

Autonomous Relocation Strategies for Cells on Wheels in Public Safety Networks

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Abstract—Lack of network availability or limited access to communication services are among the challenges that public safety officials and first responders could face during disasters. Networking infrastructure can partially (or sometimes fully) breakdown during a catastrophe. At the same time, unusual peaks in traffic load could lead to much higher blocking probability for critical communication. A possible solution for such scenarios is through the use of mobile infrastructures commonly referred to as Cells on Wheels (COW) or Cells on Light Trucks (COLT). These mobile cells can effectively complement the existing undamaged infrastructure or enable a temporary emergency network by themselves. Given the limited capacity of each cell, variable and spatially non-uniform traffic across the disaster area can make a big impact on the network performance. Not only judicious deployment of the cells can help to meet the coverage and capacity demands across the area, but also intelligent relocation strategies can optimally match the network resources to potentially changing traffic demands. Assuming that each cell can autonomously change its location, in this paper, we propose a decentralized relocation algorithm that adapts network coverage in order to increase the supported users traffic.

I. INTRODUCTION

Emergency scenarios such as natural or man-made disasters are typically characterized by unusual peaks in traffic demand caused both by people 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 unknown a priori. As the size of these possible emergency incidents is unpredictable, estimating the capacity requirements to meet the resulting variable excess traffic is nearly impossible. In addition, the network infrastructure itself is subject to breakdown and target of attacks. In such scenarios, there is a need for a quickly deployable and self-organizable communication network that can adapt itself to variations in the spatial and temporal distribution of traffic.

A viable solution to this problem is through the use of a set of mobile base stations. Portable cell sites - cells on light truck (COLT) or cells on wheels (COW) - can be used to augment the remaining communication infrastructure and keep first responders connected to their command centers. By judiciously deploying these mobile stations, we can create a temporary network to support first responders need and manage critical public safety communication throughout the disaster area.

In [2], [3] the authors proposed using a portable self-configurable cellular system to assist with damaged or destroyed network infrastructure in emergencies or other natural disasters. In their proposals, the deployment phases were not considered to be autonomous or adaptive. Therefore, as the traffic distribution changes, the network may fail to service all the traffic. In [4], the authors proposed an adaptive relocation algorithm to meet the capacity requirements of the traffic; however, the proposed algorithm is centralized and it requires information on global traffic distribution. To the best of our knowledge, there is no distributed algorithm that aims to maximize network coverage subject to capacity constraints. In this paper, we propose an adaptive self-deployment algorithm where base stations employ to autonomously relocate and maximize network coverage subject to their capacity limits. Our algorithm is a sub-optimal solution to a stochastic optimization problem that aims to maximize network coverage subject to capacity constraints. We assume that each base station has access to information about the location of its neighboring base stations and their capacity demand. The rest of this paper is organized as follows. System description, assumptions and problem formulization are provided in Section II. In Section III, our distributed adaptive relocation algorithm is presented. In Section IV, we analyze the efficiency of the proposed algorithm through extensive simulations. Finally, conclusions and future works are presented in Section V.

II. PROBLEM STATEMENT

Consider a set of mobile nodes (i.e. base stations) denoted by $S = \{s_1, s_2, \dots, s_N\}$. We assume that these mobile nodes can communicate with each other in order to form a network. Let Q represent the total geographical area (i.e. target field) which we are interested to cover. Let $P_0 = \{p_{0,1}, p_{0,2}, p_{0,3}, \dots, p_{0,N}\}$ denote the initial position of these base stations where $p_{0,i} \in Q, \forall i \in \{1, 2, \dots, N\}$.

Each user in Q connects to the base station with the strongest reference signal which is greater than some specified threshold (i.e. receiver sensitivity denoted by η_r). For simplicity, we assume a flat terrain propagation field with shadow fading which has the same distribution over the region. We assume all base stations are using equal power for transmission. We also assume that there is an interference-coordination mechanism among adjacent base stations; therefore, interference is negligible. For example, Inter-Cell Interference

Cancellation 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 [5].

