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Convolution-Based Placement of Wireless Base Stations in Urban Environment

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***Abstract*—In this paper, we introduce a novel approach for computing the number, location, and transmission powers of wireless base stations in a 2-D urban setup. The new approach utilizes 2-D convolution to extract the supply–demand correlation. Available efficient methods for computing the convolution are then used to substantially reduce the complexity of the solution. The proposed approach enables network designers to choose arbitrary antenna propagation and radio demand patterns using a simple color-coding mechanism. Simulations of the proposed algorithm show its efficiency and flexibility in solving the placement problem. In this paper, we consider only the coverage planning. Consequently, the technique in this paper is useful in networks that operate with time-division multiple-access technology. However, the work can be extended to consider simultaneous coverage and frequency planning.**

***Index Terms*—Base station (BS), cell planning, convolution, placement, wireless communications.**

I. Introduction

The placement of wireless base stations (BSs) has been a challenging problem that involves many design parameters. Existing automatic placement techniques are insufficient in both the modeling and solution phases. Modeling placement problems using optimization techniques such as simulated annealing or integer programming is usually a difficult task. In integer programming, for example, the number of variables is proportional to the number of points inside the grid, which is usually large for typical practical scenarios. In the solution phase, the number of computations dramatically increases with the number of grid points on the site map [7]. For this reason, these techniques are limited to solving placement problems with a relatively small number of grid points.

One of the first attempts to solve the placement problem was presented in [1]. In this paper, the solution of single- and multiple-transmitter problems was considered. The problem was modeled as a nonlinear program, and then, three nonlinear optimization algorithms were considered to solve this model. The work in [2] formulated the placement problem as a large-scale combinatorial optimization model. The model was then solved using the simulated-annealing approach. Similar models were developed in [3]. In [4], a variant of the Simplex method was used to solve the placement problem where the objective was to maximize the percentage coverage. A genetic approach was used in [5] to find the near-optimal location of the BSs. In [6], a sequential algorithm was formulated and used to solve the placement problem. Finally, the work in [7] considered integer programming to solve the location problem.

In this paper, we propose a fundamentally new approach for solving the BS placement problem in a 2-D urban environment. The approach is versatile and can adopt arbitrary radio propagation and demand patterns. The method uses the convolution to find the minimum number and location of BSs that satisfy the coverage requirement. The user interface of the proposed approach allows the designer to provide a color-coded map of the demand pattern and any arbitrary antenna propagation pattern. Since only coverage planning is considered in this paper, it can be useful in cellular networks that operate with time-division multiple-access technology. However, this paper can be extended to consider simultaneous coverage and capacity planning. This way, the proposed approach may be used for networks that are based on wideband code-division multiple access.

II. Problem Formulation

In this paper, we only consider the number of BSs, their locations, and the transmission power. Other parameters such as antenna height and frequency planning are not considered. Furthermore, since an urban setup is assumed, signal attenuation due to walls and obstacles is not considered. Finally, the antennas are assumed to be of a fixed type throughout the design space and have the same direction. These assumptions were made only to simplify the presentation of the proposed solution.

The objective of the placement problem is to minimize the total number of BSs N such that the virtual power inside a 2-D Euclidean space Γ is at least equal to the power threshold α at all locations. In other words

$$p(x,y) \geq \alpha \qquad \forall\, x,y \in \Gamma \tag{1}$$

where $p(x,y)$ is the virtual power at the point with coordinates (x,y).

To find an expression for $p(x,y)$, let us define the quantity $s_n(x,y)$ as the power supplied by the nth BS to the mobile station at location (x,y). This quantity simply indicates the signal strength at location (x,y) due to station n. It is dependent mainly on the radio propagation loss and the gain of the transmitter antenna. For example, for an omnidirectional antenna in free space, the quantity $s_n(x,y)$ is given by the well-known Friis equation [12]

$$s_n(x,y) = \overline{p}_n G_t G_r \left(\frac{\lambda}{4\pi h_n(x,y)}\right)^2 \tag{2}$$

where $\overline{p}_n$, G_t, G_r, and λ are the transmission power, transmitter gain, receiver gain, and wave length, respectively. $h_n(x,y)$ is the distance between point (x,y) and BS n.

