Pilot Power Management in WCDMA Networks: Coverage Control With Respect to Traffic Distribution

Iana Siomina
Department of Science and Technology
Linköping University
SE-601 74, Norrköping, Sweden
iansi@itn.liu.se

Di Yuan
Department of Science and Technology
Linköping University
SE-601 74, Norrköping, Sweden
diyua@itn.liu.se

ABSTRACT

In WCDMA networks, Common Pilot Channel (CPICH) signals are used by mobile terminals for channel quality estimation, cell selection, and handover. The strength of the CPICH signal determines the coverage area of the cell, impacts the network capacity, and thereby the quality of service, and is therefore a crucial parameter in network planning and optimization. Pilot power is the most important parameter that allows to control the strength of the CPICH signal. The more power is spent for pilot signals, the better coverage is obtained. On the other hand, a higher value of the pilot power level in a cell means higher pilot pollution in the network and less power available to serve user traffic in the cell. In this paper, we consider the problem of minimizing the total amount of pilot power subject to a coverage constraint. We present a basic model for pilot power optimization subject to a full coverage constraint as well as its extended version which allows us to study various coverage levels and to consider user traffic distribution over the network. We also propose an efficient algorithm that gives near-optimal solutions to the problem. We report our numerical experiments for a WCDMA network based on a planning scenario for the city of Berlin.

Categories and Subject Descriptors

I.6 [**Simulation and Modeling**]: Model Development

General Terms

Algorithms

Keywords

WCDMA, network planning, CPICH, pilot power, coverage, traffic

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
MSWiM'04, October 4-6, 2004, Venezia, Italy.
Copyright 2004 ACM 1-58113-953-5/04/0010 ...$5.00.

1. INTRODUCTION

Common Pilot Channel (CPICH) is a fixed rate (30 kbps, spreading factor 256) downlink physical channel that carries a pre-defined bit/symbol sequence [1]. Normally, one cell has only one CPICH (Primary CPICH, or P-CPICH). In some cases, a cell may have several additional CPICH that are called secondary CPICH (S-CPICH). The cell may have a S-CPICH, for example, when this cell contains narrow beam antenna for serving a dedicated hot-spot area, i.e., the area with a high traffic density level. In this case, a dedicated area uses the S-CPICH, whereas the P-CPICH broadcasts the pilot signal over the entire cell.

If a mobile terminal is unable to clearly receive one dominant CPICH, due to interference or coverage problems, the result is likely to be dropped calls, failed initiations, poor voice quality and/or poor data throughput. The quality of the CPICH can be measured in terms of E_c/I_0, which is a representation of the signal to interference-plus-noise ratio for spread spectrum signals. The mobile terminals scan for the CPICH signals continuously and measure the E_c/I_0 ratio of all pilot signals they can detect. In order to keep a mobile referenced to a cell, the E_c/I_0 ratio at the mobile terminal must exceed a minimum threshold at all times. (For UMTS, a typical threshold value is between -16 and -20 dB.)

Increasing or decreasing the pilot power makes the cell larger or smaller allowing us to control cell coverage. Since cells have to be planned such that the estimated traffic does not exceed the cell capacity, the acceptable cell sizes strongly depend on the current load and interference situation. Thus, involving a trade-off between power consumption and coverage, pilot power management allows controlling cell loads and improving network capacity. Another goal of pilot power management is to reduce pilot pollution and interference in the network. Previous work of analyzing the effect of pilot power on network performance can be found in, for example, [6, 8, 11, 12]. Among these, the authors of [8] show that a rule-based optimization technique for setting pilot power levels significantly outperforms a manually-designed solution in terms of network cost.

In this paper, we study the problem of providing a certain coverage level using a minimum amount of pilot power. In a real-life situation, this kind of problem is to be solved during the planning phase of the WCDMA network as well as during its maintenance. In the second case, pilot power optimization is referred to one of the mid-term tasks solved by network operators aiming to improve network capacity.

Our solution approach to the pilot power optimization problem consists of mathematical programming techniques. We present a basic model for pilot power optimization subject to a full coverage constraint as well as its extended version which allows us to study various coverage levels and to consider user traffic distribution over the network. To solve the problem, we propose an efficient algorithm based on Lagrangian relaxation with an embedded primal heuristic. Even for large-scale networks, the algorithm finds near-optimal solutions of high quality with a reasonable amount of computing effort. We report our numerical experiments for a WCDMA network based on a planning scenario for the city of Berlin.

2. SYSTEM MODELLING

2.1 Planning Parameters

Let us consider a WCDMA network with m cells, and let $\mathcal{I}$ denote the set of cells, i.e., $\mathcal{I} = \{1, \ldots, m\}$. The service area is represented by a grid of bins with a certain resolution, assuming the same signal propagation conditions across every bin. The total number of bins is denoted by n, and the set of bins is denoted by $\mathcal{J} = \{1, \ldots, n\}$.

