Autonomous Relocation Strategies for Cells on Wheels in Environments with Prohibited Areas

Ladan Rabieekenari
Institute for Systems Research
University of Maryland, College Park

Kamran Sayrafian
Information Technology Laboratory
National Institute of Science and Technology

John S. Baras
Institute for Systems Research
University of Maryland, College Park

***Abstract*—Public safety organizations increasingly rely on wireless technology for their mission critical communication during disaster response operations. In such situations, a communication network could face much higher traffic demands compared to its normal operation. Given the limited capacity of base stations in the network, such peak traffic scenarios could lead to high blocking probability or equivalently service interruptions during critical communications. At the same time, networking infrastructure can breakdown during a disaster. Proper deployment of mobile cells - Cells on Wheels - can help to enhance the network coverage or accommodate excess traffic in areas with high concentration of users. In addition, an intelligent relocation strategy can be used to efficiently adapt the cell locations to match variations in the spatial distribution of the traffic. In practical scenarios, these mobile base stations may not be able to relocate to all positions within the target field. Such prohibited areas introduce additional constraints on designing an intelligent relocation strategy. In this paper, we propose a decentralized relocation algorithm that enables mobile cells to adapt their positions in response to potentially changing traffic patterns in a field with prohibited areas. Extensive simulations show considerable improvement in supporting spatially variable traffic throughout the target field.**

I. Introduction

Emergency scenarios such as natural or man-made disasters are typically characterized by unusual peaks in traffic demand caused both by people living in the disaster area as well as the first responders and public safety personnel [1]. Such traffic hotspots that typically involve vital life-saving information are a major challenge for the communication network covering the disaster area. The exact locations and magnitudes of these traffic hot-spots within a disaster area are usually not known apriori. As the sizes of these possible emergency incidents are unpredictable, estimating the capacity requirements to meet the resulting highly variable excess traffic is nearly impossible. In addition to the above, the network infrastructure itself may be subject to full or partial beak-downs during emergencies. These situations constitute an important challenged network scenario where there is a temporary shortage of resources required to address critical communication needs.

A reasonable solution to this problem is using a set of mobile base stations that can be quickly deployed to service the excess traffic during the disaster recovery. A portable cell - a cell on light truck (COLT) or a cell on wheels (COW) - can be used to augment the remaining communication infrastructure and keep first responders connected to their command centers. By properly deploying these mobile cells, we can create a temporary network to support critical public safety communication throughout the disaster area. Such mobile networks that can be easily deployed, configured and adapted, offer the ideal solution to any disaster response effort.

The base station deployment or positioning is an important problem during network architecture design. It has been shown that the identification of the globally optimum base stations locations in a network is an NP-hard problem [2]. In practice, most of the system parameters required to find such an optimal solution is unknown. In addition, the optimal positions could change due to the variations in temporal or spatial distribution of traffic demand.

In [3] and [4] the authors proposed using a portable self-configurable cellular system to assist with damaged or destroyed network infrastructure in emergencies or other natural disasters. However, the deployment phases in all their proposed approaches were not considered to be autonomous or adaptive. As a result when the spatial distribution of traffic changes, the network may fail to adequately meet the traffic demand at various locations on the field. The autonomous adaptive relocation problem in which each mobile node has local information about the location of traffic sources in its coverage area has been considered in [5]. There, the authors proposed a distributed algorithm for adaptive relocation of wireless access networks in order to minimize the total transmission power. However, minimizing total transmission power does not guarantee increasing total covered area or total supported traffic. In addition, in their algorithm each node requires information about the location of traffic sources within its coverage area at each step in order to calculate its new location. This will incur a large overhead for their proposed algorithm. In [6], an adaptive self-deployment algorithm is proposed in which base stations are capable of autonomous relocation to simultaneously maximize coverage and supported traffic in the network. There, the authors assumed the base stations can freely relocate to all points within the target field. However, in practice structural obstacles, areas with outstanding water or other hazardous materials, or surfaces with debris are examples of prohibited areas where mobile cells are expected to avoid. Such prohibited areas introduce additional constraints on designing an intelligent relocation strategy. To the best of our knowledge, there is no distributed algorithm that aims to maximize network coverage subject to capacity constraints and prohibited areas.

