Driving the Deployment of Citywide Ubiquitous WiFi Access

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ABSTRACT

Cost-efficiency is a critical factor for citywide deployments of WiFi networks that are being planned by telecom operators and governments around the world. Building such networks by reusing the broadband infrastructure, currently used only by the mass costumer at home, is an attractive approach to follow. We tackle the problem of selecting locations from the existing broadband infrastructure to build such an overlay WiFi access network. We use an algorithm that solves the budgeted version of the Maximum Coverage Problem to select hotspot deployment points out of the available ones in an area. These points represent premises of the broadband customers where hotspots can be installed. The hotspots are placed in such a way that the connectivity demand in the given deployment area is satisfied at the lowest possible cost. The proposed algorithm is assessed by simulations, applying it to random and real datasets representing access demand, geographical distributions, and locations where hotspots can be deployed. The key findings of this study are: The connectivity demand can be satisfied by the coverage at a cost growing faster than linearly. In fact, the cost of covering the first 85% of the demand is as much as 1/4 of the one needed to satisfy it fully. Additionally, the current broadband penetration in cities, like Berlin, makes WiFi access almost ubiquitous with an average distance between nomadic users and hotspots of 200 m.

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1. INTRODUCTION

A new opportunity for achieving nearly ubiquitous wireless access emerged from the exponential growth of home wireless networking. Broadband access penetration has been constantly increasing in previous years, for example, in Europe there were 77 million DSL lines expected in 2007 [9]. Moreover, the production of WiFi chipsets encompasses the demand for wireless connectivity, and 68 million shipments of wireless devices were expected by the end of 2007 [6]. Internet usage is also growing; an average user expends 48% of her spare time on-line.

This growth in the popularity of WiFi-enabled devices generates a huge potential for wireless services and applications. For this reason, industry and academia are working towards practical solutions that would drastically change the way to access the Internet on the move. Today, users are still aware of the differences between fixed and mobile computing resources. In the future, the goal is to achieve equality in terms of resources and transparent migration between both worlds: wired and wireless.

There are some initiatives that are already tackling the challenges towards ubiquitous wireless Internet. For example, many local governments are pushing the idea of offering citywide wireless access as part of the basic infrastructure, like Paris [10], Berlin, and San Francisco (in the bay area, the existing WiFi network was bought by a star-up company, Meraki Networks [17], from Google). In the industry, there are two different trends that are being followed. On the one hand, telecom operators are expanding the coverage of cellular-a-like wireless networks such as WiMax, EDGE, or UMTS. On the other hand, small companies like Fon [15], Whisher [16], and Sharefi [18] are proposing an alternative: forming communities that share Internet access via WiFi-enabled routers.

The latter enables a safe, low-cost option for nomadic users to have wireless connectivity around urban areas. A previous approach that has been taken to offer this type of solution is the "guerrilla tactic": building community-based wireless mesh networks. However, this has proven to be difficult

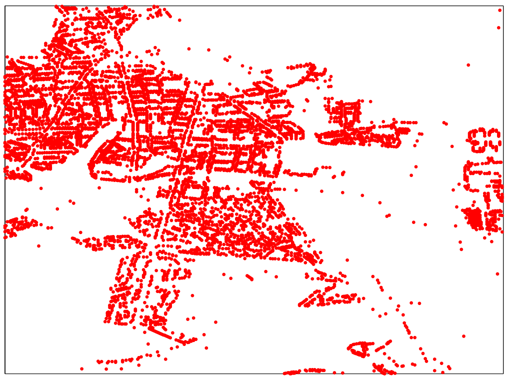


Figure 1: Map of a neighborhood in the city of Berlin (Charlottenburg) that shows the potential locations (households with broadband access) in which WiFi-enabled routers could be opened to nomadic users ($\approx 50km^2$)

to scale beyond certain size (e.g. campus-wide) and it requires additional hardware and effort that someone needs to add. As a counter option, operators are starting to collaborate with commercial ventures, for example British Telecom and Fon, to create these sharing communities boot strapping from the home broadband access network [14]. The idea behind:

To allow sharing broadband connections among private customers and third parties (nomadic users) in a controlled and secure way using WiFi-enabled routers, making better use of underutilized broadband network capacity.