Let P_i^T be the total transmission power available in cell i, and y_i be the amount of power allocated to the pilot signal in this cell[1]. Thus, the amount of the power left for other purposes in the cell is $P_i^T - y_i$. A higher value of y_i means larger coverage area for cell i, but, on the other hand, less power available to serve user traffic of cell i.

We use g_{ij} ($0 < g_{ij} < 1$) to denote the power gain between the base station of cell i and bin j. Thus, $g_{ij} y_i$ is the power of the received pilot signal from cell i in bin j. In addition to the pilot signal, bin j also receives interfering signals, including the signals for user traffic from cell i, and signals from some other base stations. The total interference can be written as

$$I_{ij} = (1 - \alpha_j) P_i g_{ij} + \sum_{k \in \mathcal{I}: k \neq i} P_k g_{kj} + \nu_j, \qquad (1)$$

where P_i ($P_i \leq P_i^T$) is the power used both for the pilot signal and the user traffic in cell i, $\alpha_j \in (0, 1)$ is the orthogonality factor in bin j to signals from cell i, and ν_j is the effect of the thermal noise in bin j.

We consider network scenarios with a high traffic load. In particular, we assume that all base stations operate at full power, which represents the worst-case interference scenario. Under this assumption, $P_i = P_i^T, \forall i \in \mathcal{I}$, and the interference in bin j with respect to cell i reads

$$I_{ij} = (1 - \alpha_j) P_i^T g_{ij} + \sum_{k \in \mathcal{I}: k \neq i} P_k^T g_{kj} + \nu_j \ . \qquad (2)$$

We assume that pilot signal from cell i can be detected in bin j if and only if its E_c/I_0 ratio is above a threshold γ_0, that is, if

$$\gamma_{ij} = \frac{g_{ij} y_i}{I_{ij}} = \frac{g_{ij} y_i}{(1 - \alpha_j) P_i^T g_{ij} + \sum_{k \in \mathcal{I}: k \neq i} P_k^T g_{kj} + \nu_j} \geq \gamma_0. \qquad (3)$$

[1]Linear scale is considered for all parameters and variables in this paper.

Using (3), it can be derived that, if cell i covers bin j, then the pilot power y_i must be at least P_{ij}, defined as

$$P_{ij} = \frac{\gamma_0}{g_{ij}} \cdot \left[(1 - \alpha_j) P_i^T g_{ij} + \sum_{k \in \mathcal{I}: k \neq i} P_k^T g_{kj} + \nu_j \right]. \qquad (4)$$

Increasing the pilot power yields better coverage. However, this is at a cost of less power available for user traffic. Our optimization problem is motivated by this trade-off – to ensure a certain coverage level using a minimum amount of pilot power.

In this paper, we distinguish between service area coverage level and traffic coverage level. The former is the proportion of bins for which (3) holds. The traffic coverage level is the ratio between the sum of the amount of traffic demand of bins where (3) holds, and the total traffic demand of the entire service area. To be able to estimate traffic coverage in the network, we introduce a new parameter, traffic demand. One possible interpretation of this parameter is the average number of active users in a bin asking for a specific service. We use d_j to denote the traffic demand in bin j, and D to denote the total traffic demand over the network ($D = \sum_{j \in \mathcal{J}} d_j$). In a real network, user traffic demand has a dynamic characteristic, and is non-uniformly distributed over the network. In static and short-term dynamic simulations, traffic demand can be modelled by a snapshot.

In many network planning scenarios, it is required that the pilot power level does not exceed some upper limit. We use Π_i^{max} to denote this limit for cell i, and assume that $\Pi_i^{max} \leq P_i^T$. In some cases, pilot power can be also bounded from below in order to control the difference in pilot power levels in adjacent cells and improve the performance of soft handover [3]. Let Π_i^{min} denote this lower limit and assume that $\Pi_i^{min} \geq 0$. The lower and the upper pilot power limits requirement can be either introduced in the model as an additional constraint, or can be handled in the preprocessing step. The latter means that P_{ij} values that are below Π_i^{min} are set to this minimum value, whereas P_{ij} values that exceed the upper limit Π_i^{max} are excluded from the list of possible pilot power settings.

2.2 A Full Coverage Model

We consider a pilot power optimization problem with the requirement of full coverage, i.e., when each bin j must be covered by at least one cell. In this case, both traffic coverage level and service area coverage level are equal to their maximum value (i.e., 1.0). Thus, we do not consider traffic distribution in this section.