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In this paper, an adaptive self-deployment algorithm is proposed in which base stations are capable of autonomous relocation to simultaneously maximize coverage and supported traffic in the network subject to prohibited areas.

The rest of this paper is organized as follows. System description, assumptions and problem formulization are provided in Section II. In Section III, a distributed adaptive relocation algorithm that simultaneously maximizes coverage and supported traffic is presented. In Section IV, we analyze the efficiency of the proposed algorithm through extensive simulations. Finally, conclusions and future work are presented in Section V.

II. Problem Statement

Consider a region $Q \subset \mathbb{R}^2$ and a set of mobile nodes (i.e. base stations) denoted by $S = \{s_1, s_2, ..., s_N\}$. These base stations can wirelessly communicate with each other. Let $P_0 = \{p_{0,1}, p_{0,2}, p_{0,3}, ..., p_{0,N}\}$ denote the initial position of these base stations where $p_{0,i} \in Q,\ \forall i \in \{1, 2, .., N\}$. For simplicity, we assume that shadow fading characteristics depend mostly on the immediate environment surrounding the user. For example, this is the case when the base station antennas are located high enough. This results in the shadow fading intensity experienced by a user at point q to be independent of its corresponding base station location. As stated earlier, base stations cannot relocate or pass through the prohibited areas; however, there might be a need to provide coverage for emergency responders when they are operating inside these areas.

We assume each user in Q connects to the base station from which it receives the strongest control reference signal that is greater than some specified threshold (i.e. receiver sensitivity denoted by η_r). We also assume interference is negligible, which can be achieved by interference-coordination among neighbor base stations. For example, Inter-Cell Interference Cancelation algorithms (ICIC) such as dynamic frequency reuse schemes can be used to mitigate inter-cell interference. There is also non-inter-cell coordinated schemes in which each base station uses orthogonal channel [7].

We define coverage area of a base station as the region where its average downlink transmitted reference signal is the strongest signal received by users and its value is greater than or equal to η_r. This corresponds to 50% coverage probability at cell-edge when shadow fading has log-normal distribution. In order to increase reliability of connection in coverage area, we can consider a fade margin η_F. Fade margin is the additional signal, above the receiver threshold, that is not necessary for communication; however, it is necessary for reliability prediction. Based on our propagation and channel loss assumptions, there exists a R_{cov} such that the average downlink transmitted reference signal is greater than $\eta = \eta_F + \eta_r$ for all points within distance R_{cov} of each base station. In order to formalize total covered area over region Q, we define Voronoi region $V_i = V(p_i)$ as follows:

$$\begin{aligned} V_i = \{ & q \in Q \mid \mathbb{E}[P_{rx}(p_i, q)] \geq \mathbb{E}[P_{rx}(p_j, q)], \\ & \forall j \in \{1, ..., N\} - \{i\}\} \end{aligned} \tag{1}$$

where $P_{rx}(p_i, q)$ is the received signal strength of base station i at point q.

Since all base stations are transmitting using equal power, Voronoi region $V_i = V(p_i)$ will be the set of points such that $\mathbb{E}[L(p_i, q)] \leq \mathbb{E}[L(p_j, q)]$. $\mathbb{E}[L(p_i, q)] = \mathbb{E}[L_s(p_i, q)] + \mathbb{E}[L_p(p_i, q)]$ holds where L_s and L_p represent shadow fading and pathloss respectively. Since L_s is almost the same at point q with respect to different base stations, V_i will be the set of all points $q \in Q$ such that $\mathbb{E}[L_p(p_i, q)] \leq \mathbb{E}[L_p(p_j, q)]$. This is equivalent to $dist(q, p_i) \leq dist(q, p_j)$. As a result, the Voronoi region $V_i = V(p_i)$ is the set of all points $q \in Q$ such that $dist(q, p_i) \leq dist(q, p_j)$ for all $i \neq j, i \in S$. To construct the Voronoi diagram, the bisectors of each base station and its neighbors need to be drawn first. Among all polygons generated by these bisectors, the smallest one which contains the base station is the Voronoi polygon of that base station. It follows from defined coverage model and Voronoi polygon, that any point in a Voronoi polygon which is not in coverage area of the base station associated with that polygon cannot be in coverage area of any other base station either. Thus, in order to find the so-called ”coverage holes”, i.e. the points that are not in coverage area of any base station, each base station would only need to check its own Voronoi polygon.

