusions and Future Work

In this paper, we have studied the problem of dynamic mBS placement to meet the critical communication requirements of FRs in an ad hoc PSN. By considering the class of FRs and the applications, we provide an efficient dynamic mBS placement algorithm. The simulation results have been presented with different UE mobility models and mBS deployments. Thorough analysis has been done with consideration of UE's average SINR, the 5th percentage SINR of the deployment and the distance between UE and mBS. The simulation result provides in depth understanding of various deployments in different scenarios of FRs.

Future work in this field can address a simplification we made in this work. Specifically, the interference from neighboring mobile base stations can be taken into consideration when designing the network topology and assignment.

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