Efficient Mobile Base Station Placement for First Responders in Public Safety Networks

Chen Shen[1](✉), Mira Yun[2], Amrinder Arora[1], and Hyeong-Ah Choi[1]

[1] Department of Computer Science, George Washington University, Washington DC 20052, USA
{shenchen, amrinder, hchoi}@gwu.edu
[2] Department of Computer Science and Networking, Wentworth Institute of Technology, Boston, MA, USA
yunm@wit.edu

Abstract. We consider the problem of mobile base station placement to meet the critical communication requirements of first responders in an ad hoc public safety network. By considering the class of first responders and UE applications, we provide an efficient base station placement algorithm to maximize critical communication needs according to priority levels. We present simulation results that compare two proposed algorithms with each other and with a baseline algorithm. Our results show that the algorithm of weighted priority and GBR significantly improves connectivity and coverage parameters compared to others.

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

1 Introduction

Public Safety Networks (PSNs) aim to provide the most critical communication capabilities to the public safety community during both day-to-day operations and large scale events and emergencies [1]. Since disasters and emergencies can occur unexpectedly and exhibit various scales and classes of damage, PSNs may need to deployed as an ad hoc mobile network. In order to support a wide spectrum of new user equipment (UE) applications of first responders in a timely manner, the PSN must be deployed promptly and efficiently [2,3].

Connectivity and coverage among UEs of some or all first responders are the most basic requirements in many PSNs [4,5]. When the first responders 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 first responders. 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

K. Arai and R. Bhatia (Eds.): FICC 2019, LNNS 70, pp. 634–644, 2020.
https://doi.org/10.1007/978-3-030-12385-7_46

transportation and installation of the mobile base stations (mBSs). It is likely that these mechanisms will continue to evolve over time. For example, in a recent study from AT&T [6], the concept of the 'Flying Cow' or 'Cell on Wings' used in the extreme hazardous scenario serving the first responders 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.

We design our performance metrics of priority based on the work in [1], where the features of QoS, priority and preemption in PSN are studied. For the mBS placement evaluation, we apply the model in [7] where the LTE structure is used for first responders. We extend the wireless network coverage in [8] by using the mBSs instead of flexible network configuration. We determine the optimal location to place mBSs in order to achieve maximum coverage for the various public safety scenarios where the priorities of first responders and the communication applications are emphasized.

The rest of this paper is organized as follows. Section 2 outlines the system model and problem statement. Section 3 describes the proposed method for finding optimal solution. Section 4 presents the empirical results regarding the performance of the algorithm and compares the different algorithms. Finally, Sect. 5 summarizes the paper and outlines ideas for future research.

2 System Model and Problem Statement

2.1 System Model

We are given a set of n UEs $\{U_1, \ldots, U_n\}$ and their guaranteed demand bit rate (GBR) $D_U(i)$ and priority $P_U(i)$ for that UE and its application. UEs can move over time, and the location of the ith UE at tth time slot is given by $L_U(i)$. Further, we are given λ mobile base stations (mBSs), $\{B_1, \ldots, B_\lambda\}$, which can be moved and configured to meet the needs of UEs. Depending on the location of the UEs and the mBSs, the UE will be affiliated to the mBS with the best signal-to-interference-plus-noise ratio (SINR).

2.2 Objective Function

The communication in PSN usually classifies first responders and the communication applications by different priorities. To represent the priority numerically in the simulation, we introduce the concept of a priority matrix where a priority value is selected for the first responder in a specific priority class and the communication application [1]. An illustrative example of priority matrix used in our simulation is shown in Table 1. The chief contribution of the construct of priority matrix is that it allows for the operational policy to be determined *at runtime* by the operator of the PSN. The algorithms proposed in this paper simply accept the priority matrix as an input and maximize the coverage based on the matrix provided.

Table 1. Table of priorities

UE's/application priority class	Immediate Peril	Responder emergency	Out of service
Mission critical voice	100	50	20
Audio	50	25	10
Video streaming	20	10	5
Periodic sensor data	10	5	1

Next, we design a metrics of performance considering UE's priority and its GBR and denote it as UE's satisfaction score (SS). With UE's location and its affiliated mBS's configuration, the satisfaction score is set to UE's priority is its GBR requirement is met. The satisfaction score is set to 0 if the GBR is not met. The goal is to maximize the total satisfaction score with specific weights on UE's priority and GBR in mBS placement. The process is illustrated as the following.