The coverage area of each base station within its Voronoi polygon is called the local coverage area of that base station. Total covered area in Q is equal to sum of local covered areas, so we define the coverage metric as follows:

$$O(p_1, ..., p_N) = \sum_{i=1}^{N} \int_{V_i} f(dist(q, p_i)) d_q \tag{2}$$

Where $f(x)$ is equal to 1 if $x \leq R_{cov}$ otherwise $f(x) = 0$.

In practice, the communication range of a base station to other base stations is bounded. This is a limiting factor for the base stations to reach their neighbors, and can potentially result in wrong Voronoi polygons around some of the base stations, negatively affecting the efficient detection of coverage holes in Voronoi polygons.

We are also assuming that the spatial distribution of traffic sources in the target field is non-uniform, and slowly variable which is due to change in user demand and its position. So traffic hot-spots location and their capacity demand may change during time. As a result, a base station deployment that is servicing traffic at time t_0, may not meet the traffic demand at time t_1. This can be either due to having overloaded base stations or having traffic which is not in coverage area of any base station. Let $\mathcal{O}_i = \{o_1, ..., o_k\}$ denote the set of overloaded Voronoi neighbors of base station i. If we assume that the total traffic demand throughout the target field is less than the total network capacity (i.e. capacity of a base station multiplied by the number of base stations), then it is imaginable that the overload scenarios faced by few base stations can be overcome by judicious relocation of all base stations in the network. Besides that, relocations that aim to increase coverage in the area, are needed to service the users that are not in coverage area of any base station.

In this paper, we propose a strategy where mobile base stations adaptively and autonomously adjust their positions in order to maximize the supported traffic and eliminate the base station overload situations in traffic hot-spot zones. Given the aforementioned traffic constraint, our proposed relocation algorithm also tries to maximize the network coverage area at the same time. Let P_n denote the locations of base stations at iteration n, we are interested to find a distributed algorithm in which P_n converges to P^* for a given traffic distribution and such that:

$$P^* = \underset{p_1,\dots,p_M}{\arg\max} \sum_{i=1}^{N} \int_{V_i} f(dist(q,p_i))d_q \qquad (3)$$
$$s.t. \quad \mathbb{E}[\rho_i] \leq 1 \qquad \forall i \in \{1,...,N\}$$

where ρ_i denotes the capacity demand of base station i which is the sum of the required resources of all users u connected to cell i by a connection function which gives the serving cell i to user u.

$$\rho_i = \sum_{u \in U_i} \rho_{i,u}, \quad \rho_{i,u} = \frac{s_{i,u}}{s}, \quad s_{i,u} = \left\lceil \frac{\sigma_u}{e_{i,u}} \right\rceil$$

where U_i denotes the set of users which are supposed to connect to cell i. $s_{i,u}$ denotes the number of resources used by node u. s denotes the total number of available resources at each base station. σ_u represents the required bit rate of user u in order to transmit data. $e_{i,u}$ is the bandwidth efficiency of user u. The $\lceil x \rceil$ represents the minimum integer larger than x. We are interested to propose a relocation algorithm that can achieve autonomous adaptive base station deployment subject to the capacity constraints.

III. Proposed Algorithm

Our proposed approach is an iterative algorithm; where in each iteration every base station first broadcasts its location along with the capacity demand from users in its coverage area to other neighboring base stations. Each base station then uses this information to calculate its new location. The new location is calculated through an adaptation of simulation optimization algorithm presented in [8]. The basic strategy of the algorithm in [8] is to generate a sequence of feasible and improving solutions. If the constraint is well satisfied, then the variables change in the direction which improves the objective function. If the constraint function is not satisfied, the variables change in a direction which satisfies the constraint.