Two important factors for a successful deployment based on this principle are: (a) cooperation with Internet Service Providers (ISPs) that owned the access infrastructure, and (b) control on the process of **opening** home routers to nomadic users, in order to keep a low-cost and efficient deployment of this virtual access-sharing overlay, on top of the actual ISP network.

This paper describes the challenges of selecting locations to open up the existing broadband connections for sharing, so that the service demand of third parties (i.e., nomadic users) is fulfilled in a cost-effective manner. In order to do this, the following steps were performed: (1) formalize the problem, (2) decide on the algorithm to model the problem, (3) implement the algorithm, and (4) test the model with different datasets.

The rest of the paper is organized as follows. Section 2 summarizes the relevant work done in the areas of network planning algorithms and broadband sharing solutions. Section 3 frames the formal description of the problem and the algorithm chosen to solve it. Section 4 mentions the implementation details of the model, followed by Section 5 that discusses the experiments performed to evaluate the solution, as well as the collected results. Finally, Section 6 includes conclusions and future activities.

2. RELATED WORK

The sharing approach towards enabling pervasive wireless access in cities just loom, not much has been published on this topic. However, this section includes work done on two related areas. First, it summarizes the theory used to define and solve the problem of deploying a virtual access overlay on top of an ISP's data network. Then, it includes some of the published work on broadband sharing and community-based approaches to provide connectivity.

Before the formalization of the problem and the selection of an algorithm to solve it, a thorough review of previous methods was done in order to decide the correct action path. The work reported by Johnson in [5] and Khuller et al. in [8] is of great relevance to this paper. Johnson introduced the Set Covering Problem, which can be explained as: Given a finite family $F = \{F_1, F_2, \ldots, Fp\}$ of sets, find a subset F' of F such that the union of elements in F' is equal to the union of elements in F. The measure to minimize is the sum of the cardinality of each element in F'.

Khuller et al. in [8] described a budgeted version of the Set Covering Problem, called Budgeted Maximum Coverage Problem (BMCP), which associates a cost to each element in F, and a weight for each element in the union of the elements in F. Moreover, a budget B is added as a constraint. The solution, again, is a subset F' of F where the total cost of elements in F' does not exceed B, and the total weight of elements covered by F' is maximized. Furthermore, Khuller et al. presented an approximation algorithm to solve BMCP, which achieves an approximation factor of $(1 - 1/\epsilon)$. Other papers related to *Covering Problems* are [3, 7, 13].

In more practical terms, Amaldi et al. [1] tackled the problem of appropriate positioning of indoor WiFi access points in order to achieve network effectiveness. The authors describe a similar approach to the one presented in this paper. They use a greedy phase for selecting the routers to be installed, and they also employ hyperbolic and quadratic objective functions together with a local search phase while considering network performance. However, the work diverts from the one in this paper in the following aspects. First, in the case of [1] the hotspots can be installed after planning for the optimum coverage, whereas in the present scenario the hotspots need to be located in places provided with a broadband connection. Second, Amaldi et al. target indoor environments; the present paper describes an algorithm that works for citywide scales. Last, this solution considers various constraints such as budget and service demand, while the work in [1] focuses on achieving optimum network capacity by reducing interference.

The rest of this section discusses projects related to broadband sharing using WiFi technology. In these lines, Hakegard et al. performed a thorough study of capacity and coverage of WiFi technology in broadband sharing scenarios, the results are reported in [2]. The authors investigated the possibility of providing open broadband wireless access using fixed broadband access lines (privately owned). This scenario is the one assumed by the model described in this paper. The paper concludes that it is feasible to provide outdoor coverage based on the concept of sharing households' Internet access.

Solarski et al. [12] evaluated the performance of the IEEE 802.11 technology in urban environments, and analyzed the impact of typical conditions such as inter-floor connectivity inside buildings, vertical height of the router's location, and indoor router's location. Using the collected data, the authors estimated the potential service range and capacity when sharing broadband connections between home and nomadic users.

Jon Crowcroft et al. [11] presented a mechanism to enable safe WiFi sharing with legitimate guests. The authors described how to architect a citywide cooperative network based on secure tunneling of the data. The authors discuss some security concerns related to this type of deployments, and they do not deal with the deployment challenges of such a sharing overlay.