Let us also introduce the term $d(x,y)$ to represent the radio demand level at point (x,y). This quantity is affected by the different coverage priorities and the extra signal attenuations at location (x,y).

Then, we can define the virtual power p at location (x,y) as the difference between the supply and demand of radio coverage, i.e.,

$$p(x,y) = \max_{n=[1,N]} \{s_n(x,y)\} - d(x,y). \tag{3}$$

We assume here that the mobile station at location (x,y) will connect to the BS that delivers the *maximum* signal power.

Manuscript received February 19, 2007; revised September 14, 2007, December 14, 2007, and January 21, 2008. First published February 15, 2008; current version published November 12, 2008. This work was supported by the King Fahd University of Petroleum and Minerals. The review of this paper was coordinated by Dr. P. Lin.

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Digital Object Identifier 10.1109/TVT.2008.918707

The objective of the placement problem is to find the minimum number of BSs and their locations that will satisfy power constraint (1), where $p(x,y)$ is given by (3).

A. Discretization of the Model

To solve the placement model previously discussed, the continuous space is first discretized into a finite number of points that form a uniform grid of size (I,J). The number of divisions in the grid depends on the required resolution and computation limitations. The variables $p(x,y)$, $s_n(x,y)$, and $d(x,y)$ are discretized in 2-D Euclidian space to form the matrices P, S_n, and D, respectively. Therefore, the optimization problem can be written in matrix format as

$$\min \quad N \tag{4}$$

subject to

$$P_N = \max_{n=[1,N]} \quad \{S_n\} - D \geq \alpha\Theta \tag{5}$$

where P_N denotes the power pattern matrix of size $(I \times J)$ after assigning N BSs, S_n is the power supply matrix for the nth BS, D is the demand pattern matrix, and Θ is a matrix full of ones. More details about designing demand matrix D will be provided in Section IV-B. Notice that this constraint states that all the elements of matrix P_N should be greater than the power threshold α.

Matrix S_n can be broken down into the convolution of two matrices as follows:

$$S_n = A \otimes X_n \tag{6}$$

where the symbol $\otimes$ indicates the 2-D convolution. Matrix A (of size $(I_A \times J_A)$) is a fixed propagation pattern matrix of the transmitter radio antenna. The design of this matrix will be discussed in more detail in Section IV-A. Matrix X_n indicates the location of BS n. If we denote this location by the coordinates (u_n, v_n), then X_n has all its elements equal to zero, except at (u_n, v_n), where it is equal to "1." In other words

$$X_n(i,j) = \begin{cases} 1, & \text{at } (u_n, v_n) \\ 0, & \text{elsewhere.} \end{cases} \tag{7}$$

For the sake of illustration, suppose that

$$A = \begin{bmatrix} 30 & 50 & 30 \\ 50 & 100 & 50 \\ 30 & 50 & 30 \end{bmatrix} \text{ and } X_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

Then

$$S_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 30 & 50 & 30 \\ 0 & 50 & 100 & 50 \\ 0 & 30 & 50 & 30 \end{bmatrix}.$$

The convolution values outside the range of matrix X_n are simply truncated. Notice that the objective of the convolution here is to surround the unique nonzero element in X_n with propagation matrix A. Therefore, the convolution operation in this case can very efficiently be performed by simply shifting the elements of matrix A by (u_n, v_n).

Notice also that minimizing the number of BSs N is equivalent to minimizing the summation norm of the location matrices X_n for all BSs. In view of this fact, the optimization problem can finally be written as

$$\min \quad \left\| \sum_{n=1}^{N} X_n \right\| \tag{8}$$

subject to

$$P_N \triangleq \max_{n=[1,N]} \quad \{X_n \otimes A\} - D \geq \alpha\Theta. \tag{9}$$

The representation of the placement problem in this matrix format helps when borrowing useful tools from the matrix theory to find a near-optimal heuristic solution for this problem. This will be discussed in the next section.