Intuitively, the proposed algorithm aims to maximize network coverage while ensuring that base stations can meet their corresponding traffic demand. Each base station tries to increase its local coverage, when the capacity constraints of itself and its neighbors are satisfied. We refer to this phase as coverage improvement phase. On the other hand, if the capacity constraint of a base station is not satisfied (i.e. overload situation), it makes a request for help by sending a signal to the neighboring base stations. We refer to this phase as load balancing phase.

In order to calculate moving direction in both phases, we need to be able to calculate gradient of an integral function in a Voronoi polygon. Gradient of function f is the direction which increases f fastest. The region in Voronoi polygon of node i in which the average power of received signal is greater than the receiver sensitivity is denoted by $\mu(p_{t,i})$. $\mu(p_{t,i})$ can be defined by k relations $h_j(p_{t,i},q) \leq 0$ for $j = 1,...,k$. $h_j(p_{t,i},q)$ are boundary functions which consist of both Voronoi boundaries and coverage boundary of the mobile base station. By concatenation of the boundary functions $h_j(p_{t,i},q)$ as $h(p_{t,i},q) = [h_1(p_{t,i},q),...,h_k(p_{t,i},q)]^T$, this region can be represented by $h(p_{t,i},q) \leq 0$. Denote the boundary of $\mu(p_{t,i})$ by $\partial\mu(p_{t,i})$. The boundary of the region corresponds to the equalities in the above formulation. Note that this boundary has k segments, where each segment can be expressed as:

$$\partial_j \mu(p_{t,i}) = \{q \in \mu(p_{t,i}) : h_j(p_{t,i},q) = 0\} \qquad (4)$$

Consider the following integral function over the region:

$$F(p_{t,i}) = \int_{\mu(p_i,t)} z(p_{t,i},q)d_q \qquad (5)$$

where $z(.,.)$ is a given function. The gradient of $F(p_{t,i})$ with respect to $p_{t,i}$ can be computed as [9]:

$$\nabla_{p_{t,i}} F(p_{t,i}) = \int_{\mu(p_{t,i})} \nabla_{p_{t,i}} z(p_{t,i},q)d_q$$
$$- \sum_{j=1}^{k} \int_{\partial_j \mu(p_{t,i})} \frac{z(p_{t,i},q)}{\|\nabla_q h_j(p_{t,i},q)\|} \nabla_{p_{t,i}} h_j(p_{t,i},q)d_q \qquad (6)$$

In the coverage improvement phase, each base station moves in the direction which increases local coverage fastest. The local coverage area of each base station can be formulated as

$$J(p_{t,i}) = \int_{\mu(p_{t,i})} d_q \qquad (7)$$

Each base station can calculate gradient of its local coverage function as [9]

$$\nabla_{p_{t,i}} J(p_{t,i}) = \int_{\partial\mu(p_{t,i})} \frac{q - p_{t,i}}{\|q - p_{t,i}\|} d_q \qquad (8)$$

where $\partial\mu(p_{t,i})$ is the portion of the perimeter of the sensing disk which is inside V_i. Figure 1 provides a geometrical interpretation of equation 8. It is desired in this figure to maximize the gray region by properly relocating the base station i inside the polygon. As Figure 1 shows, the gradient of the local coverage is toward right.

In the load balancing phase, a base station moves in the direction which would result in the fastest offloading of traffic from the overloaded Voronoi neighbors. Since we do not have any information about traffic distribution in the area, we assume traffic sources of each base station is uniformly distributed within its coverage area. Let $\varphi(q)$ denote the estimated traffic density at point q for overloaded areas, we set $\varphi(q)$ for the rest of area to 0. The amount of offloaded traffic from overloaded neighbor base stations when base station i is at $p_{t,i}$ is as follows:

$$G(p_{t,i}) = \int_{\mu(p_{t,i})} \varphi(q)d_q \qquad (9)$$

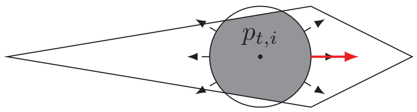


Fig. 1. Geometrical interpretation of the gradient function with respect to $p_{t,i}$ for coverage improvement phase