3. PROBLEM DEFINITION

In this section we present the mathematical formulation of the problem of deploying a citywide WiFi network on top of existing ISP broadband access networks, for the rest of the paper **Deployment Problem** (DP). This section also includes the algorithm selected to solve DP based on a reduction from DP to BMCP [8]. Informally, DP chooses the best places (points) over a set of possible locations to open up the broadband connections, where "best" means: the set of points through which the deployment approximates to satisfy, as close as possible, a predefined demand function.

3.1 Deployment problem

To define DP formally, we state some assumptions and definitions. The area covered by a WiFi-enabled broadband device or router is assumed to be a circle. In addition, each router has certain capacity that can be expressed in terms of bandwidth, throughput, or users served. Hence, the 2-tuple (r_w, c_w) is used to represent a router w and to denote its *coverage radius* and *service capacity*, respectively.

In DP, the router characteristics (i.e., coverage radius and service capacity) can be chosen from a finite set. Let $R = \{(r_i, c_i)\}$ be the finite set of different router types that can be deployed. It is assumed that a router can be deployed only in places with an existing broadband connection to Internet (e.g. DSL connection, cable modem, etc.). Thus, a set of *possible points* to deploy a router is part of the input to DP. Let $P = \{p : p \in \Re^2\}$ be the set of possible points in which routers can be set up. In the present case, it is assumed that the size of R is smaller compared to the size of P, a constant for the size of the input. This assumption is based on the fact that there are fewer different combinations of router characteristics used in commercial hardware. This is a consequence of the existing standards and regulations in the industry.

The *total area* that can be covered by an access sharing overlay network is defined using P and R. This area is defined by the union of the biggest router (i.e., the circle with the maximum radius) placed at each possible point. The total area is the reachable area using P and R and is denoted by $\breve{P}$. For the implementation, explained in the next section, the smallest rectangle containing $\breve{P}$ is used as the *work area.*

The *service demand* is defined as a function over $\breve{P}$, $N : \breve{P} \rightarrow \mathcal{M}$, where $\mathcal{M}$ is a space with the same measure as the service capacities of the routers, e.g., bandwidth, throughput, served users, etc., and $N(p)$ represents the service demand in point $p \in \breve{P}$. Since for the implementation, the work area is defined as the smallest rectangle that contains $\breve{P}$, N is defined over this rectangle with $N(p) = 0$ when p is not in $\breve{P}$ but in the work area. Moreover, there is a *cost function* C defined over PXR that for each pair (p, w) of a point $p \in P$ and a router $w \in R$, $C(p, w)$, assigns the cost to deploy w in p.

A *deployment* D is defined as a set of pairs (p, w), point and router, where the pair (p, w) means that router w is placed at point p. The *cost* of a deployment D is the sum of the cost of each pair in D, i.e., $C(D) = \sum_{(p,w)\in D} C(p, w)$, where $C(D)$ denotes the cost of D.

The *service capacity* of a deployment in a given point is the service offered by the deployment at that particular location. Formally, it is say that router w placed at point p *covers* point q if the distance between p and q is smaller than w's coverage radius r_w. The service capacity of deployment D at point p is the sum of the capacities of all routers in deployment D that cover point p. Let $D(p)$ denote the service capacity of D in p. Then, the service capacity of a deployment is the surface generated by its service capacity in each point of the total area, i.e., the service capacity of D is the function $D : \breve{P} \rightarrow \mathcal{M}$, where $D(p)$ is the service capacity of D at point p.

The problem is constrained by a budget B, consequently, the cost of a deployment must be smaller than the budget in order to represent a potential solution to the problem. The goal of DP is to find a deployment restricted by the budget with a service capacity that matches, as close as possible, the service demand. This means to find the deployment that minimizes $\int_{\breve{P}} \max\{N(p) - D(p), 0\}dp$ among those with $C(D) \leq B$.

The statement of the Deployment Problem (DP) is as follows:

Input:

- Set $P = \{p : p \in \Re^2\}$ of possible points.
- Set $R = \{(r, c) : r \in \Re, c \in \mathcal{M}\}$ of different types of routers.
- Demand function $N : \breve{P} \rightarrow \mathcal{M}$.
- Cost function $C : PXR \rightarrow \Re$.
- Budget $B \in \Re$.