We define the coverage area of a base station as the geographical region where the average received signal strength 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 the reliability of connections in the coverage area, we can consider a fade margin η_F which increases coverage probability at cell edge. Our propagation and channel loss assumptions imply that there exists a R_{cov} such that the average received signal strength is greater than $\eta = \eta_F + \eta_r$ for all points at distance less than or equal to R_{cov} of each base station. In order to formalize the average total covered area over region Q , we define the Voronoi region $V_i = V(p_i)$ as follows:

$$V_i = \{q \in Q \mid \mathbb{E}[P_{rx}(p_i, q)] \geq \mathbb{E}[P_{rx}(p_j, q)], \forall j \in \{1, \dots, N\} - \{i\}\} \quad (1)$$

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 and pathloss is proportional to distance, the Voronoi region $V_i = V(p_i)$ will be the set of all points $q \in Q$ such that $dist(q, p_i) \leq dist(q, p_j)$ for all $i \neq j$, $i \in S$.

Based on the defined coverage model, if the coverage area of a base station does not include a point within its Voronoi region, that point (called coverage hole) cannot be in the coverage area of any other base station. We define the coverage metric as follows:

$$O(p_1, \dots, p_N) = \int_Q \max_{i \in \{1, 2, \dots, N\}} f(dist(q, p_i)) d_q = \sum_{i=1}^N \int_{V_i} f(dist(q, p_i)) d_q \quad (2)$$

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

We are also assuming that the spatial distribution of traffic sources in the target field is non-uniform, and slowly variable. This implies that, the amount of traffic in the coverage area of each base station or equivalently its traffic load is also changing. This could lead to situations where one or more base stations are located in traffic hot-spots; and therefore, cannot meet the traffic demand within their coverage area (i.e. become overloaded). 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. However, in order to enhance the performance, such relocations should increase the total traffic served by the network, with the ultimate objective of meeting the total target area traffic demand.

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:

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

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 . III. ALGORITHM DESCRIPTION

Our proposed approach, described in Algorithm 1, makes use of the location and capacity demand of each base station and the base stations in its neighborhood. It applies an adaptation of simulation optimization algorithm presented in [6], which makes use of feasible direction method to carry out constrained optimization. The basic strategy of the algorithm in [6] is to generate a sequence of feasible and improving solutions. If the magnitude of the constraint function is less than a lower threshold, it means the constraint is well satisfied; then, the variables change in order to improve the objective function. If the constraint function is not satisfied and it is greater than an upper threshold, the variables change in order to satisfy the constraint.

Intuitively, Algorithm 1 aims to maximize the network coverage while ensuring that base stations are not over utilized. This is accomplished in two phases. 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 and asking them to get closer. We refer to this phase as load balancing phase. In this phase, the neighboring base stations can relocate closer to the overloaded base stations if they have available capacity. As a result of their moves, some of the traffic in the coverage area of the overloaded base station may be offloaded onto the neighboring base stations. The sequence of these relocations is expected to improve the overall traffic support throughout the target area. As several neighboring base stations could be in similar situations with varying degrees of excess traffic, the algorithm uses the concept of a virtual force to determine the final direction along which an underloaded base station should move.

The virtual force exerted by s_j on s_i is denoted as \vec{F}_{ji} , with the direction from s_i to s_j . The final aggregate virtual force on each base station is the vector summation of the virtual forces from all Voronoi neighbors. These virtual forces will result in base stations moving toward areas with heavy traffic demands i.e. traffic hot-spots. If the aggregate virtual force to a node is zero and the node is not over utilized, it will move in a direction that increases its local coverage. If the aggregate virtual force is not equal to zero, then the moving direction of that node will be the same as the direction of the virtual force vector.