Here $z(p_{t,i}, q) = \varphi(q)$ which is not a function of $p_{t,i}$. So first term in equation 6 will be equal to zero. Based on the definition of $\varphi(q)$, $\varphi(q)$ is nonzero only on the Voronoi edges which are besides overloaded neighbor base stations. As a result by using 6, we have:

$$\nabla_{p_{t,i}} G(p_{t,i}) = \\ -\sum_{j=1}^{|\mathcal{O}_i|} \int_{\partial_j \mu(p_{t,i})} \frac{\varphi(q)}{\|\nabla_q h_j(p_{t,i}, q)\|} \nabla_{p_{t,i}} h_j(p_{t,i}, q) d_q \qquad (10)$$

where $\partial_j \mu(p_{t,i})$ is the part of Voronoi polygon V_i which is mutual between base station i and o_j. $h_j(p_{t,i}, q)$ represents the equation of $\partial_j \mu(p_{t,i})$ and it is equal to $(p_{o_j,t} - p_{t,i})^T (q - \frac{p_{t,i} + p_{o_j,t}}{2})$. The gradients can be computed as follows:

$$\frac{\partial h_j(p_{t,i}, q)}{\partial p_{t,i}} = p_{t,i} - q \qquad (11)$$

$$\frac{\partial h_j(p_{t,i}, q)}{\partial q} = p_{o_j,t} - p_{t,i} \qquad (12)$$

after applying 11 and 12 to 12, we have:

$$\nabla_{p_{t,i}} G(p_{t,i}) = \sum_{j=1}^{|\mathcal{O}_i|} \int_{\partial_j \mu(p_{t,i})} \varphi(q) \frac{q - p_{t,i}}{\|p_{o_j,t} - p_{t,i}\|} d_q \qquad (13)$$

$\nabla_{p_{t,i}} G(p_{t,i})$ is the direction which offloads the traffic from the overloaded neighbor base stations fastest.

Figure 2 provides a geometrical interpretation of equation 13. In this figure, $p_{k,t}$ is the only overloaded neighbor of $p_{t,i}$. Same weight is assigned to all the points within the gray area. As Figure 2 shows, the gradient of the $G(p_{t,i})$ is toward $p_{k,t}$.

If base station i is on the border of a prohibited region and the moving direction calculated by the gradient function is blocked by the prohibited region, the gradient is not a valid moving direction. In this case, base station moves in a valid direction which has the largest positive directional derivative. Directional derivative of objective function F with respect to direction u can be calculated as follows:

$$D_{\overrightarrow{u}} F(p_{t,i}) = \nabla_{p_{t,i}} F(p_{t,i}).\overrightarrow{u} = \|\nabla_{p_{t,i}} F(p_{t,i})\| \|\overrightarrow{u}\| \cos(\theta)$$

where θ is the angle between $\nabla_{p_{t,i}} F(p_{t,i})$ and $\overrightarrow{u}$. As a result among all valid moving directions, the one with the smallest θ (and positive $\cos(\theta)$), is increasing the objective function fastest. This will result in detouring the prohibited region.

After base station i calculates its moving direction at step t, it moves by $a_{t,i}$ meters toward the calculated direction. $a_{t,i}$ denotes step size sequence for iterative updates of base station i's location. $a_{t,i} = A_i g(step(t, i))$, where A_i is the scaling factor and $g(step(t, i))$ is the decaying factor which gradually decreases from 1 to 0. $step(t, i)$ is initially set to 1 and each time base station i moves, it is incremented by 1. Choice of $a_{t,i}$ can affect the speed of convergence of the algorithm. In order to adjust $a_{t,i}$ to achieve proper convergence speed, we propose to use the following procedure:

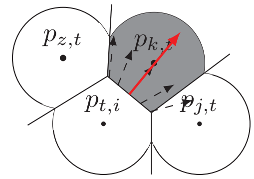


Fig. 2. Geometrical interpretation of the gradient function with respect to $p_{t,i}$ for load balancing phase when base station located at $p_{k,t}$ is overloaded

- If over the last M relocations of base station i, the moving direction remains the same, then let $A_i = 2a_{t-1,i}$ and set $step(t, i) = 1$.
- If over the last M relocations, the new location of base station i falls out of its corresponding Voronoi polygon, then let $A_i = \frac{a_{t-1,i}}{2}$ and set $step(t, i) = 1$.