Algorithm 1: Objective Function Evaluation

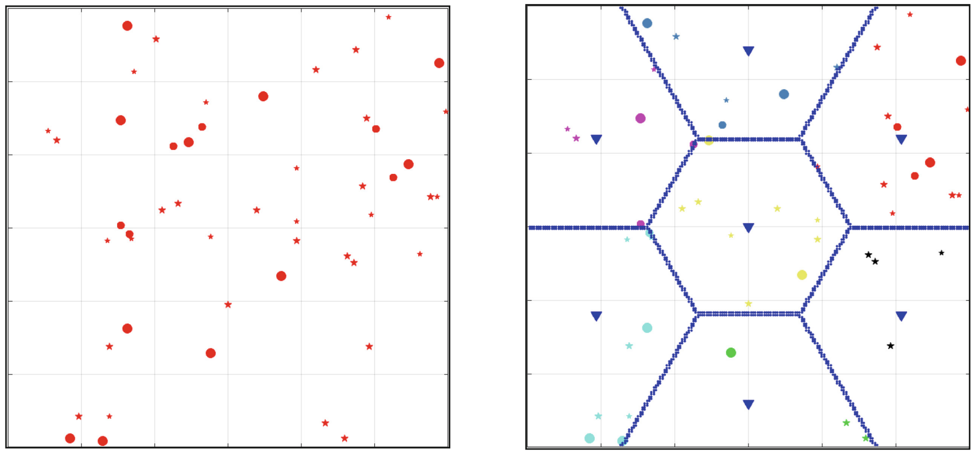
With the mBSs' placement and UEs' affiliation;
Maximize $\sum_{i=1}^{n} SS_i$;
if *GBR is met* **then**
  $SS_i = P_U(i)$;
else
  $SS_i = 0$;
end

3 Algorithms for Mobile Base Station Placement

We compare three algorithms of mBS deployment for dynamic coverage. The performance of the algorithm is measured by the total satisfaction score of all UEs. We define a square region of interest (ROI) and UEs can move inside it. Figure 1a illustrates a case of UE distribution where each dot represents a UE and the larger ones have higher priority over smaller ones and circular dots have higher priority over the stars.

3.1 Static Equal-Sized Blocks (SESB)

The first algorithm is a simple static algorithm that is used as a baseline for comparison. In this algorithm, the mBSs are deployed statically with equal-sized blocks. The mBSs serve the UEs that fall in their blocks, regardless of UEs' priority or their GBR. Figure 1b gives an illustrative case of 7 mBSs serving 50 UEs. The mBSs are represented by blue triangles and UEs with the same color



(a) UEs Placement with Different Priorities (b) SESB mBSs placement

Fig. 1. UEs placement and constant mBS placement

are affiliated with the same mBS. While SESB may appear to be a very simple algorithm, as we observe in comparison results, SESB has the advantage of simple deployment and low costs associated with moving mBSs. This is especially true, since the UEs can move around in a manner that is not predictable and an algorithm that tries to follow the UEs can suffer from low performance if and when the UEs subsequently move away.

3.2 *K*-Means mBSs Clustering

This algorithm uses k-means clustering based on the UEs location. A random initial deployment of mBSs can fit the convergence of k-means clustering. As a practical matter though, we set our initial mBSs deployment as the above SESB and then apply k-means iteration for faster clustering. With the initial deployment of mBSs and UEs' affiliation, during each iteration, the new location of each mBS will be the geometric center or centroid of its current affiliated UEs. Algorithm 2 illustrates this process. We set the iteration number (MAX_ITER) of 15 where the locations of mBSs usually converge with no further change. Figure 2a shows the final clustering of 7 mBSs.