Output:

A deployment $D = \{(p, w) : p \in P, w \in R\}$ in which

$$C(D) = \sum_{(p,w)\in D} C(p, w) \leq B$$

and that minimizes $\int_{\breve{P}} \max\{N(p) - D(p), 0\}dp$.

3.2 Solving the Deployment Model

The Budgeted Maximum Coverage Problem (BMCP) [8] is used to solve DP. The BMCP is defined as follows: A collection of sets $F = \{F_1, F_2, \dots, F_m\}$ with associated costs $\{c_i\}_{i=1}^{m}$ is defined over a domain $X = \{x_1, x_2, \dots, x_n\}$ of elements with associated weights $\{w_i\}_{i=1}^{n}$. The goal is to find a collection of sets $F' \subseteq F$, such that the total cost in F' does not exceed a given budget B, and the total weight of elements covered by F' is maximized. In the statement of DP the uncovered service demand is minimized, which is equivalent to the BMCP maximization, the total weight covered.

In order to transform an instance of DP into an instance of BMCP, the input of DP is transformed into an input of BMCP. Thus, DP may be solved using the algorithm proposed by Khuller et al. in [8] to solve BMCP. The transformation builds an equivalent set F in BMCP from P and R in DP. The weights are given by the demand function N and the costs by the cost function C.

Algorithm 1 Solve DP:

Generate F from P and R;
$G \rightarrow \{\emptyset\}$; $C \rightarrow 0$; $U \rightarrow F$;
while $U \neq \{\emptyset\}$ **do**
  Select F_i in U that maximizes $\frac{1}{C(F_i)} \int_{F_i} \max\{N(p) - D(p), 0\}dp$
  if $C + C(F_i) \leq B$ and $\int_{F_i} \max\{N(p) - D(p), 0\}dp > 0$ **then**
    $G \rightarrow G \bigcup F_i$
    $C \rightarrow C + C(F_i)$
  end if
  $U \rightarrow U \backslash F_i$
end while
OUTPUT G

The construction goes as follows: for each pair (p, w) in PXR generate an element in F defined by the region covered by w placed at p. Since it is assumed that the size of R is a constant, this mapping does not increase the size of the input—F is linear with respect to the size of P. Thus, the solution proposed by Khuller et al. can be applied to solve DP (see Algorithm 1 for the pseudo-code).

4. ALGORITHM IMPLEMENTATION

The implementation was designed following procedural programming techniques because the use of functions, variables, and modules simplify the implementation of algorithms coming from a mathematical context. The following software and hardware was used during the implementation and evaluation of the algorithm: MATLAB 7.03 running on a IBM personal computer with an Intel Pentium M processor 1.86 GHz and 1.00 GB of RAM.

Figure 2 shows the flow chart of the algorithm showing the main functions and the execution sequence. The first two steps (1)(2) of the algorithm load the input variables, described in Section 3, and estimate the total demand that can be covered in the case that all routers were opened to third-parties. This is calculated by adding the coverage area that each router $w \in R$, placed at point $p \in P$, covers inside the demand area N. The coverage area and service capacity of each router vary according to different factors such as interference generated from the environment, position with respect of the user, and number of users connecting to the network. These factors might be represented in the input by using different router characteristics.