III. Solution of the Placement Problem

The optimization problem (8) and (9) is solved in this paper using a simple and efficient heuristic approach. This approach turned out to offer high flexibility in choosing arbitrary propagation and demand patterns. It also allows a simple user-interface modeling of the problem and provides the solution in a relatively short time. The solution approach uses the convolution operation as a core process to measure the correlation between the supply and demand of wireless coverage. Efficient ways to compute convolution are then used to substantially reduce the required computation complexity.

A flowchart of the proposed algorithm is shown in Fig. 1. To determine the amount of power consumption associated with placing a BS at a certain grid point, antenna propagation matrix A is convolved with the existing power pattern P_{n-1} that resulted from previously assigned BSs, i.e.,

$$Y_n = A \otimes P_{n-1}, \quad P_0 = -D. \tag{10}$$

The role of the convolution here is given as follows: For each point on the current power pattern P_{n-1}, the antenna propagation A is centered at that point and dot-multiplied with the intersecting sector of P_{n-1}. The multiplication values are then summed up, and the answer is stored at the corresponding point in Y_n. This convolution process is repeated for all other points in P_{n-1}.

The coordinates that correspond to the minimum value of matrix Y_n indicates the highest consumption. This point is chosen as the location of the nth BS

$$(u_n, v_n) = \arg\min_{(i,j)} \quad Y_n. \tag{11}$$

Once a new BS location is chosen, location matrix X_n is constructed from (7). The power matrix is then updated as follows:

$$P_n = G_n - D, \qquad n = 1, 2, \ldots, N \tag{12}$$

where G_n is the accumulated supply of power (by stations 1 through n). This matrix can iteratively be computed from

$$G_n = \max\{G_{n-1}, S_n\} = \max\{G_{n-1}, A \otimes X_n\} \tag{13}$$

starting from the zero matrix ($G_0 = \mathbf{0}$). In summary, given the propagation and demand matrices A and D, the location of the BSs is determined by iterating (10)–(12). The algorithm terminates when

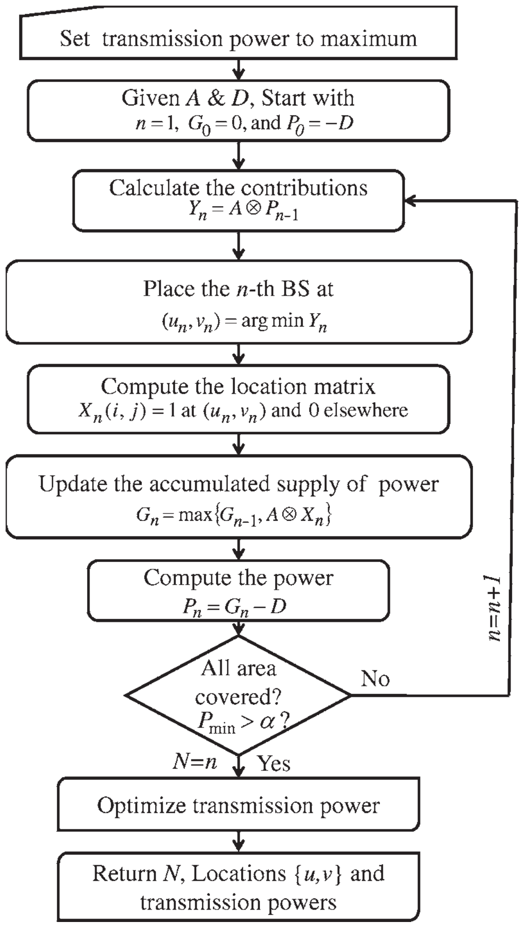

Fig. 1. Flow diagram of the proposed placement algorithm.

the constraint (9) is satisfied, or, equivalently, the minimum power $p_{\min}(n) \triangleq \min\{P_n\}$ exceeds threshold α. The algorithm then returns the total number of stations N, their locations, and the minimum power value $p_{\min}$.