We use the following two types of variables in the model.

$$y_i = \text{The pilot power of cell } i, \qquad (5)$$

$$x_{ij} = \begin{cases} 1 & \text{if cell } i \text{ covers bin } j \text{, i.e., } \gamma_{ij} \geq \gamma_0, \\ 0 & \text{otherwise.} \end{cases} \qquad (6)$$

The problem formulation for the case of full coverage is presented below.

$$
\begin{aligned}
[M1] \quad P^* \quad &= \min \sum_{i \in \mathcal{I}} y_i && (7)\\
\text{s.t.} \quad & \sum_{i \in \mathcal{I}} x_{ij} \geq 1, \quad \forall j \in \mathcal{J} && (8)\\
& P_{ij} x_{ij} \leq y_i, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} && (9)\\
& \Pi_i^{min} \leq y_i \leq \Pi_i^{max}, \quad \forall i \in \mathcal{I} && (10)\\
& x_{ij} \in \{0,1\}, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J} && (11)\\
& y_i \in \Re^+, \quad \forall i \in \mathcal{I} && (12)
\end{aligned}
$$

In M1, constraints (8) ensure full coverage. By constraints (9), pilot power level of cell i is greater than or equal to the maximum P_{ij} value among its bins. Constraints (10) ensure that pilot power level for each cell i is within a given interval.

In the next section, we present a more sophisticated and generalized model that allows various levels of the coverage requirement and considers traffic distribution over the network.

2.3 A Generalized Model for Various Coverage Levels With Respect to Traffic Distribution

Full coverage[2] of the service area is a desired network property, but in real-life networks providing a full CPICH coverage is usually very expensive both from economic and resource consumption point of view. A slight decrease in the coverage level enables considerable reductions in the pilot power and network resource utilization in general[3]. Thus, in practice, a guaranteed coverage level of 95-98% would be sufficient for any WCDMA network.

To be able to examine the impact of coverage level on the total pilot power consumption, we modify the right-hand side of the coverage constraints (8) in the following way,

$$\sum_{i \in \mathcal{I}} x_{ij} \geq z_j, \quad \forall j \in \mathcal{J}, \tag{13}$$

where $\{z_j\}$ is a set of binary variables defined as follows,

$$z_j = \begin{cases} 1 & \text{if bin } j \text{ is to be covered by at least one cell,} \\ 0 & \text{otherwise.} \end{cases}$$

Let $\beta \in (0, 1]$ denote the required level of traffic coverage ($\beta = 1.0$ corresponds to the case of full coverage). Then, to introduce the coverage requirement into the model, the following constraint has to be added,

$$\sum_{j \in \mathcal{J}} d_j z_j \geq \beta D. \tag{14}$$

We observe that in the case of uniform traffic distribution the traffic coverage requirement, (14), becomes equivalent to the service coverage requirement, i.e., to the constraint

$$\sum_{j \in \mathcal{J}} z_j \geq \beta n. \tag{15}$$

[2]By *full coverage* we mean 100% coverage of the service area.

[3]In system management, this phenomenon is known as Pareto's Principle or the 80/20 Rule, which says that 20% of efforts always are responsible for 80% of the results.

We denote the final formulation of the generalized model by M2. The formulation has the same objective as M1 and contains the constraints (9), (10), (13), and (14). In networks with uniform traffic distribution, constraints (14) can be substituted by (15). We also observe that M1 is a special case of M2 when $\beta = 1.0$, therefore we consider M2 as a generalized model for our pilot power optimization problem.

M2 is a quite straightforward linear-integer formulation for the pilot power optimization problem, but from a computational point of view, however, this formulation is not efficient. In particular, its linear programming (LP) relaxation is very weak (i.e., the LP-optimum is often far away from the integer optimum). Even for small networks, solving M2 to optimality is out of reach of a standard branch-and-bound solution technique. In our numerical experiments, a state-of-the-art integer programming solver [4] did not manage to find optimal or near-optimal solutions within any reasonable amount of time. In Section 4.1, we propose an enhancement to M2 that substantially improves the quality of the LP-relaxation and allows us to solve the problem even for large networks.

3. AD HOC SOLUTION FOR THE CASE OF UNIFORM PILOT POWER

In the case of uniform pilot power, the pilot power is set to be the same for all cells. Uniform pilot power is a possible solution to our pilot power optimization problem. This solution can be computed analytically.

We use y^U to denote the pilot power level used by all cells in the solution of uniform pilot power. A necessary condition for covering bin j is that y^U is at least as big as the minimum of P_{ij} among all cells, i.e., $y^U \geq P^j$, where $P^j = \min_{i \in \mathcal{I}} P_{ij}$. Let D^j denote the total amount of traffic demand in the network from the covered bins if the uniform pilot power level is equal to P^j, i.e., $D^j = \sum_{l \in \mathcal{J}: P^l \leq P^j} d_l$. To guarantee a certain level of traffic coverage, the total traffic demand from all the covered bins has to be at least βD, i.e., if $y^U = P^{j^*}$, then $D^{j^*} \geq \beta D$ must hold.