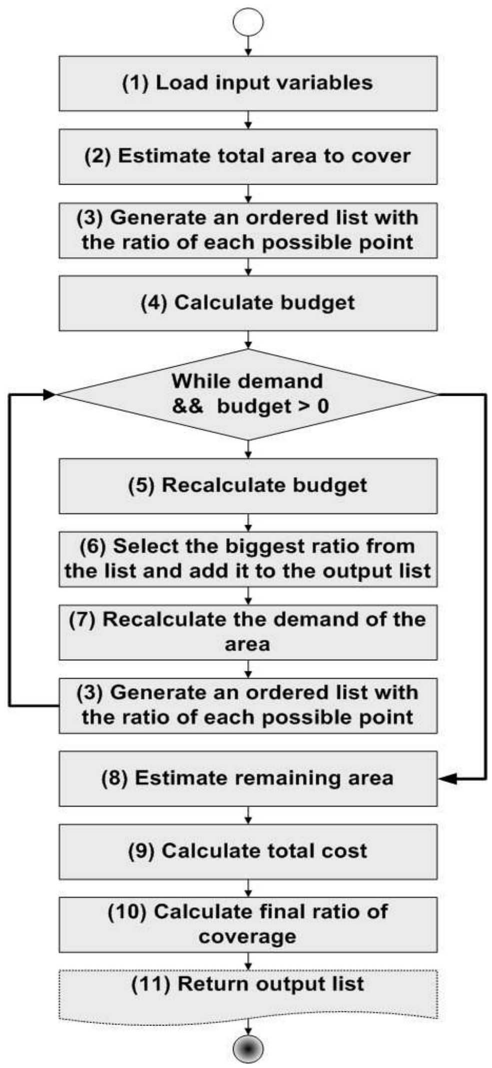


Figure 2: Flow chart

Step (3) computes for each pair (p, w) the integral

$$\frac{1}{C(p,w)} \int_{F(p,w)} \max\{N(q) - D(q), 0\}dq,$$

where $F(p, w)$ represents the circle covered by w placed at p. This calculation gives the ratio between the new demand and the cost.

A first implementation of the algorithm, using the quadratic functions available in MATLAB, demanded an extremely high computational effort, which in the experiments translate into several days of processing due to the global-scale (citywide) of the access network being deployed. To enhance this situation, the work area described in Section 3 was defined using a mesh grid with x and y ranges representing

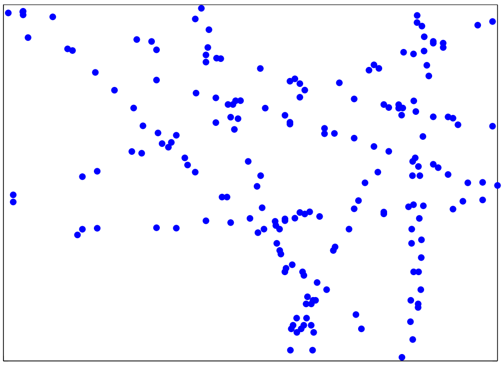


Figure 3: Example of an input for the algorithm: Set of possible points in a random city

Figure 4: Output of the algorithm deployment using the real locations dataset as the input. The figure shows the final area covered using the algorithm deployment.

axis coordinates. The demand N, as well as the possible points p with their respective coverage area, were mapped to the work area and saved into files. Then, it was possible to use matrices to compute the described operations and the computational time decreased from days to hours. Furthermore, the mesh grid allows changing the precision of the integral, and as the processing time increases with the precision, a mesh grid enables to manage the computational time by adjusting this setting.

In step (4) the budget is calculated. In general the budget is an input of the problem, however, in the performed experiments (discussed in Section 5) a standard budget depending on the rest of the inputs is computed(see Equation (1)).

After obtaining the budget in step (4), the main loop begins. The next three steps (5)(6)(7) reduce the budget by the cost of the previous deployment (5), select the 2-tuple (p, w) with the greatest ratio and add this tuple to a final *output list* (6), and modify the demand function N accordingly (7), reducing this function in the area covered by the selected router w placed at p. Since the demand function N is modified, the calculation of the ratio between the demand covered and the cost of deploying the routers has to be updated (step (3) is executed one more time).

When the loop ends, an estimation of the remaining area to be covered is computed, as well as the total cost of the solution. The final ratio of coverage ($(T-R)/T$, where T is the total demand that can be covered and R the remaining demand) is also computed. In the final step (11) the algorithm returns the output list with the chosen points for the deployment.

5. EXPERIMENTS AND RESULTS

This section includes the discussion on the experiments performed in order to evaluate the implementation described in Section 4, and it is twofold. The first part includes the inputs of the experiments such as cost function, demand function, budget, and distribution of broadband connections. The second part presents the results and includes a discussion on the main findings.

5.1 Simulations

Some experiments were designed to understand the behavior of cost versus efficiency (cost-efficiency) in a certain deployment as a result of the algorithm 1. These experiments were repeated several times and only the budget changed (increased) in each iteration. After every run the ratio between the demand covered by the solution and the total demand that could be covered was computed. This process was repeated until the total demand was completely fulfill, or the ratio was equal to 1.