3.3 GBR and Priority Weighted *K*-means Clustering

In order to consider both UE's location and priority, we introduce the GBR and priority weighted k-means clustering algorithm. We calculate mBSs placement to maximize critical communication needs according to UE's priority and GBR. The algorithm also uses an iterative process to approach the best result. Similarly starting with the SESB initial placement of mBSs and UEs' affiliation, during each iteration, the location of each mBS will be updated with the combined

Algorithm 2: k-means mBSs clustering

```
Initial SESB mBSs placement and UE's affiliation;
iter = 1;
while iter < MAX_ITER do
    for i = 0; i < λ; i = i + 1 do
        num_UE = 0;
        X = 0;
        Y = 0;
        for j = 0; j < n; 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 ;
    iter = iter + 1 ;
end
```

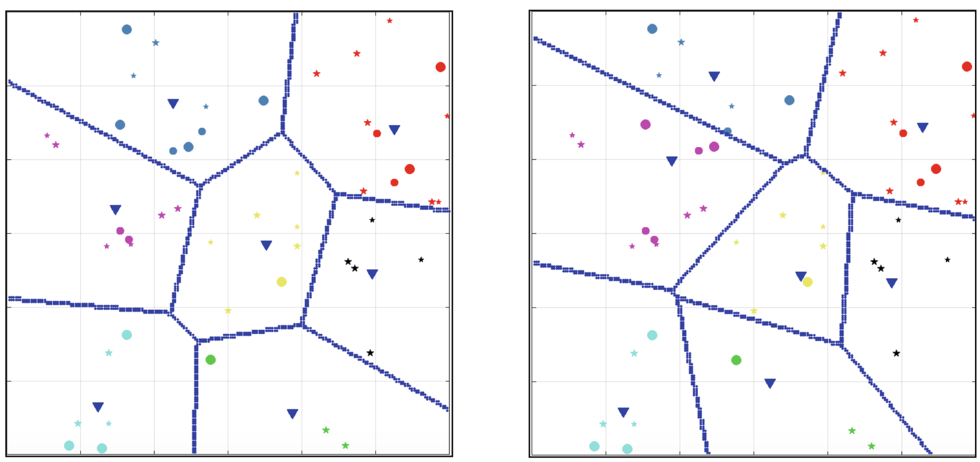
weights as $D_U(i)^\alpha * P_U(i)^\beta$ for U_i. The new coordinate of U_i will be $C_{new} = \frac{\sum C_{current} * D_U(i)^\alpha * P_U(i)^\beta}{\sum D_U(i)^\alpha * P_U(i)^\beta}$, which guarantees the convergence of iteration. Algorithm 3 demonstrates this process and the input value of α and β can be customized for different weights over priority and GBR. After 15 times of iteration, Figure 2b shows the UEs clustering with weighted GBR and priority on the mBSs' placement.

3.4 Placement Evaluation

In this section, we describe the overall process of how an entire placement is evaluated to receive a unified objective score for the placement. The overall process can be understood as follows. First, the UE is affiliated to the mBS with the best SINR. Then the SINR in dB is converted into channel quality indicator (CQI) value. CQI is an indicator carrying the information on current communication channel quality. According to CQI value, the modulation and coding schemes are selected and then the bit rate based on current radio condition can be calculated. Finally, if the UE's GBR is met, the satisfaction score of UE is set to the UE's priority. Otherwise, the satisfaction score is set to zero. Figure 3 illustrates this process. This process is repeated for all UEs to calculate an aggregate score.

Algorithm 3: GBR and Priority weighted k-means clustering

```
Initial SESB mBSs placement and UE's affiliation;
Initialize α and β ;
iter = 1 ;
while iter < MAX_ITER do
    for i = 0; i < λ; i = i + 1 do
        num_W = 0;
        X = 0;
        Y = 0;
        for j = 0; j < n; j = j + 1 do
            if U_j ∈ B_i then
                num_W = num_W + D_U(i)^α * P_U(i)^β ;
                X = X + U_j.x * D_U(i)^α * P_U(i)^β ;
                Y = Y + U_j.y * D_U(i)^α * P_U(i)^β ;
            end
        end
        B_i.x = X ÷ num_W ;
        B_i.y = Y ÷ num_W ;
    end
    affiliate UE to mBS ;
    iter = iter + 1 ;
end
```