A straightforward approach is to sort the bins in ascending order with respect to P^j. The first element in the sorted sequence, for which the corresponding value of D^j is not less than βD, yields the minimum uniform pilot power that satisfies the coverage requirement. Mathematically, the analytical solution can be presented as follows,

$$y^U = \min_{j \in \mathcal{J}: D^j \geq \beta D} P^j. \tag{16}$$

The uniform pilot power approach is efficient in simple propagation scenarios, where the signal attenuation is essentially determined by distance. In such scenarios, if fairly uniformly distributed traffic and equally-spread base stations are assumed, the sizes of the cells will be roughly the same. However, in an in-homogenous planning situation (e.g., a mix of rural and downtown areas), a uniform level of pilot power is not an efficient solution from the power consumption point of view. There is therefore a need of mechanisms that can determine the optimal levels of the pilot power. In this section, we derived analytically the solution of uniform pilot power. In the next section, we present the algorithm that allows us to find a near-optimal solution for the general case.

4. SOLUTION APPROACH

4.1 An Enhanced Formulation

As was mentioned in Section 2.3, the formulation of the generalized model, M2, is straightforward, but from a computational point of view it is inefficient. To avoid the weakness of M2, we derive an enhanced formulation to the problem.

First of all, to simplify the formulation, we remove constraints (10), i.e., the pilot power limits constraints, from the formulation M2. Instead, as explained in Section 2.1, we set the lower pilot power limits in the preprocessing step. To consider the upper limits, for each bin j, we define a set $\mathcal{I}(j) \subseteq \mathcal{I}$ which contains all the cells that may cover bin j with a feasible pilot power level, i.e., $\mathcal{I}(j) = \{i \in \mathcal{I}: P_{ij} \leq \Pi_i^{max}\}$.

We utilize the fact that, in an optimal solution, the pilot power of any cell will attain a value that belongs to a discrete set. In particular, in an optimal solution to M2, $y_i = P_{ij}$ for some bin j. This is because unless additional bins can be covered, further increase of y_i will make the solution non-optimal.

We introduce the following notation. For cell i, we sort P_{ij} in ascending order, and use a sequence $b_1^i, b_2^i, \ldots, b_{l-1}^i, b_l^i, \ldots$ to denote the sorted indices of bins. Thus, we obtain the sequence $P_{ib_1^i} \leq P_{ib_2^i} \leq \ldots \leq P_{ib_{l-1}^i} \leq P_{ib_l^i} \leq \ldots$, where b_l^i is the bin at position l in the sorted sequence for cell i. We use B_i to denote the total number of bins in the sorted sequence for cell i. (Usually B_i is much less than n, because the bins, for which the required pilot power exceed Π_i^{max}, can be ignored.) Moreover, we consider the sorted sequence of power levels for cell i in the following incremental fashion:

$$
\begin{aligned}
&P^I_{ib_1^i} = P_{ib_1^i} \quad , \\
&P^I_{ib_2^i} = P_{ib_2^i} - P_{ib_1^i} \quad , \\
&\ldots \\
&P^I_{ib_l^i} = P_{ib_l^i} - P_{ib_{l-1}^i} \quad , \\
&\ldots \\
&P^I_{ib_{B_i}^i} = P_{ib_{B_i}^i} - P_{ib_{B_i-1}^i} \quad .
\end{aligned}
$$

For any $l \in \{2, \ldots, B_i\}$, the value of $P^I_{ib_l^i}$ is the additional power needed for cell i to cover bin b_l^i, provided that cell i already covers bin b_{l-1}^i. The pilot power of cell i thus equals $\sum_{l=1}^{B_i} P^I_{ib_l^i} x_{ib_l^i}$. The total amount of pilot power can therefore be expressed as $\sum_{i\in\mathcal{I}} \sum_{l=1}^{B_i} P^I_{ib_l^i} x_{ib_l^i}$.

With the above notation, the model discussed in Section 2.3 can be reformulated as follows.

$$
\begin{aligned}
[M3] \quad P^* \quad &= \min \sum_{i\in\mathcal{I}} \sum_{l=1}^{B_i} P^I_{ib_l^i} x_{ib_l^i} && (17)\\
\text{s.t.} \quad &\sum_{j\in\mathcal{J}} d_j z_j \geq \beta D && (18)\\
&\sum_{i\in\mathcal{I}(j)} x_{ij} \geq z_j, \ \forall j \in \mathcal{J} && (19)\\
&x_{ib_{l-1}^i} \leq x_{ib_l^i}, \ \forall i \in \mathcal{I}, \forall l \in \{2, \ldots, B_i\} && (20)\\
&x_{ij} \in \{0,1\}, \ \forall j \in \mathcal{J}, \forall i \in \mathcal{I}(j) && (21)\\
&z_j \in \{0,1\}, \ \forall j \in \mathcal{J} && (22)
\end{aligned}
$$

The enhanced formulation, M3, is much more efficient than M2 in terms of the solution quality of the LP-relaxation. It can be proved that the LP-relaxation of M3 is at least as strong as that of M2.

