# UTRAN RESOURCE PLANNING BASED ON A PTAS USING A COMPLEX PROFIT FUNCTION[1]

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## ABSTRACT

The planning of the UMTS system, partly based on the W-CDMA radio interface, presents new challenges for the radio access network planner. Its complexity and interference-limited multiple access scheme needs new approaches and design methods that need to be extensively tested and brought to maturity till the moment of massive introduction of UMTS which is expected in the near future.

Our approach develops and refines an existing theoretical method of UMTS cell planning [1], claiming to have made it more adequate from the system-engineering viewpoint. Through simulations we have tested the overall performance and the computational complexity of the method.

Abbreviations: BS – base station, MS – mobile station, PTAS – polynomial time approximation scheme

## FORMAL DEFINITION OF THE PROBLEM

The proposed task to be solved is a generalization of MTSN (Maximize number of totally supplied demand nodes – [2]). Inputs are the number B of potential base station (BS) locations, provided by the operator, the number n of mobile stations (MS) along with their locations and a fixed budget, meaning a maximal number b of BS that can be installed. The MS generation method will not be further elaborated within this paper, further information is available in [4]. The task is to find the maximum of a profit function P, without exceeding the budget b. In the profit function several aspects of the radio interface are considered, those ones that are considered important from the system operation viewpoint. The expression of the profit function is the following:

$$P = C_b \cdot \frac{\sum_{k=0}^{N_{served}-1} B_k^{MS}}{\sum_{l=0}^{N-1} B_l^{MS}} + C_{inst} \cdot \left[1 - \frac{\# BS_{inst}}{b}\right] + C_{pload} \cdot \left[2 - \frac{\sum_{k=0}^{b-1} P_k^{BS}}{\sum_{l=0}^{b-1} P_{l,tot}^{BS}} - \frac{\sum_{o=0}^{N_{served}-1} P_o^{MS}}{\sum_{p=0}^{N_{served}-1} P_{p,tot}^{MS}}\right] +$$

$$+ C_{p\,\mathrm{var}} \cdot \left[2 - \frac{\mathrm{var}\left(P^{BS}\right)}{M\left\{P^{BS}\right\}} - \frac{\mathrm{var}\left(P^{MS}\right)}{M\left\{P^{MS}\right\}}\right] + C_{bter} \cdot \left[1 - \frac{\sum_{k=0}^{b-1} B_k^{BS}}{b \cdot B_{\max}^{BS}}\right] + C_{b\,\mathrm{var}} \cdot \left[1 - \frac{\mathrm{var}\left(B^{BS}\right)}{M\left\{B^{BS}\right\}}\right] + C_{nu} \frac{N_{served}}{N} \tag{1}$$

where $C_b$ - weight of the profit related to the served aggregate bitrate, $B_k^{MS}$ - served downlink bitrates, $B_l^{MS}$ - requested downlink bitrates, $N_{served}$ - number of served MS, $N$ - number of MS in the system, $C_{inst}$ - weight of the profits related to the minimal number of installed BS, $\# BS_{inst}$ - number of installed BS in the system, $b$ - budget or the maximal number of BS that can be installed, $C_{pload}$ - weight of the profit related to the minimal interference load of the system, $P_k^{BS}$ - sum of power values of $BS_k$ towards the served MS, $P_{l,tot}^{BS}$ - maximal power of $BS_k$, $P_o^{MS}$ - transmitted power of $MS_o$, $P_{p,tot}^{MS}$ - maximal power of $MS_p$, $C_{p\,\mathrm{var}}$ - weight of the profit related to the uniformity of the power load in different

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points of the system, var(.) – variance operator, M{.} – median value operator, $C_{bter}$ - weight of the profit related to the minimal bitrate load of the base stations, $C_{b\,\mathrm{var}}$ - weight of the profit related to the uniformity of the bitrate load in different points of the system, $C_{nu}$ - weight of the number of served users versus the overall number of users.
The method consists of an maximization of P, meaning an optimal system for the given set of weights.
The task to be solved is NP-complete. In order to efficiently solve it, heuristic methods or polynomial time approximation schemes (PTAS) are necessary. Within this paper we have used the approach from [1] with slight modifications, briefly presented in the following.
The planned area is tessellated into little squares of side D. $l^2$ little squares make up a bigger square which we called sub-area. We consider only the sub-areas in which there is at least one BS position and at least one user. Thus from the number n of users we come to a number N of sub-areas, where $N \le n$. At first we delete all BS locations and MS-s from the outer frame of width D of each sub-area. In this way the influence of neighboring sub-areas upon each other is smaller, but an inherent error is introduced. An optimal profit vector $\mathbf{p}_i$ is evaluated for every sub-area through exhaustive search, where i is the ordinal number of the sub-area and $m_i$ is the number of BS, smaller than the minimum of b and C, where C is the maximal number of base stations that the operator is willing to install within a sub-area. The profit matrix $\underline{\mathrm{P}}$ is formed from these vectors:

$$\underline{\underline{\mathbf{P}}} = \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \\ \vdots \\ \mathbf{p}_N \end{bmatrix} = \begin{bmatrix} P(1,0) & P(1,1) & P(1,2) & \cdots & P(1,\min(C,b)) \\ P(2,0) & P(2,1) & & & P(2,\min(C,b)) \\ P(3,0) & & & & \\ \vdots & & & & \vdots \\ P(N,0) & & & \cdots & P(N,\min(C,b)) \end{bmatrix} \tag{2}$$

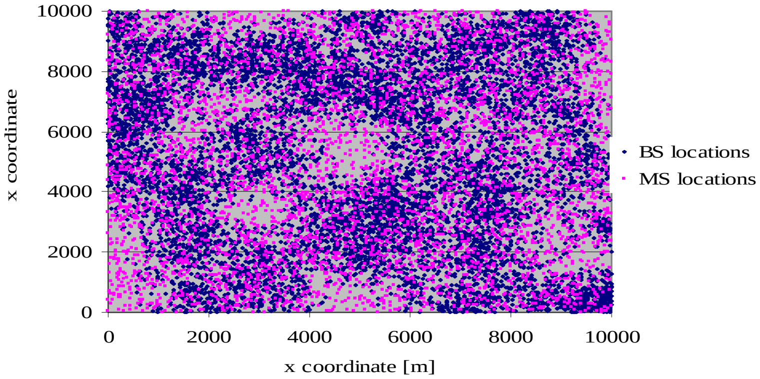
It has to be mentioned that within a sub-area the same cost function given in (1) is used, the only difference is that in the numerators the sum limits are specific to the sub-areas rather than to the planned area. In fact, summing up the profits of the different sub-areas of a tessellation gives the profit from (1) of the planned area.
The task becomes thus the selection of optimal values from these profit vectors such as the budget still holds:

$$\sum_{i=1}^{N} P(i, m_i) = \max, \ \sum_{i=1}^{N} m_i \le b \tag{3}$$

The selection is done within these sub-areas using a knapsack-like ordering of the local optimums and selection of a proper combination that would optimize the profit [1].
In order to compensate for the error that occurs along with the mentioned deletion of BS-s and MS-s the optimization is redone using $l^2$ different tessellations into sub-areas, by shifting the sub-area boundaries to the left and downwards. The number $l^2$ is the result of the fact that after l shifts in a given direction we get back to the initial tessellation, therefore the number of different tessellations is $l^2$. The global optimum of the $l^2$ local optimums is our approximation for the real optimum.

## INPUTS FOR OUR ALGORITHM. SIMULATION RESULTS

Given that, to our knowledge, there is no experience whatsoever in predicting the kind of bit-rates and the special distribution of users using these different bit-rates in third generation systems, we have chosen to use simple clustered



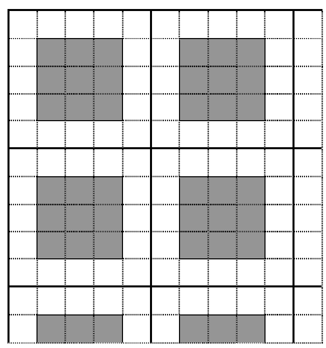



**Fig. 1. BS and MS layout** **Fig. 2. Fragment from a tesselation into subareas, l=5**

spatial stochastic processes to generate the MS-s and simple stochastic processes to generate the BS-s. We also assumed that there are a greater number of users that request little bit-rates and smaller number of users requesting high bit-rate services, which seems a valid assumption, at least within the first periods of usage. Fig. 1. shows a layout of 10000 MS-

s and 5000 possible BS positions to choose from. Fig. 2. presents an example of tessellation. Grey areas are taken into consideration, white areas are avoided, being the outer frame of width D that is being neglected. l is 5 in this case.
Given a clustered architecture and the outcome of the optimization on one realization of the spatial process [4], several realizations have been considered to see how the outcome behaved in handling the changed spatial user configurations. This seems a valid approach in a first view, because one would expect greater agglomerations for example in shopping malls and office buildings. A second view should also include line processes to describe users distributed along streets.
The first results presented in the paper show that the approach produces good results with regard to the inputs that have been selected. Basis for this affirmation has been the comparison with the behavior for randomly chosen base station locations and the relative good behavior for the case of different realizations of the clustered Poisson processes.
Fig. 1 presents the geometrical layout for the instance of the input problem that we intend to analyze in the following.