(a) K-means Clustering Placement (b) GBR and Priority Weighted K-means

Fig. 2. K-means and GBR, priority weighted K-means clustering

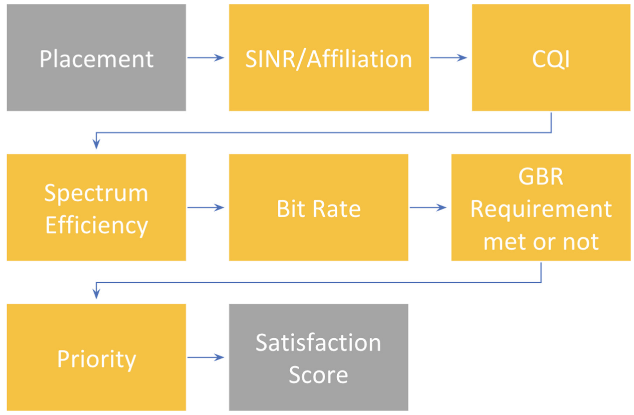


Fig. 3. Placement evaluation processes

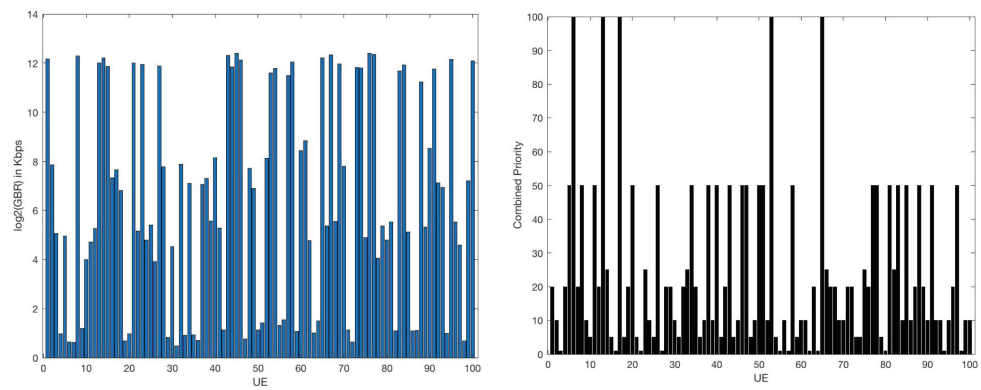
4 Empirical Results

In this section, we compare three proposed algorithms in Sect. 3 of the total UEs' satisfaction score for selected simulation scenarios. Before we explain the specific scenarios, we also discuss the mobility model since that has a significant impact on the performance.

4.1 Mobility Model and Movement Dynamics

Due to the obvious and deep reliance of First Responders on mobile Internet-enabled devices, many mobility models for ad hoc networks and cellular networks have been proposed and analyzed [9,10]. Since mobility models are application and scenario dependent, different mobility patterns are able to provide different impacts on overall network performance. Thus, researchers have repeatedly tried to understand the nature of mobility with respect to various mobility parameters. In this work, we use the well accepted random waypoint (RWP) mobility model [11] due to its simplicity and popularity. Our simulation starts with the UEs uniformly distributed in the rectangle as shown in Fig. 1a. Each UE chooses a random destination and a speed that is uniformly distributed between $[0, 4]$ m/s. Once UE arrives at the destination, it pauses for a random time uniformly distributed in $[0, 60]$ s.

Regardless of the choice of the model for this paper, we agree that the RWP model can not adequately represent all aspects and scenarios of a complete public safety network. In order to capture the movement patterns in disaster scenarios, a few disaster relief mobility models have been proposed. Event-driven and role-based (EDRB) mobility model [12] presented that environmental events and roles, such as civilians, police, firefighters, and ambulances, directly affect a node's movement patterns. Different set of mobility patterns are embedded into different object roles. In reference point group mobility (RPGM) model [13], mobile nodes are organized by groups according to their logical relationships. Each group acts seemingly independently of the other groups, and the random motion of each user within the group are implemented via RWP model. Overlap mobility model of RPGM allows that different groups carry out different tasks over the same area. Since each group has a unique motion pattern, speed, and scope, the rescue team, medical assistant team, psychologist team, etc. can be modeled differently over the disaster recovery area. Thus, we acknowledge that there are many other mobility models that can be used as directions for our future work.



(a) GBR distribution (b) UEs' Priorities Distribution

Fig. 4. UEs' GBR and priorities distribution

4.2 Simulation Scenarios

We implement our simulation in MATLAB for 2000 seconds of first responders' movement. The network consists of between 1 and 9 mBSs serving from 20 to 150 UEs in a grid size of 1 km^2. The maximum communication range of each UE is 300m. All the results are computed as the average of 100 repetitions. We use the free space radiation model where best SINR converts into the closest mBS.