4.2 Algorithm Overview

The algorithm is based on Lagrangian relaxation and has two main parts, one of which is aimed to solve a relaxed problem. In the second part, we adjust the current solution of the relaxed problem to a feasible solution that satisfies all the constraints of the enhanced model, M3. The first part, which gives us a lower bound, is to be solved iteratively, within a chosen number of steps, independently on the second part, using a standard subgradient method. The second part implies the performing of the adjusting procedure in each iteration step and at the end it provides the best feasible solution found. We use three stopping criteria for the subgradient solver: maximum number of steps (500 steps), dual gap less than 1%, and maximum number of consecutive steps during which the lower bound has not been improved (50 steps).

The iterative procedure consists of the following steps:

1. *Construct the relaxed problem.* See Section 4.3 for more details.

2. *Solve $m+1$ subproblems.* For a given set of Lagrange multipliers, we solve one knapsack problem for the z-variables, and m Lagrangian subproblems (one for each cell) to find a coverage map in terms of the x-variables.

3. *Find the lower bound.* Calculate the Lagrangian function.

4. *Find a feasible solution.* Adjust the solution of the relaxed problem to a feasible one. See Section 4.4 for more details.

5. *Save the best feasible solution.* Compare the best feasible solution found up till now to the current solution obtained in step (4) and choose the solution with the minimum value of objective function, i.e., the minimum amount of total pilot power.

6. *Check stopping criteria.* The stopping criteria are maximum number of steps, dual gap, and maximum number of consecutive steps during which the lower bound has not been improved. If one of these criteria is satisfied then go to step (9).

7. *Update Lagrangian multipliers*

8. *Repeat steps (2)-(8).*

9. *Save result.*

4.3 Lagrangian Relaxation

A Lagrangian relaxation that exploits the structure of the problem is the core of the algorithm presented in Section 4.2. We relax the coverage constraints (19) using Lagrange multipliers, $\{\lambda_j\}, j = 1, \ldots, n$, and construct the following relaxed model.

$$[R1] \qquad \min \qquad \sum_{i\in\mathcal{I}}\sum_{l=1}^{B_i}(P^I_{ib^i_l}-\lambda_{b^i_l})x_{ib^i_l}+\sum_{j\in\mathcal{J}}\lambda_j z_j \quad (23)$$

$$\text{s.t.} \qquad \sum_{j\in\mathcal{J}} d_j z_j \geq \beta D \quad (24)$$

$$x_{ib^i_{l-1}} \leq x_{ib^i_l},\ \forall i\in\mathcal{I}, \forall l\in\{1,\dots,B_i\} \quad (25)$$

$$x_{ij}\in\{0,1\},\ \forall j\in\mathcal{J}, \forall i\in\mathcal{I}(j) \quad (26)$$

$$z_j\in\{0,1\},\ \forall j\in\mathcal{J} \quad (27)$$

We decompose the problem R1 into $m+1$ independent subproblems. For each cell i, we can solve the problem which minimizes $\sum_{l=1}^{B_i}(P^I_{ib^i_l}-\lambda_{b^i_l})x_{ib^i_l}$ subject to the corresponding constraints from (25).

A simple way to solve the i^{th} subproblem is to find, for every cell i, $\arg\min_{K=1,\dots,B_i}\{\sum_{l=1}^{K}(P^I_{ib^i_l}-\lambda_{b^i_l})\}$, and then assign 0's and 1's to the x-variables to realize the minimum.

To find the optimal values of the z-variables, we solve a problem that minimizes $\sum_{j\in\mathcal{J}}\lambda_j z_j$ subject to constraint (24). Applying a simple substitution $z_j = 1-\bar{z}_j$, this problem is easily transformed to a standard 0-1 maximum knapsack problem which can be solved using a standard dynamic programming algorithm.

Solving m subproblems gives the optimal coverage map which, however, does not necessarily satisfies the traffic coverage requirement given by constraints (24). Therefore, to find a feasible solution, we apply a heuristic procedure discussed in Section 4.4.

4.4 A Heuristic Procedure

Our primal heuristic procedure consists of the following two phases:

- Increase the coverage area of cells unless the coverage constraint is satisfied;
- Reduce the number of over-covered bins, i.e., bins for which the left-hand side of (19) is strictly greater than z_j.

If there are several cells that may cover an uncovered bin in the first phase, we choose the cell with the least additional power needed to cover this bin. Note also that covering an uncovered bin also implies that all the bins for which the pilot power is less than or equal to what is needed to cover this bin, will also become covered.