A. Solution Verification

Since the analytical solution for the placement problem given by (8) and (9) is not available, we follow two numerical approaches to verify the proposed solution. First, the algorithm is implemented on simple models where solutions are known, and the results are then compared [8]. Second, the solution is verified by performing an exhaustive search on all possible locations. The search challenges the algorithm by trying to find one of the following:

1) a lower number of BSs that meets the coverage requirements ($p_{\min} > \alpha$);
2) a different location of the same number of stations that provides better power coverage (higher $p_{\min}$).

IV. Network Design Considerations

One of the main advantages of the proposed scheme is that it can provide high flexibility for network designers to choose arbitrary radio propagation and demand patterns by selecting proper structures of matrices A and D. In the following, we describe in more detail the role of these matrices in the network design process.

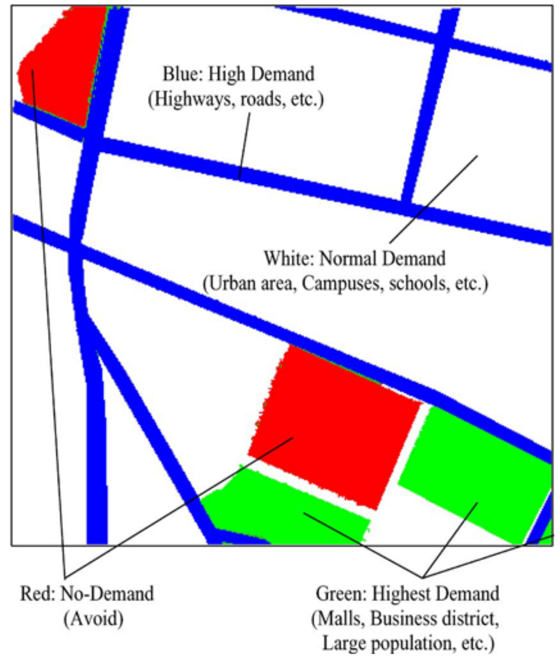

Fig. 2. Example of representing the demand levels using color codes on a real map.

A. Design of Propagation Pattern Matrix A

Propagation pattern matrix A describes the power propagation and path loss model for the BS antenna. An example of matrix A is

$$A = \begin{bmatrix} 3 & 4 & 5 & 6 & 6 & 6 & 5 & 4 & 3 \\ 4 & 5 & 7 & 9 & 10 & 9 & 7 & 5 & 4 \\ 5 & 7 & 11 & 17 & 20 & 17 & 11 & 7 & 5 \\ 6 & 9 & 17 & 33 & 50 & 33 & 17 & 9 & 6 \\ 6 & 10 & 20 & 50 & 100 & 50 & 20 & 10 & 6 \\ 6 & 9 & 17 & 33 & 50 & 33 & 17 & 9 & 6 \\ 5 & 7 & 11 & 17 & 20 & 17 & 11 & 7 & 5 \\ 4 & 5 & 7 & 9 & 10 & 9 & 7 & 5 & 4 \\ 3 & 4 & 5 & 6 & 6 & 6 & 5 & 4 & 3 \end{bmatrix}. \tag{14}$$

The numbers represent the power attenuation due to path loss for an omnidirectional antenna. The numbers are normalized, starting with 100% at the center. Basically, any other propagation patterns can be represented by choosing proper values inside A.

B. Design of Demand Pattern Matrix D

Demand pattern matrix D plays a major role in the design of wireless networks using the proposed approach. It gives the designer the flexibility to choose any arbitrary demand patterns. Fig. 2 shows an example of a color-coded map that represents the coverage demand pattern in different parts of a real map. Each color represents a level of demand. In this example, the regions in green have the highest demand. Blue and white represent the high- and normal-demand regions, respectively. Red represents the no-demand regions, within which, the algorithm should avoid placing BSs.

The algorithm then interprets this colored map and builds demand matrix D with values that are proportional to the demand level. The positive values in D would result in high consumption in Y_n [see (10)] and therefore will be chosen first for BS locations. On the other hand, regions with no demand are reflected by negative values in D. Consequently, these regions will have low consumption, and therefore, the algorithm will avoid placing BSs at these locations. Finally, normal demand is represented by zero values in D. This choice is intentionally made to further reduce the computation complexity, as will be described in Section VI.