An *input set* is composed of five parts: the set of possible points, the set of different router characteristics, the demand function, the cost function, and the budget. Two different input sets were employed to test the implementation; these are called *real city* and *case city*. The corresponding set of possible points are shown in figures 1 and 3, respectively.

The budget B is defined in both cases as follows:

$$B = c(T/\bar{w})C \tag{1}$$

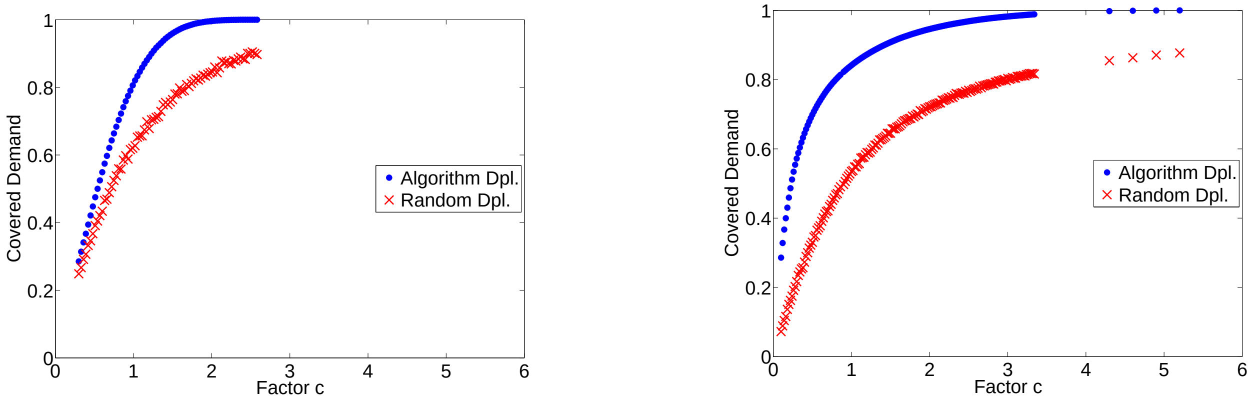
where T represents the total demand that can be covered by running the algorithm, $\bar{w}$ is the average service capacity covered by the routers in R, and C is the average deployment cost of a router. Finally, c is the variable factor used to increase the budget evenly, and it is called *over provisioning factor*. Notice that when $c \geq 1$ the algorithm has enough budget to give a solution that fully covers the demand (if this is geographically possible), and when $c < 1$ the solution restricted by the budget cannot fulfill the complete service demand.

For both input sets, the cost is defined equal to 1. Hence, in Equation (1) C constant value is 1. The rest of the components are detailed for each input set in the next section.

Case city

The first type of input was randomly generated; it is called *case city*. A case city is expressed as follows: a $[0, 1] \times [0, 1]$ square is defined as the work area, representing 1 km^2. Over

Figure 5: Over provisioning in a broadband sharing scenario.



(a) Random Data

(b) Real Data

this square *random streets* are described, each one limited by a line between two random points chosen in opposite borders of the square. A set of possible points (192 points) was randomly selected over the random streets (Figure 3).

The demand function N is defined using random streets. Over each random street a service demand is associated with a particular behavior. As the deployment intends to represent a citywide network, it is assumed that the demand grows on the sidewalks' area, and it decreases closer to the buildings and to the traffic areas. To represent this, the sum of two Gaussian distributions is utilized along the streets; each peak demand is placed at one of the two sidewalks of a street. The sides of the distributions represent the possible buildings or the traffic zone of a street. The final demand function is the sum of the demands across all the random streets. As a simplification, only one type of router with radius 0.04 and capacity 0.5, modeling 40 m and 5 $Mbps$, was deployed.

The experiment was done using 6 different sets of random points. For each run, the value of the over provisioning factor was increased starting from 0.3 and adding 0.03 to the value in each iteration. The process was repeated until the solution given by the algorithm completely fulfilled T (total service demand). Figure 5(a) shows the output of these experiments, these results will be discussed in the next section.