In the above procedure, the value of M is also important. Small M could result in incorrect updates due to small amount of information, while a large choice of M increases the convergence time due to the slow update frequency of $a_{t,i}$. If over the last M relocations, the total relocated distance by base station i is too small or too large, this means $a_{t,i}$ has not been properly chosen for the current network status. This could be either due to the size the area or rapid change in the traffic pattern.

$\Pi_i(.)$ in Algorithm 1, represents the projection function. If $p_{t,i} + a_{t,i} < \overrightarrow{D}_i >$ falls out of the Voronoi polygon of base station i, then $\Pi_i(p_{t,i} + a_{t,i} < \overrightarrow{D}_i >)$ will be projected in the polygon. Besides that, in both phases, when base station reaches the boundary of a prohibited area, it stops.

To conserve energy and decrease unnecessary nodes relocation in the network while providing an acceptable service quality, we also propose a stopping criterion. If the base station is in the coverage enhancement phase and the magnitude of coverage hole is less than ϵ_{cov}, it will not move any further. If the base station is in the load-balancing phase and the total amount of overloaded traffic within its neighbors is less than ϵ_{lb}, it will not move any further. We can achieve a trade-off between stopping time and performance by changing ϵ_{lb} and ϵ_{cov}. Larger ϵ_{lb} and ϵ_{cov} will decrease the stopping time which is at the cost of worse performance.

Remark: The problem investigated in this paper is a non-convex optimization problem with unknown information about location of users within the target field. Thus, the proposed algorithm will not necessarily result in the optimal solution.

IV. Simulation and Results

Consider a target area of size $1800m \times 1800m$. This target area size is comparable with case 3 of Scenario III cited in the FCC report on the Public Safety Nationwide Interoperable Broadband Network [1]. Several mobile base stations that are connected to a wireless backhaul network are expected to provide communication services to users in this area. It is assumed that each base station has 50 resource blocks of 180KHz in size. It is also assumed that the carrier frequency is 700MHz, channel bandwidth is 10MHz, and transmission power of

Algorithm 1 Autonomous adaptive deployment algorithm

▷ Each base station s_i broadcasts its location $p_{t,i}$ at time t and its capacity demand ρ_{s_i} to its neighbors and then constructs its Voronoi polygon based on the similar information it receives from other base stations
▷ Each node $s_i \in S$ calculates its new location as follows:
Calculate $\nabla_{p_{t,i}} G(p_{t,i})$ by equation 13
if $\nabla_{p_{t,i}} G(p_{t,i}) \neq \overrightarrow{0}$ **and** $\rho_{s_i} \leq 1$ **then**
  ▷ Choosing a valid moving direction which offloads traffic from overloaded neighbors fastest
  $< \overrightarrow{D}_i >= \arg\max_{\overrightarrow{D}_i : \|\overrightarrow{D}_i\|=1} \overrightarrow{D}_i . \nabla_{p_{t,i}} G(p_{t,i})$
else if $\rho_{s_i} \leq 1$ **then**
  ▷ Choosing a valid moving direction which increases local coverage fastest
  Calculate $\nabla_{p_{t,i}} J(p_{t,i})$ by equation 8
  $< \overrightarrow{D}_i >= \arg\max_{\overrightarrow{D}_i : \|\overrightarrow{D}_i\|=1} \overrightarrow{D}_i . \nabla_{p_{t,i}} J(p_{t,i})$
end if
$p_{t+1,i} = \Pi_i(p_{t,i} + a_{t,i} < \overrightarrow{D}_i >)$

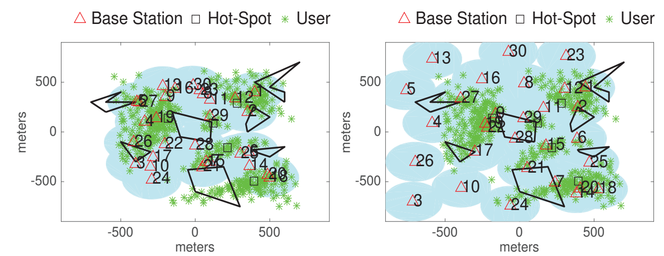
each base station is equal to 16.39dBm/resourceblock. The receiver's sensitivity is considered to be -90dBm. Each base station has limited power in communicating with other base stations. It is assumed transmission power of each base station for communication between each other is equal to 36dBm.