Authors in [7] have proposed an autonomous and distributed relocation algorithm to improve coverage in mobile sensor

Algorithm 1 Autonomous adaptive deployment algorithm

- 1: Each base station s_i broadcasts its location $p_{i,t}$ at time t and its capacity demand ρ_{s_i} to its Voronoi neighbors $\mathcal{N}(s_i)$ and then constructs its Voronoi polygon based on the similar information it receives from other base stations
- 2: **for** each $s_j \in \mathcal{N}(s_i)$ **do**
- 3: $\vec{u}_{ji} = \frac{p_{j,t} - p_{i,t}}{\|p_{j,t} - p_{i,t}\|}$
- 4: $\vec{F}_{ji} = \max\{\rho_{s_j} - 1, 0\} \vec{u}_{ji}$
- 5: $\vec{F}_i = \vec{F}_i + \vec{F}_{ji}$
- 6: **end for**
- 7: \triangleright Each node $s_i \in S$ calculates its new location as follows:
- 8: **if** $\vec{F}_i \neq \vec{0}$ **and** $\rho_{s_i} \leq 1$ **then**
- 9: \triangleright Load-balancing phase
- 10: $\langle \vec{D}_i \rangle = \langle \vec{F}_i \rangle = \frac{\vec{F}_i}{|\vec{F}_i|}$ which is normalized vector \vec{F}_i to unit length
- 11: **else if** $\vec{F}_i = \vec{0}$ **and** $\rho_{s_i} \leq 1$ **then**
- 12: \triangleright Coverage improvement phase
- 13: **if** moving to c_i improves local coverage **then**
- 14: $\langle \vec{D}_i \rangle = \frac{c_i - p_{i,t}}{\|c_i - p_{i,t}\|}$
- 15: **end if**
- 16: **end if**
- 17: $p_{t+1,i} = \Pi_i(p_{t,i} + a_{t,i} \langle \vec{D}_i \rangle)$

networks. The algorithm iteratively updates the location of each node in a way that improves its local coverage in the previously constructed Voronoi polygon. The rationale behind the algorithm is that when the mobile nodes are evenly distributed, none of them should be too far from any of the Voronoi edges or vertices. So a point inside a Voronoi polygon that has the longest distance from the nearest Voronoi vertex/edge is selected as the candidate destination point to relocate. The following theorem proves that there is no degradation in the local coverage of each base station at each coverage improvement round. Therefore, we can employ the algorithm in [7], in order to calculate the relocation direction of each base station in the coverage improvement phase.

Theorem 1. Consider the set $S = \{s_1, s_2, \dots, s_N\}$ of nodes described in the previous section, and let p_i denote the location of node s_i . Let V_i and $\mu(\cdot)$ denote the Voronoi region of node s_i and the area function respectively. $C(p_i, r)$ represents a circle with radius r centered at p_i . If $\exists p'_i \in V_i$ s.t. $\mu(V_i \cap C(p'_i, r)) > \mu(V_i \cap C(p_i, r))$, then

$$\mu(V_i \cap C(q, r)) \geq \mu(V_i \cap C(p_i, r)) \quad \forall q \in L_{p_i, p'_i}$$

Where L_{p_i, p'_i} denotes the line which endpoints are p_i and p'_i . If the local coverage of node s_i at point p'_i is greater than its initial local coverage (which is at point p_i), then its local coverage at any point on the line segment which endpoints are p_i and p'_i is greater than or equal to the initial coverage.

Proof. Proof of this theorem has been omitted for brevity. \square

Based on Theorem 1, if moving base station i to p'_i improves its local coverage, then the local coverage of base station i increases or remains the same if it moves to any point on the line segment between p_i and p'_i . Therefore, to guarantee there is no local coverage degradation in the coverage improvement phase, we define the moving direction to be the unit vector

connecting current location to the destination point obtained by the algorithm in [7].

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. $a_{t,i} = A_i g(\text{step}(t, i))$, where A_i is the scaling factor and $g(\text{step}(t, i))$ is the decaying factor which gradually decreases from 1 to 0. $\text{step}(t, i)$ 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:

- 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 $\text{step}(t, i) = 1$.
- 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 $\text{step}(t, i) = 1$.

$\Pi_i(\cdot)$ in Algorithm 1, represents the projection function. If s is in load-balancing phase, and if $p_{t,i} + a_{t,i} \langle \vec{D}_i \rangle$ falls out of the Voronoi polygon of base station i , then $\Pi_i(p_{t,i} + a_{t,i} \langle \vec{D}_i \rangle)$ will be projected in the polygon. Otherwise, if $p_{t,i} + a_{t,i} \langle \vec{D}_i \rangle$ falls out of the line segment whose endpoints are c_i and $p_{t,i}$, $\Pi_i(p_{t,i} + a_{t,i} \langle \vec{D}_i \rangle)$ will be projected onto c_i .