In the second phase, we use the fact that if bin j is covered by several cells, and among them there is a cell, say cell i, for which all other bins than j and covered by cell i demand a less pilot power than P_{ij}, then we can reduce the pilot power level in cell i by P^I_{ij}.

The second phase follows right after the first one, but in order to improve the result the second phase may be applied twice, i.e., before and after the first phase.

5. A CASE STUDY

In this section, we investigate the impact of coverage level on the total pilot consumption and present computational results obtained for a test network originating from a planning scenario for the city of Berlin. The planning scenario was provided by the Momentum project group [5]. The test network has the following characteristics: 50 sites, 148 cells, and 22500 bins. The total service area is 7500 x 7500 m^2. The bin size is 50 x 50 m^2.

In our computational experiments we consider the enhanced formulation of the problem derived in Section 4.1. The model parameters are set to the following values:

- E_c/I_0 target $\gamma_0 = 0.01$;
- maximum power $P^T_i = 20$ W for all cells;
- upper pilot power limit $\Pi^{max}_i = 2.5$ W for all cells;
- lower pilot power limit $\Pi^{min}_i = 0$ W for all cells, i.e., we do not limit the pilot power levels from below;
- thermal noise $\nu_j = 1.5488\cdot 10^{-14}$ for all bins;
- the orthogonality factor $\alpha_j \in \{0.327, 0.633, 0.938\}$ depends on the channel model in bin j (typically urban, mixed, or rural area).

The traffic demand is given as a static load grid that contains the expected average number of users in each bin at one instance in time [2]. In our numerical experiments, we considered traffic demand for speech-telephony service. Figure 1 shows the distribution of traffic demand over the network for this specific service for the Berlin city.

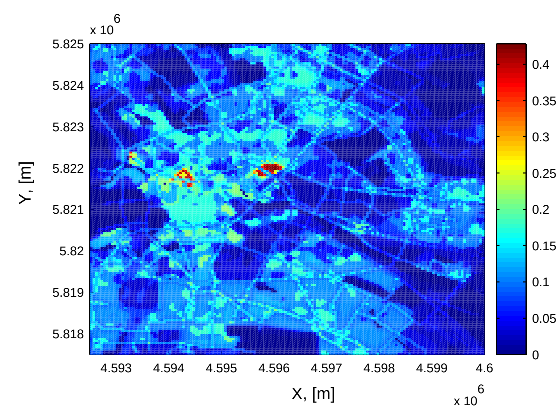

Figure 1: Traffic demand for speech-telephony service for the city of Berlin.

The power gains, g_{ij}, are the predicted values for a specific network configuration [2]. These values are given via propagation grids for each cell i and include path loss and shadowing (or slow fading) components. The shadowing was modelled statistically as a zero-mean log-normal distribution with a standard deviation of 8 dB [10].

We examine the results obtained by the relaxation-based algorithm discussed in Section 4 and compare to those obtained for the uniform pilot power case discussed in Section 3. All computational experiments have been conducted on a Pentium 4-M laptop with a 1.8 GHz CPU and 512 MB RAM. For the tested network, the computational time for the relaxation-based algorithm is 3-6 minutes, depending on coverage level requirement. The range of computing time is a reasonable amount of time for such a big network. Moreover, a state-of-the-art integer programming solver [4] did not manage to find optimal (or any near-optimal) solution for the same test network because of lack of memory.

Table 1 and Table 2 present two sets of solutions obtained for various coverage levels: solutions obtained by the relaxation-based algorithm and analytical solutions for uniform pilot power. For each of these two solutions, we show the total power consumption and the average power per cell. We note that solutions obtained by the relaxation-based algorithm significantly outperform those of uniform pilot power, especially for higher levels of traffic coverage. In Table 1 we also present the lower bounds obtained from the Lagrangian relaxation as well as the relative gaps between the best feasible solutions found and their lower bounds. We observe that the solution for the full coverage case has the smallest gap, 5.71%. The gap slightly increases when the traffic coverage level decreases, but the quality of all presented solutions is high enough from the network planning point of view.

Table 1: Numerical solutions for various coverage levels.

Traffic coverage level β	Pilot power, [W] Total	Av. per cell	Lower bound	Gap, [%]
1.00	114.40	0.7730	108.22	5.71
0.99	99.94	0.6753	93.07	7.38
0.98	94.61	0.6392	86.93	8.83
0.97	89.01	0.6014	82.54	7.84
0.96	86.21	0.5825	78.91	9.25
0.95	83.44	0.5638	75.78	10.11
0.94	80.98	0.5472	72.97	10.98
0.92	75.48	0.5100	67.49	11.84
0.90	71.77	0.4849	63.79	12.51

Table 2: Ad hoc solutions for uniform pilot power for various coverage levels.