We assume that traffic hot-spots are distributed with Poisson point process (PPP), and users (i.e. traffic sources) are generated based on the model in [10]. In this model, first a random location is assigned to each user. Then, each user u is moved toward its closest traffic hot-spot HS_u by a factor of $\beta \in [0,1]$. So, the user's new location u^{new} is calculated as $u^{new} = \beta HS_u + (1-\beta)u$. β has a Gaussian distribution with mean $\mu_\beta \in [0,1]$ and variance $\sigma_\beta = \frac{0.5-|\mu_\beta - 0.5|}{3}$. A large μ_β will result in users being closer to traffic hot-spots, while small μ_β will lead to a uniform distribution of traffic. Each user is generating traffic with the rate of 64kbps, 128kbps or 256kbps based on a uniform distribution.

The path-loss at distance d of a base station is modeled as $40\log(d) + 30\log(f) + 49$ where d is in km and f is in MHz. In addition, shadow fading with a standard deviation of 5dB is also considered. A spatially correlated shadow fading environment with correlation function $r(x) = e^{-\frac{x}{50}}$ was generated as described in [11]. Using the path-loss model and receiver sensitivity, R_{cov} is calculated to be 200m. Mobile base stations employ our proposed algorithm to autonomously relocate and provide better support of traffic within the target area. Node relocation, control signaling exchange and all other updates are carried out using a 60s simulation time-step. It is assumed that each base station can relocate up to a maximum of 60m during a time-step. We set $a_{t,i} = \frac{200}{step(i,t)}$, a decreasing function of $step(i,t)$ and slowly converging to 0. We set $\epsilon_{lb} = 2$ and $\epsilon_{cov} = 3m^2$.

In the first two scenarios we show the improvement in the performance by execution of Algorithm 1 during time. Then, we show how much the proposed algorithm improves the performance considering uniform initial deployment by averaging over 100 different scenarios.

First, we consider the capacity and coverage performance of the network considering an initial random deployment of mobile base stations at the center of a $800m \times 800m$ target field. For example, Figure 3(a) shows the initial positions of the base stations (marked by red triangles) along with initial user distribution (marked by green asterisk). Prohibited areas are shown by black polygons. In our simulations, μ_β is equal to 0.6. Given this initial deployment, base stations 1, 18 and 19 encounter high traffic demands beyond their capacity limits. With the execution of our proposed relocation algorithm, base stations that have available capacity relocate closer to traffic hot-spots. When the capacities of base stations meet the traffic demand within their coverage area, they will continue relocating to expand network coverage within the target field. In this way, traffic hot-spots that were originally outside the coverage area of the initial deployment will get an opportunity to be discovered. The above process continues until all base stations can meet their respective traffic demands and maximum network coverage is achieved. Figure 3(b) shows the final base station positions after 20 time-steps. After 20 time steps, the total amount of excess traffic at neighbors of each base station does not exceed ϵ_{lb}, so none of the base stations deploy load balancing phase. Besides that, none of the neighbor base stations of 3, 5, 10, 13 and 26 are overloaded, so they deploy coverage improvement algorithm and relocate in order to increase the total covered area. Figure 4 shows how network coverage and the total supported user traffic evolve during the execution of our proposed algorithm. As observed, Algorithm 1 results in increasing the supported user traffic from 80% to 97% as well as improving the network coverage from 41% to 74%.