Data rate between 200 and 4000 Kbps can be expected to support high definition (HD) video conferencing. 30 Kbps for voice communication and between 1 and 800 Kbps for sensory data including temperature, light, motion and chemical can be expected [14]. In the simulation, the UE's application data rate requirement (GBR) is generated as four normal distributions which represents four classes of application priorities where each follows the normal distribution. Figure 4a shows an example of GBR distribution. The UE's location in simulation is generated as uniform distribution in the ROI and the UE's priority class also follows the uniform distribution. Figure 4b shows an example of UEs' combined priority distribution.

4.3 Empirical Results for Static Case

For the static case, without considering UEs' mobility, the simulation has been run for 15 different experimental configurations where the satisfaction score is

Table 2. Empirical Results for Static Case

Satisfaction score averaged over 100 repetitions					
Exp index	Num of mBS	Num of UE	SESB	k-means	Weighted k-means
1	1	20	45.20	46.75	54.30
2	2	30	118.59	139.62	211.71
3	3	50	283.06	339.28	453.97
4	4	50	401.43	479.02	611.44
5	4	80	652.31	715.20	901.11
6	5	100	968.68	1169.7	1331.3
7	6	100	1189.8	1384.2	1562.8
8	7	100	1286.9	1511.7	1696.2
9	7	120	1597.5	1867.1	1999.6
10	7	150	1977.3	2274.4	2462.2
11	8	100	1452.4	1759.1	1917.1
12	8	120	1751.8	2074.9	2218.6
13	8	150	2161.4	2516.9	2632.0
14	9	120	2055.1	2277.3	2374.1
15	9	150	2549.1	2791.4	2912.3

averaged over 100 repetitions. The number of mBS is from 1 to 9 and the number of UE is accordingly from 20 to 150. The simulation results of the satisfaction scores show dominant benefit of Weighted k-means over the other two algorithms in the static case. Table 2 shows the satisfaction scores of the three proposed algorithms of different experimental configurations.

4.4 Empirical Results for Mobile Case

Our static simulation results clearly show that weighted priority and GBR significantly improves connectivity and coverage among different priority level requirements. We have four experiments with 7 or 9 mBSs serving 150 UEs. UEs apply either RWP model which is depicted in Sect. 4.1 or following the nearest leaders who have high priority. In our simulation, we define the leaders who have at least 50 priority value which is explained in Sect. 2.2. Table 3 shows the satisfaction scores of the three proposed algorithms in four different experimental configurations.

Since the mBS placement algorithms presented in this work are static and do not adequately take the mobility of UEs into consideration, the scores of SESB shows little fluctuation and the scores of the other two algorithms degrade gradually as the simulation time grows. In order to provide a dynamic mBSs placement algorithm for real world PSN scenario, both the first responders' mobility model and dynamic mBSs placement cost can be considered in future work.

Table 3. Empirical results for mobile case

Satisfaction score of 150 UEs				
Mobility model	Num of mBS	SESB	k-means	Weighted k-means
Random Waypoint	7	1455.9	1565.1	1728.7
Follow Leader	7	1599.0	1691.2	1570.1
Random Waypoint	9	1967.9	1874.0	1832.3
Follow Leader	9	1984.9	1887.9	1951.8

5 Conclusions

In this paper, we have studied the problem of mobile base station placement to meet the critical communication requirements of first responders in an ad hoc public safety network. By considering the class of first responders and the applications, we provide an efficient base station placement algorithm to maximize critical communication needs according to priority and application bit rate requirement. The simulation results have been presented with different network configurations of mBSs and the UEs. In static model, our results clearly show that the algorithm of weighted priority and GBR significantly improves connectivity and coverage parameters compared to two others. In order to provide prompt reaction to the dynamic environmental changes, we consider UEs' mobility models in mobile model simulation.

The future research can consist of studying different mBSs placement cost parameters and thus design the joint algorithm for dynamic coverage that also considers the cost of moving the different base stations. Also, as discussed in the empirical results, significantly more work can be done to validate the presented algorithm using a wider set of mobility models. Finally, as one narrow but specific item, in the GBR and priority weighted k-means clustering algorithm, future research can explore the suitable values of α and β.

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