Using this color-coding technique, network designers can set any arbitrary levels of demand. Although the example in Fig. 2 shows only four demand levels, this number can be increased, as desired.

C. Penalizing Boundaries of the Demand Grid

Since the design space is always provided as a confined rectangular region, demand matrix D needs to be surrounded by a negative frame value w, as illustrated by the following example:

$$D = \begin{bmatrix} w & w & w & w & w & w & w \\ w & -5 & -5 & 0 & 0 & 0 & w \\ w & -5 & -5 & 0 & 0 & 0 & w \\ w & -5 & 0 & +10 & +10 & +5 & w \\ w & 0 & 0 & +10 & +10 & +5 & w \\ w & 0 & 0 & +10 & +10 & +5 & w \\ w & w & w & w & w & w & w \end{bmatrix}. \quad (15)$$

The purpose of the penalty w is to push the locations of the BSs inward and therefore increase the coverage efficiency. The value of w is chosen using a simple line search. In the case of a tie, the algorithm will pick the value of w that results in the higher $p_{\min}$. This way, not only will the number of stations be minimized, but the minimum power will also be maximized, reflecting an improved overall coverage.

V. Optimization of the Transmission Power

After assigning the BSs, their transmission powers can now be adjusted. A simple and efficient gradient-based algorithm is used to adjust these powers. In each iteration, the power of each station is reduced by a fixed amount, and the corresponding change in total coverage is measured. The station that has the minimum effect on coverage is chosen for power reduction. This process is repeated until the reduction in coverage can no longer be tolerated. In the simulation section, we implement this scheme and show that it results in an optimal relation between the transmission power and the total radio coverage.

VI. Computation Complexity

In this section, the computation complexity of the proposed approach is highlighted. From the preceding discussions, the proposed scheme has an outer loop and an inner loop. The outer loop searches for the optimal frame value w^*, whereas the inner loop implements the algorithm in Fig. 1 to find the location of the BSs.

For the outer loop, a simple line search was found to be sufficient for finding w^*. The search is limited to the integer values in the range $[w_{\min} - 0]$. Still, a more efficient search algorithm could be adopted to find this value.

In the inner loop shown in Fig. 1, the only computationally expensive operation is the convolution $A \otimes P_{n-1}$. The cost of the convolution operation can substantially be reduced from m^2 to $m \log(m)$ using available fast convolution techniques [9]–[11]. This feature makes the proposed solution feasible, even for large grid sizes. In Fig. 3, we show the simulated and theoretical time needed to assign one BS using fast convolution averaged over 100 runs. This feature makes the proposed approach highly efficient, even for large grid sizes.

In addition, there are two features inherited in the proposed approach that can further reduce the complexity of the solution.

1) Since normal demand is represented by zero values in D and since $P_0 = -D$, power matrix P_n usually starts full of zeros. This matrix is then filled up with nonzero values as new BSs are assigned. Therefore, the sparsity of matrix P_n can be exploited while computing the convolution to reduce the number of complex operations. For example, zero elements can be avoided while computing the convolution.
2) The search space for locations reduces as new BSs are assigned. Therefore, the number of complex operations in the convolution can substantially be reduced by ignoring those locations already meeting the coverage requirement.

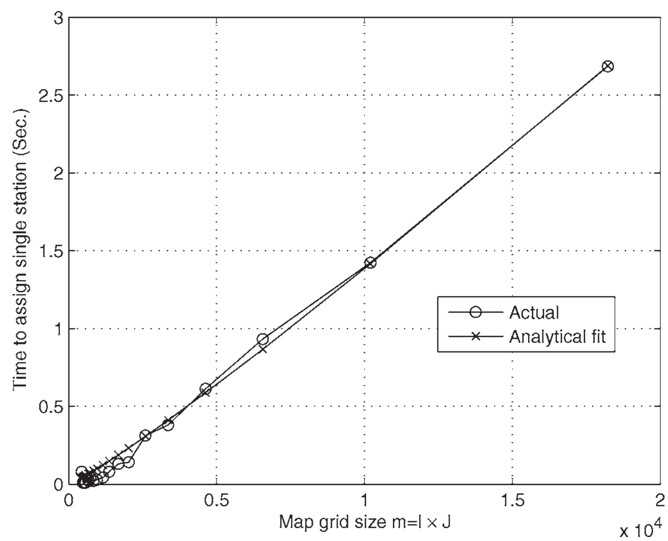

Fig. 3. Time needed to place a single station as a function of the grid size $m = I \times J$ using fast convolution. The analytical fit is obtained from $\rho m \log(m)$, where ρ is a constant related to the machine's processing time.