Real city

The second dataset applied to evaluate the algorithm contains data points describing the real distribution of broadband connections in the neighborhood of Charlottenburg, Berlin. The data includes completely anonymous geographical locations of over $41,000$ DSL-lines that represent the set of possible points for the algorithm (see Figure 1). To select the set of possible points the following selection criterion was applied: only the routers located in the lower floors and close to a window are useful to provide outdoor coverage (see urban WiFi evaluation in [12]). This lead to a number of $7,161$ possible points in the Charlottenburg zone.

To make the simulation as realistic as possible, the service demand is computed using the information collected from a collocated cellular network (over the same geographical area), and it is based on the IP traffic data gathered from the cellular base stations. The demand function is formulated inside a particular *coverage zone* surrounding the base stations, which can include more than one possible point (router). The total IP traffic (data services) of each base station is assigned to this zone as the correspondent total demand. The reasoning behind it is that a good starting point to estimate the future demand of nomadic users in a citywide WiFi network can be the current data services usage in cellular networks.

For this experiment a set of router characteristics is defined using four different radius (29 m, 47 m, 53 m, 59 m) and four different service capacities (1000 $kbps$, 2000 $kbps$, 6000 $kbps$, 16000 $kbps$). The radius were defined based on the standard $ITU - RM$.1225 for pedestrian outdoor environments [4] in order to obtain the maximum coverage distance of an standard router. This coverage distance depends on the Line-Of-Sight (LOS) between the router and nomadic users and the materials of the obstacles in between. Thus, the coverage model was calculated for different materials, and four were randomly selected for these experiments. Moreover, several indoor locations were considered for the router, affecting the LOS component (based on the study published in [12]). The remaining router characteristics were taken from existing commercial technical specifications.

Finally, the total capacity was calculated based on average speeds for broadband DSL connections. standard speed for DSL lines. When all these elements were compute, a 2-tuple of radius and capacity was associated to each point $p \in P$. In these runs, the over provisioning factor increases 0.01 every iteration, and the initial value was set to 0.1. Intuitively, $c = 1$ means that there are enough "resources" to fulfill the total demand, when there is no coverage overlapping among the hotspots installed.

To validate the efficiency of the *algorithm deployment*, the solution is compared to a *random deployment*. The latter implies that the sharing overlay network is built by opening up routers in random locations within a specific area, without any sort of control on the process. In these simulations both, the random deployment and the algorithm deployment select the same amount of routers to share the broadband connection. The results are discussed in the next section.

5.2 Over provisioning

Figures 5(a) and 5(b) show the outcome of the experiments using case city and real data as inputs, respectively. The X-axis represents the over provisioning factor and Y-axis the percentage of covered demand. The dots represent the results of an algorithm deployment and the crosses the results of a random deployment.

Figure 5(a) shows that when modeling a case city (based on the rules mentioned in Section 5.1) the resulting deployment fulfills the total demand when the over provisioning factor is equal to 2. A random deployment covers only around 85% of the demand at the same c factor value. For the case of the real dataset (i.e., Charlottenburg), Figure 5(b) shows that the total demand is covered for an over provisioning equal to 5 while, again, a random deployment covers around 85% for the same over provisioning.

A possible reason for the difference between the final over provisioning factors in both cases can responded to the density of the set of possible points. For example, in the case city the density of possible points is lower than in the real city, conducting to a more efficient use of the routers. In a scenario with lower density, the overlapping of two routers (in terms of coverage) is less. From figures 5(a) and 5(b), it can be observed that the deployment cost grows faster than the percentage of demand covered.

5.3 Average distance

Even when the goal of the present method is not to cover an area in terms of extension, it is interesting to analyze the algorithm from the angle of coverage efficiency. Therefore, the minimum and average distances between any point and a location within WiFi coverage are calculated. In order to do this a new grid with a density 10 times bigger than the main grid is created and the distance from each of its points to the covered area is computed. This computation is repeated varying the budget B when increasing the value of the over provisioning factor.

Figure 6 shows that for evaluating distances the algorithm deployment has a similar behavior compared to a random deployment. The dots show the average distance using the algorithm and the crosses show the average distances using a random deployment. For these experiments the work area was a rectangle of approximately 50 km^2, and the possible deployment locations were given by the real dataset (see Figure 1) of DSL locations in Berlin.