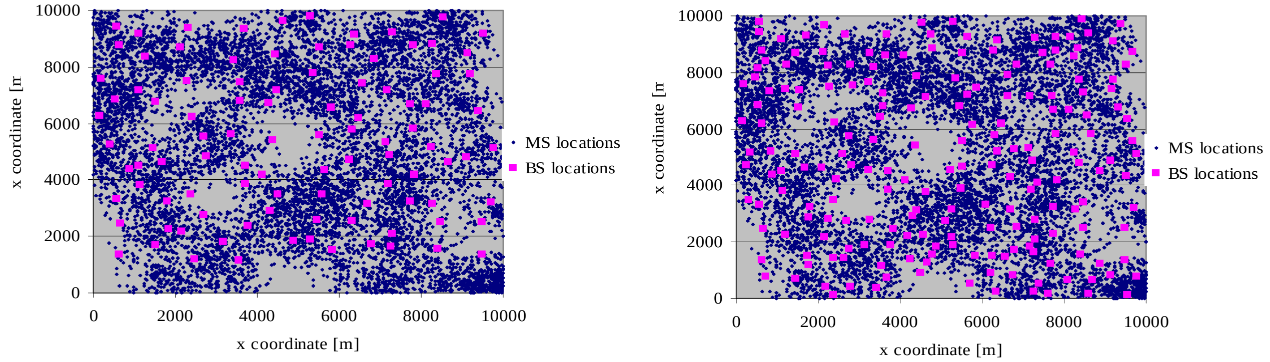



**Fig.3. Optimization for b=100 and b=200, served bitrate only**

Fig.3. presents the optimization considering only the served bitrate in the profit function ($C_b$=1 and every other C is 0). A database of 10000x10000 m$^2$ has been tested, with 10000 users and 5000 potential base station locations from which one could choose an amount equal to the budget b. The tessellation has been done with D=100m and l=10, meaning 10x10 subareas, each made of 10x10 squares. The propagation has been modeled using the COST 231 Walfisch-Ikegami model with the following parameters: average rooftop height of 5m, average street width of 10m, average distance between buildings of 20m, average base station height of 20m, average mobile station height of 2m, metropolitan area, f=2.1GHz frequency band, non line-of-sight case (as proposed in [5]). Mobiles have an $E_b/N_0$ rate in the uplink of 2.4dB and in the downlink of 5.7dB, thermal background noise of 1.0e-15 W/Hz (30% of the cases) and 1.4e-15 W/Hz (70% of the cases), orthogonality of 1, uplink bitrates of 64 kbps (30% of the cases) and 12.2 kbps (70% of the cases), downlink bitrates of 64 kbps (30% of the cases) and 144 kbps (70% of the cases). The maximal transmitted power of each mobile has been considered 125 mW. As for base stations, the maximal transmitted total power has been chosen 20W and the background noise has been 1.0e-15 W/Hz for each location. These parameters were taken as realistic values except for data rate distributions, for which there doesn't exist any valid approximation. C was chosen to be 5.
In the case of relatively low budgets (b=100) one can observe that the knapsack algorithm fails to account for the relatively high user density at the right bottom corner of the database (first part of fig.3.). However, as the budget increases, the knapsack ordering becomes more precise, as the profit quantum gets smaller. Therefore in the second part of fig.3. one can observe that the base stations are assigned within the user agglomerations even at the extremes of the database. It has to be mentioned, that the algorithm has not accounted for different tessellations, only one tessellation has been considered, so the found solution must be seen as a suboptimal one.