The savings in computations achieved by the proposed approach allows for the consideration of other design parameters, such as antenna height, direction, and frequency planning.

VII. Simulation

In this section, we demonstrate the performance of the proposed placement algorithm through some examples. Matlab was used to implement the algorithm on a 2.1-GHz personal computer with 256 MB of memory. The Matlab program provides a friendly user interface. It inputs a color-coded map, which is similar to that of Fig. 2, in a common image format (JPEG) and then constructs the corresponding demand pattern matrix D, following the process described in Section IV-B. It also constructs A from the antenna parameters set by the user. It then computes the number of BSs and their locations and shows them on the color-coded map. The program also returns the final minimum power $p_{\min}$ and the percentage of coverage of each assigned BS.

In our simulations, the size of matrices D and A is fixed at 41×61 for each (corresponds to 2501 possible locations). Furthermore, the power threshold is arbitrarily fixed in all simulations to $\alpha = 1\%$.

To test the proposed approach, the same problem as that in [8] and [7] is considered. In this problem, a configuration of seven hexagonal cells is to be covered with omnidirectional antennas having the same radius as the cells. The solution for this problem is obvious; exactly seven BSs are needed, which should be located at the centers of the cells. To implement the proposed approach, the edges of the seven cells are drawn using a popular drawing software and then directly fed to the algorithm. The walls are mapped as large positive values in D. The results are shown in Fig. 4. The algorithm achieved 99.7% coverage in seven iterations. Solving the same problem with genetic algorithm (GA), for example, would need more than 1000 generations to get the

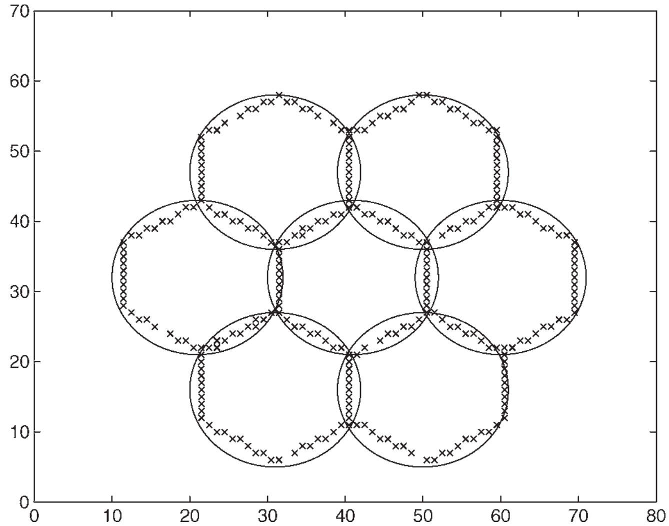

Fig. 4. Solution of the seven hexagonal cells problem.

TABLE I
EXAMPLE OF COLOR CODES AND THEIR CORRESPONDING VALUES INSIDE DEMAND MATRIX D

Color	Demand	Value inside D
Green	*Highest*	20
Blue	*High*	10
White	*Normal*	0
Red	*No − Demand*	−20

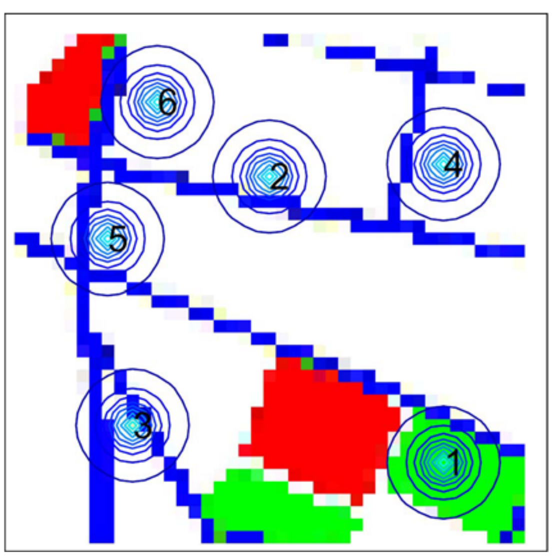

Fig. 5. Result of the placement problem with omnidirectional antenna and a given demand map.