To conserve energy and decrease unnecessary nodes relocation in the network while providing acceptable service quality, we also propose a stopping criterion. If the base station is in coverage enhancement phase and point c_i (in Algorithm 1) cannot improve the coverage by a threshold ϵ_c , it will not move any further. If the base station is in load-balancing phase and the magnitude of \vec{F} is less than ϵ_{lb} , it will again not move. 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 at the cost of possibly worse performance.

IV. SIMULATIONS AND RESULTS

Consider a target area of size $1800m \times 1800m$. 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 each base station is equal to 16.39dBm/resourceblock. The receiver's sensitivity is considered to be -90dBm.

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 [8]. 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 $u^{new} = \beta HS_u + (1 - \beta)u$. 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 base station is modeled as $40 \log(R) + 30 \log(f) + 49$ where R is in km and f is in MHz. In addition, shadow fading with a standard deviation of 5dB is also considered. 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 $a_{t,i} = \frac{200}{step(t,i)}$, $\epsilon_{lb} = 0.04$ and $\epsilon_{cov} = 1m^2$.

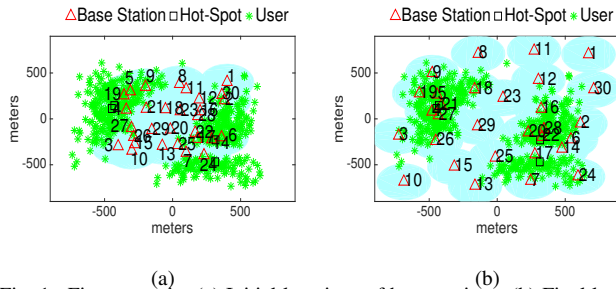


Fig. 1. First scenario: (a) Initial locations of base stations; (b) Final locations of base station after execution of Algorithm 1

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 1(a) shows the initial positions of the base stations (marked by red triangles) along with initial user distribution (marked by green asterisk). Given this initial deployment, base stations 4, 6, 19 and 24 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 1(b) shows the final base station positions after 30 time-steps. Figure 2 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 66% to 96% as well as improving the network coverage from 35% to 77%.

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 3. With an initial uniform deployment of base stations, occurrences of traffic hot-spots will cause several base stations to face traffic above their capacity limits. These situations result in a low average supported traffic of only 70%. Using Algorithm 1, the base stations will adaptively relocate

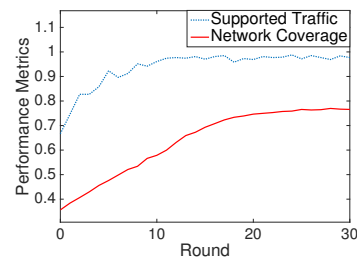


Fig. 2. Network coverage and supported traffic during execution of Algorithm 1 (first scenario)

to meet non-uniformities in the traffic demand; and therefore, the average supported traffic in the network will increase to 96%.

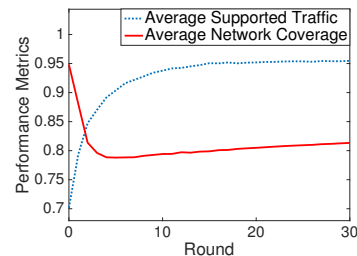


Fig. 3. Average network coverage and supported traffic during execution of Algorithm 1 (assuming a uniform initial deployment)

V. CONCLUSIONS

The variable nature of the spatial distribution of traffic along with the large peak-to-average traffic ratio necessitates judicious and adaptive deployment of cells during emergencies. The execution of our proposed distributed algorithm will effectively adapt the overall network coverage in order to maximize the supported user traffic. Simulations show that substantial gain in performance can be achieved under typical usage scenarios. The authors plan to continue this study for scenarios where the network is composed of a mixture of static and mobile stations.

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