(a) (b)

Fig. 3. First scenario: (a) Initial locations of base stations; (b) Final locations of base station after execution of Algorithm 1

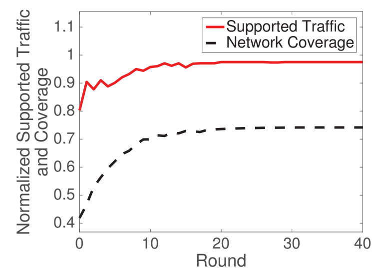
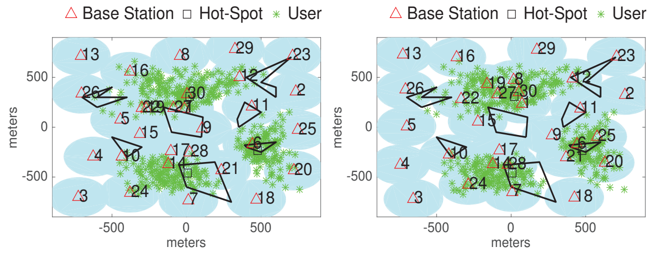


Fig. 4. Network coverage and supported Traffic during execution of Algorithm 1 (first scenario)

Next, after the base stations converge to their final positions in Figure 3(b), we consider a scenario where traffic hot-spots locations change. This is shown in Figure 5(a). With this new traffic distribution, base stations 6 and 30 will face high traffic demands above their capacity limits. Again, using



(a) (b)

Fig. 5. Second scenario: (a) Initial locations of base stations; (b) Final locations of base station after execution of Algorithm 1

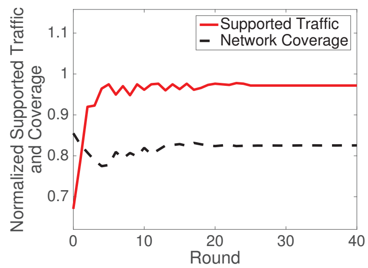


Fig. 6. Network coverage and supported Traffic during execution of Algorithm 1 (second scenario)

Algorithm 1, the base stations will autonomously relocate to new positions in order to adapt to new traffic hot-spots and accommodate the corresponding demand. Final base station positions are shown in Figure 5(b). Figure 6 depicts changes in the area coverage and supported traffic during the execution of our algorithm. As observed, the supported user traffic increases from 67% to 97%. The tradeoff in supporting almost all traffic demand in this scenario is the decrease in the overall network coverage from 85% to 82%.

Next, we investigate the performance of our proposed algorithm by averaging over 100 different scenarios assuming a uniform initial deployment and random spatial traffic demands (i.e. μ_{beta}, number of hot-spots and their location). The results are shown in Figure 7. With an initial uniform deployment of base stations, occurrences of traffic hot-spots will cause several base stations to face traffic demands above their capacity limits. These situations result in a low average supported traffic of only 67%. Using Algorithm 1, the base stations will adaptively relocate to meet non-uniformities in the traffic demand; and therefore, the average supported traffic in the network will increase to 93%.

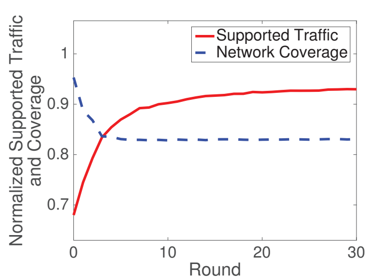


Fig. 7. Average network coverage and supported traffic during execution of Algorithm 1 (assuming a uniform initial deployment)

V. Conclusions and Future Work

Cells on Wheels are a cost effective solution to complement a public safety network during emergencies. The variable nature of the spatial distribution of traffic throughout the target field along with the large peak-to-average traffic ratio necessitates judicious and adaptive deployment of the cells. Assuming, autonomous mobile base stations, we have proposed a distributed relocation algorithm that effectively adapts the overall network coverage in order to maximize the supported user traffic. In practice, there might be situations where mobile cells are not able to move to all locations within the target field due to the existence of various obstacles or other prohibited areas. Our proposed algorithm iteratively determines the best relocation direction for mobile cells while avoiding any prohibited area. Simulations show that substantial gain in performance can be achieved under typical usage scenarios. Further research is required to study the impact of various system parameters on the overall performance and convergence speed of the algorithm. In this paper, it was assumed that all base stations are mobile, new strategies will be required if the overall network consists of a combination of mobile and static base stations. The authors plan to investigate this case in the future.

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