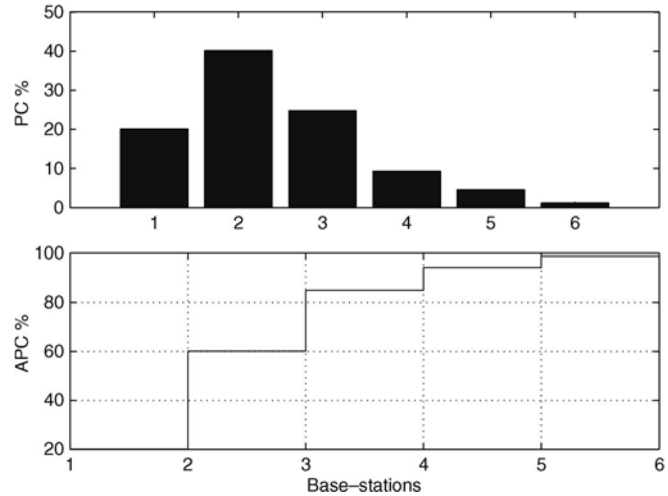

Fig. 6. Percentage of coverage (PC) and accumulative percentage of coverage (APC) for the BSs in Fig. 5.

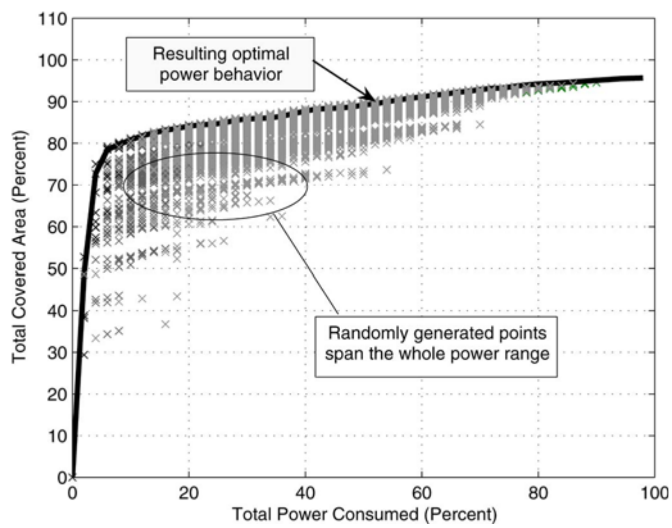

Fig. 7. Optimum total coverage in terms of the total power consumed by all stations (in percentages).

same coverage [8]. Furthermore, the fact that the model can be built by simply drawing the cell boundaries and feeding the drawing to the algorithm makes the proposed approach much more attractive when compared with the cumbrous modeling process demanded by the GA.

Next, the nontrivial example of Fig. 2 is used in simulation. The numerical weights assigned to the four demand colors in this example are listed in Table I. Again, an omnidirectional antenna is assumed. Fig. 5 shows the resulting placement of the BSs. In this case, six BSs were sufficient to meet the coverage requirement. Notice that, as expected, the first BS was located at the green region (corresponds to the very high demand region). In addition, the algorithm avoided the placement of any BS at the red region (corresponds to the no-demand region). The minimum power returned by the algorithm is $p_{\min} = 1.0724$, which is just above the required power threshold $\alpha = 1$. The optimal frame value w^* in this example is -86. The percentage of coverage and accumulated percentage of coverage for this example are shown in Fig. 6. The second BS covered about 40% of the area, whereas the sixth BS covered about 1% only. This means that, if 99% of the total coverage is sufficient, then the sixth station can simply be removed. The algorithm returned the results in less than 2 min.