The deployments based on the described algorithm have a minimum average distance of ~ 200 m, whereas for random deployments the minimum average distance is around 173 m. It is correct to assume that when $c = 0.34$ the random deployment has reached its minimum average distance, while

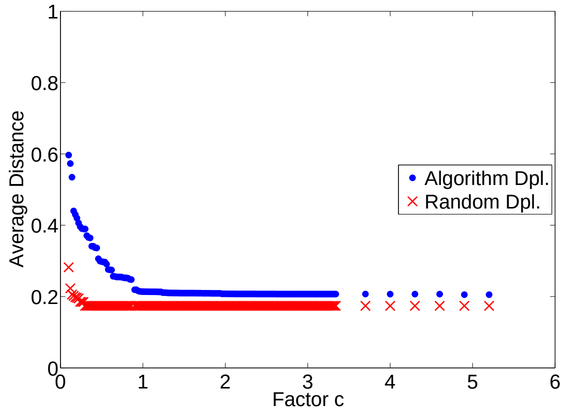


Figure 6: Average distance in random vs. DP deployments using the real DSL distribution dataset.

for the same over provisioning factor the solution obtained using Algorithm 1 has an average distance equal to 365 m.

This can be explained due to the fact that this algorithm is design to cover demand, not to maximize the wireless coverage. This means that if a certain point has a high demand, then the algorithm will deploy many routers in the same location, until the demand is fulfilled as much as possible. In the case of random deployments, routers are installed in random points independently of the local demand. For example, in the case of an over provisioning factor equals to 0.34, the random deployment has reached its minimum average distance, covering less demand than the solution obtained using Algorithm 1.

Moreover, Figure 6 also shows that for the Charlottenburg area the average distance to the nearest hotspot is around 200 m, even when increasing the over provisioning. Thus, a nomadic user walking in this area could access the Internet by reaching the nearest hotspot within 180 s, considering the typical walking speed of 5 km/h.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we have shown that citywide deployments of WiFi networks can be driven with the correct tools that assist network engineers in this challenging task —to achieve the needed cost-effectiveness during the installation. It is shown that this deployment problem can be tackled using a modification of the well-known BMCP algorithm. An implementation of this version of the BMCP algorithm was programmed and evaluated using different input sets. As a result of the evaluation experiments, the following conclusions were drawn:

- The deployment cost grows faster than linearly with respect to the percentage of demand covered.
- Covering the area where there is some connectivity demand is not enough to cover the total connectivity demand. In fact, covering the area with the demand fulfills less than 40% of the total demand in the studied real city and 50% in the randomly-generated city.

- Covering 99% or more connectivity requires a budget that is a few times higher than the budget needed to offer some connectivity in an area. In fact for this study, it is the factor of 2 for the random city and the factor of 4 for the real city.
- The average distance to the nearest hotspot in the deployment area, covered only where connectivity exists, stays around 200 m. Consequently, the nomadic user can access Internet by reaching the nearest hotspot within 160 s walking at a typical speed of 5 km/h. Nevertheless, the complete service demand is not fulfill.

The intended future work includes further development of the current model implementation to build a user-friendly software tool. Even though the main functionality is to locate a set of suitable places to deploy routers, this tool could provide more information. For instance, the application may compute the minimum, maximum, or average distance from any point in the region to a place with WiFi access, and this information can be used to develop location-based mobile services. Other useful data that the application could provide is to select the most appropriate characteristics of routers for a specific deployment.

In terms of the algorithm special additions are proposed for future versions. Overall the input of the algorithm could be conveniently modified to improve results. The existing interference in the network generated by the fixed broadband access lines might be estimated, thus, modifying the coverage and capacity values of the routers while maintaining independence with its main flow.

The objective function could be modified as it pursues a deployment where the given demand area is satisfied at the lowest possible cost; a modified objective function will improve the results in particular scenarios, assigning, for example, greater importance to a certain zone of the demand that must be covered.

In terms of visualization, the goal is to show the results in real maps mapping geographical coordinates into the simulation grid. The demand could be seen in a 3D graphical application, in which the fulfilled demand can be verified at any point while the locations for the routers are selected.

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