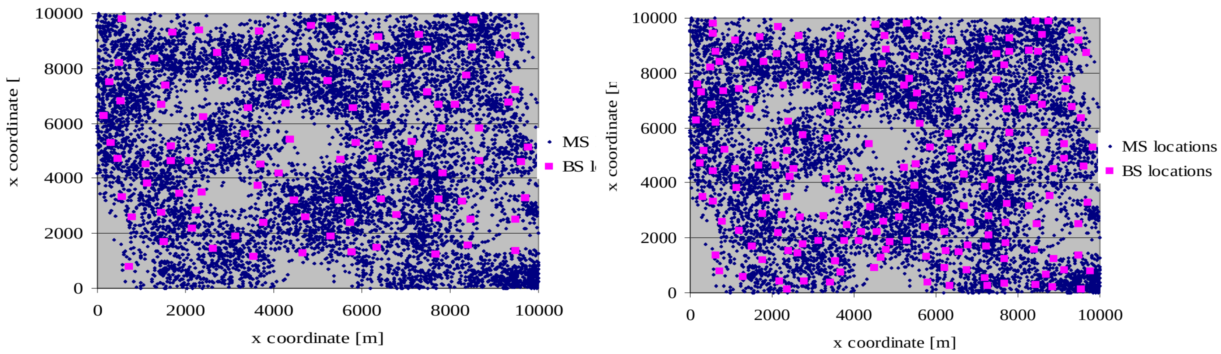



**Fig.4. Optimization for b=100 and b=200, served number of users only**

Fig.4. presents simulation results when only the weight for the served number of users $C_{nu}$ has been accounted for. The parameters has been the same. Visually one cannot observe any major differences from the bitrate-only case. This is the consequence of the fact, that the chosen bitrates are not very dissimilar, therefore the “served user” criteria and the “served bitrate” criteria does not lead to very different results.
More complex functions, considering the simultaneous effect of several factors with different weights has not been considered yet. On one hand, it is difficult to decide, how the weight factors should be chosen in order to correctly reflect our view about the functioning of the system. On the other hand, it is supposed, that enhancements are necessary within the knapsack algorithm for the case when profit inversions might occur within the profit matrix.

## CONCLUSIONS, FURTHER WORK

We are concluding that our algorithm succeeds in finding appropriate base station layouts for large areas. Its advantage consists in the polynomial dependence on the dimensions of the area and on the number of users to be served and potential base station locations to be chosen from., which makes it scalable.
One of the disadvantages consists on the exhaustive search that has to be performed in every sub-area. From this viewpoint it becomes obvious, that the computational complexity increases significantly with the number C of base stations that we allow to simultaneously be installed within one sub-area (this is in fact an exponential dependence). One has to keep C to relative low values in order to efficiently solve the task (5 in our simulations). With C=5 the running time of an instance of the problem has been approximately 10 hours on a Pentimu3/450MHz. From this aspect further work will be done in replacing the exhaustive search within the sub-areas with heuristic methods (genetic algorithms and simulated annealing).
The second disadvantage consists in that within a sub-area the evaluation of the profit function is not trivial. If increasingly dissimilar users are considered (for instance, users having very dissimilar bitrate requirements), given a certain budget, it is not obvious, which users will have to be dropped and which one will have to be served in order to obtain the maximum sub-profit within the area. If only one weight is considered (i.e. the case of the optimization for the number of served users), simple decisions could be built in: users with high bit-rates and great distances from the serving base stations will not be served, being increasingly resource-demanding. But, on the other hand, if several weights are considered, the decision of which users to be dropped is difficult to make on a heuristic basis. At this phase the BS-MS links are established on a first-coming-first-served basis, till the end of resources was reached. This seems realistic, from the following aspect: in a real-world system the optimum will not be reached, the mobiles will be served as they arrive in the system, in other words, in the way we model it. Practically, this has been achieved by a hash function applied on the set of users. Several outcomes of this procedure have been generated in a random manner and an average profit per subarea per tested number of base stations has been evaluated. The number of realizations has been chosen so that several evaluations of the profit for the same layout would not lead to significant differences (10 realizations per sub-area in our case).
The third disadvantage is related to the knapsack algorithm itself. In [1] it has been shown, that the polynomial time is valid provided the elements within one row of the profit matrix are not decreasing. Otherwise on has to test every single element within the profit matrix which would cause the loss of polynomial time.
For simple profit functions one can easily see that adding a base station to an existing configuration cannot reduce the profit. For example, if served bitrates are the only terms, then this is quite obvious. However, if other terms, related to the interference and the variance of the load in bitrate are also considered, it is theoretically possible, that in some rows of the profit matrix inversions occur. Investigations have to be done to point out the exact cases when this might occur and the knapsack algorithm has to be improved in order to account for these cases.

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