The transmission power is then optimized using the scheme described in Section V. The resulting optimal relation between the total covered area and the total power consumed is shown in Fig. 7 (measured in percentages of full scale). The result is challenged by comparing it with thousands of randomly generated points that span the whole power range. It is clear that the proposed gradient-based scheme produces the optimum power behavior, i.e., the minimum reduction in coverage for the maximum reduction in transmission power. As a numerical example, suppose that it is desired to reduce the total transmission power to 54% of the full scale. Then, from Fig. 7, the total coverage will be reduced to 90% of the full scale. For this case, the algorithm results in the following optimum transmission powers for the five stations: $\{70.00\%, 0.00\%, 60.00\%, 80.00\%, 60.00\%\}$. Notice that the second station can now be removed since it no longer contributes to the coverage.

VIII. Conclusion

In this paper, we have proposed a novel approach for the placement of wireless BSs. The proposed approach computes the number of BSs, their locations, and the transmission powers that satisfy the power coverage requirements. The proposed approach provides a flexible means for choosing arbitrary power propagation and demand patterns, making it potentially suitable for real applications. The proposed approach uses the 2-D convolution as a core process. This results in substantial reduction in complexity by utilizing available fast methods for computing convolution. Simulations of the new algorithm show its efficiency and flexibility in solving wireless placement problems.

Acknowledgment

The author would like to acknowledge Prof. S. Selim for his valuable reviews and comments on this paper.

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Optimal Frame Splitting for Downlink MIMO Channels With Distributed Antenna Arrays

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***Abstract*—A frame-splitting (FS) scheme is proposed to exploit spatial diversity in the downlink wireless transmission from a base station (BS) to a mobile station (MS) that has multiple receive antennas. The BS has multiple geographically distributed arrays, each consisting of multiple transmit antennas. The scenario comprises a number of downlink multiple-input–multiple-output (MIMO) channels from different BS arrays to an MS with mutually independent Rayleigh-fading processes. A data frame from the BS for the MS is split into portions, which are consecutively transmitted from multiple BS arrays. For the FS transmission scheme, the distribution of information capacity is formulated on the basis of the FS fractional lengths of the portions. Analytical evaluation of the outage probability reveals the optimal setting of FS fractional lengths for the maximum diversity advantage based on knowledge of the long-term average signal-to-noise ratios (SNRs) of the downlink MIMO channels.**

***Index Terms*—Distributed antennas, diversity, multiple-input multiple-output (MIMO), outage capacity, Rayleigh fading, Wishart matrices.**

I. Introduction

Deploying multiple antennas is an effective means to improve the performance of wireless communications. Multiple transmit and multiple receive antennas are installed to construct a multiple-input multiple-output (MIMO) wireless channel. Analysis of the information capacity distribution of a MIMO channel in [1] and [2] suggested a great increase in spectrum efficiency. Transmitting independent data streams in parallel through multiple antennas (for example, the Bell Laboratories layered space–time architecture (BLAST) [3]) exploits the high spectrum efficiency of the MIMO channel. This effect is known as spatial multiplexing [4].

The distributed antenna system (DAS) was proposed in [5] and [6]. Instead of being colocated at a wireless base station (BS), multiple antennas are deployed at geographically dispersed locations within a wireless service area and are connected with a central BS by fiber/coaxial cables. From the viewpoint of wireless system architecture, the DAS brings many benefits, such as a reduction in transmission power, tolerance to large-scale fading, and improvement in link quality and coverage [5]–[7].

To gain the benefits from both the MIMO channel and the DAS wireless architecture, the antennas that are deployed at dispersed loca-

Manuscript received October 7, 2006; revised July 10, 2007, December 19, 2007, and December 21, 2007. First published February 2, 2008; current version published November 12, 2008. This work was supported by the Ministry of Internal Affairs and Communications under the grant "Research and development of fundamental technologies for advanced radio frequency spectrum sharing in mobile communication systems." The review of this paper was coordinated by Prof. M. Juntti.

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Digital Object Identifier 10.1109/TVT.2008.917254