Traffic coverage level β	Pilot power, [W] Total	Average per cell
1.00	356.44	2.4084
0.99	184.73	1.2482
0.98	160.48	1.0843
0.97	144.83	0.9786
0.96	133.72	0.9035
0.95	125.33	0.8468
0.94	118.59	0.8013
0.92	107.68	0.7276
0.90	98.97	0.6687

Figure 2 illustrates the total amount of pilot power versus traffic coverage level both for uniform pilot power solutions and for solutions obtained by the relaxation-based algorithm. The lower bounds are plotted using a dashed line.

Figures 3 and 4 demonstrate the solution obtained for the full coverage case. Figure 3 presents the best server map for pilot power. For every bin, the color is the power of the CPICH signal that has the highest E_c/I_0 ratio in the bin. Figure 4 illustrates the CPICH coverage map for the service area. The color of a bin represents the number of CPICH

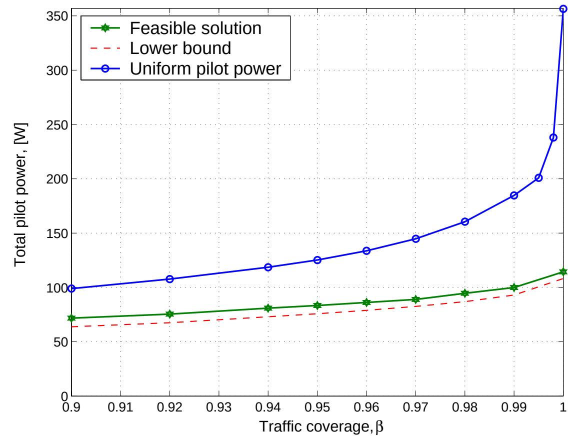

Figure 2: Total pilot power depending on traffic coverage β.

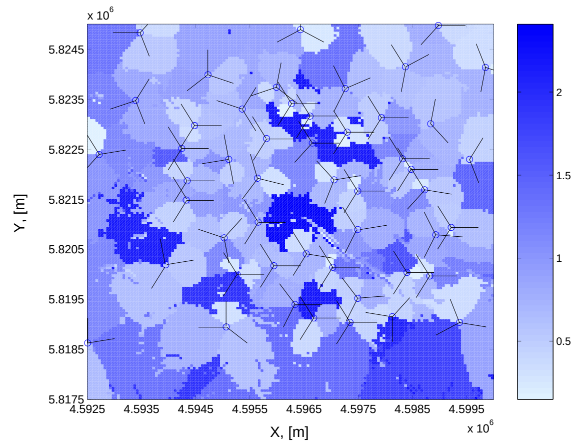

Figure 3: Optimized pilot power levels, $\beta = 1.0$.

signals that can be detected by a mobile terminal in this particular bin.

Figures 5 and 6 illustrate the pilot power map and the coverage map for the solution obtained when the required traffic coverage level is set to 0.95, or 95%. The white pixels correspond to those areas where a mobile terminal cannot detect any CPICH signal.

6. CONCLUSIONS

Engineering of WCDMA networks gives rise to many optimization problems. In this paper, we have addressed the problem of providing service coverage using a minimum amount of pilot power. We presented two mathematical models and a solution approach based on a Lagrangian relaxation technique. The approach is aimed to find a near-optimal solution within a reasonable amount of computing time.

Several conclusions can be drawn from our computational study. First, even for the scenario of worst-case interference, full coverage by CPICH signals needs less than five percent of the total power in a network. Second, a slight decrease in the degree of coverage enables considerable reductions in the pilot power. Coverage versus power consumption is thus an important trade-off in WCDMA network design. Moreover, optimized pilot power considerably outperforms the uniform

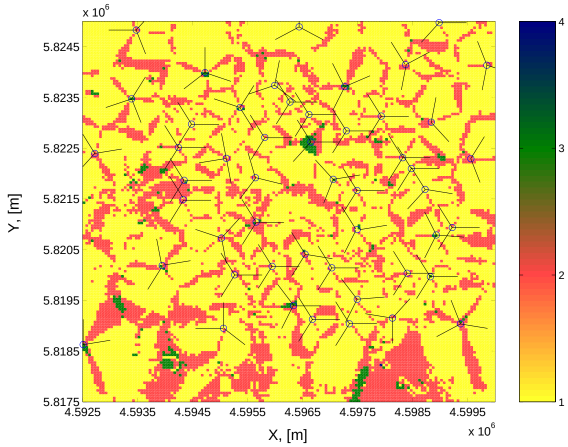

Figure 4: CPICH coverage map, $\beta = 1.0$.

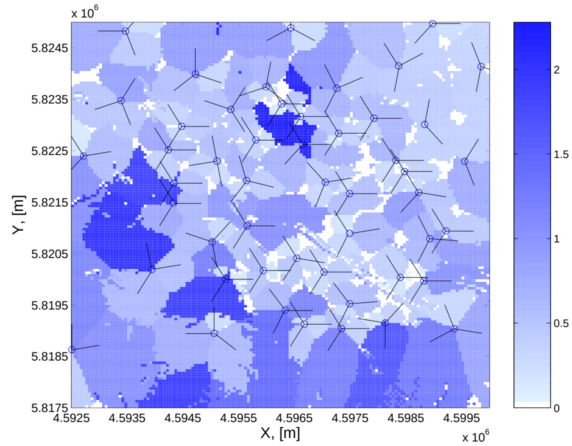

Figure 5: Optimized pilot power levels, $\beta = 0.95$.

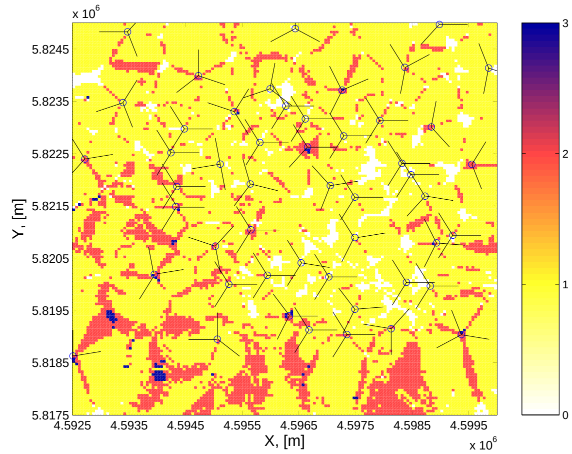

Figure 6: CPICH coverage map, $\beta = 0.95$.

pilot power approach discussed in Section 3, and, therefore, mathematical models can be very helpful for maximizing power efficiency in WCDMA networks.

7. ACKNOWLEDGMENTS

The authors wish to thank Fredrik Gunnarsson at Ericsson Research, Linköping, Sweden, for the technical discussions. The group of the MOMENTUM project is also acknowledged for providing the test data for Berlin and Lisbon, [5]. This work is financed by CENIIT (Center for Industrial Information Technology), Linköping Institute of Technology, Sweden.

8. REFERENCES

[1] 3GPP, TSG RAN, Physical Channels and Mapping of Transport Channels onto Physical Channels (FDD), 3G 25.211, Ver. 5.0.0.

[2] A. Eisenblätter, H.-F. Geerdes, T. Koch, U. Türke, E. Meijerink, A. Fügenschuh, *"XML Data Specification and Documentation"*, Project report D5.1-XML, IST-2000-28088, MOMENTUM, 2003.

[3] A. Eisenblätter, T. Koch, A. Martin, T. Achterberg, A. Fügenschuh, A. Koster, O. Wegel and R. Wessäly, "Modelling Feasible Network Configurations for UMTS", Telecommunications Network Design and Management. G. Anandalingam, S. Raghavan (editors), Boston: Kluwer Academic Publ, pp. 1-24, 2002.

[4] ILOG. Ilog CPLEX 7.0, User's manual, August 2000.

[5] IST-2000-28088 Momentum Project, http://momentum.zib.de.

[6] D. Kim, Y. Chang, and J. W. Lee, "Pilot power control and service coverage support in CDMA mobile systems", *Proceedings of IEEE Vehicular Technology Conference (VTC '99)*, pp. 1464-1468, 1999.

[7] J. Laiho, A. Wacker, T. Novosad (editors). Radio Network Planning and Optimization for UMTS. John Wiley & Sons Ltd., 2002.

[8] R. T. Love, K. A. Beshir, D. Schaeffer, and R. S. Nikides, "A pilot optimization technique for CDMA cellular systems", *Proceedings of IEEE Vehicular Technology Conference (VTC '99)*, 1999.

[9] I. Siomina and D. Yuan, "Pilot Power Optimization in WCDMA Networks", *Proceedings of WiOpt'04: Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks*, pp. 191-199, March 2004.

[10] T. Winter, U. Türke, E. Lamers, R. Perera, A. Serrador, L. M. Correira, *"Advanced simulation approach for integrated static and short-term dynamic UMTS performance evaluation"*, Project report D2.7, IST-2000-28088, MOMENTUM, 2003.

[11] J. Yang and J. Lin, "Optimization of pilot power management in a CDMA radio network", *Proceedings of the 52nd IEEE Vehicular Technology Conference (VTC Fall'00)*, pp. 2642-2647, September 2000.

[12] H. Zhu, T. Buot, R. Nagaike, S. Harmen, "Load balancing in WCDMA systems by adjusting pilot power", *Proceedings of the 5th International Symposium on Wireless Personal Multimedia Communications*, pp. 936-940, vol.3, 2002.