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Naseer Ul Islam Muhammad, Roger Abou-Jaoude, Christian Hartmann,  
Andreas Mitschele-Thiel

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# Self-Optimization of Antenna Tilt and Pilot Power for Dedicated Channels

Muhammad Naseer ul Islam  
Technische Universität  
Ilmenau  
[muhammad.naseer-ul-islam@tu-ilmenau.de](mailto:muhammad.naseer-ul-islam@tu-ilmenau.de)

Roger Abou-Jaoude  
Technische Universität  
München  
[roger@mytum.de](mailto:roger@mytum.de)

Christian Hartmann  
Technische Universität  
München  
[hartmann@tum.de](mailto:hartmann@tum.de)

Andreas Mitschele-Thiel  
Technische Universität  
Ilmenau  
[mitsch@tu-ilmenau.de](mailto:mitsch@tu-ilmenau.de)

**Abstract**— In Radio Access Networks (RAN), fixed configurations result in poor network efficiency. This sub-optimal performance is a direct result of user mobility and traffic patterns which changes over time and space. In this paper, we present a framework for a self-optimizing RAN, which adapts Antenna Tilt and Pilot Power according to the current load in the system. The framework uses distributed optimization and network performance-based optimization triggers. Additionally, we introduce the concept of Coupling Matrix, to avoid the traditional global network optimization. For realistic evaluations, we simulated our framework using a moving hot-spot user traffic model. This enables our framework to work under non-uniform traffic distribution with dedicated channels in a WCDMA network. The simulation results show significant performance gains, while ensuring the scalability and reduced complexity of the optimization problem.

**Keywords** - Antenna Tilt, Coupling Matrix, Pilot Power, Self-optimization, Tabu Search.

## I. INTRODUCTION

The simultaneous demand of multiple users for radio resources changes both in time and space. Under these conditions, it is impossible for Radio Access Networks (RANs) with a rigid fixed configuration to exhibit optimal coverage and capacity performance. Therefore network parameters are adapted from time to time to match the growing demands of the users. Traditionally, these adaptations are performed manually at fixed limited times during the lifespan of a network. To support modern user applications, RANs are becoming more and more complex. This complexity is a direct result of a multitude of tunable parameters required to support the stringent Quality of Service (QoS) requirements of user applications, as well as, the trend of deploying large number of Base Stations (BS) with small coverage areas to increase the network capacity. Therefore, manual adaptation of the network parameters is becoming extremely difficult and sometimes even impossible [4].

In literature, automated antenna tilt and pilot power optimization is seen as a solution to the above problems. Some studies focus on the effects of antenna tilt on the network performance [5] and [6]. Others [7] – [12] focus on finding the optimal antenna tilt and pilot power levels in

different network scenarios. They often assume global knowledge of the network state and perform the optimization in a centralized manner. Both of these factors limit the scalability of these approaches as the network size increases. Additionally the signaling complexity also increases, as extra information has to be exchanged between the central optimization entity and the Base Stations (BSs). Some decentralized approaches [13] and [14] also exist, but they rely on multiple adaptations in a trial and error method to find the optimal parameter configuration. Such an approach, although solves the problem of scalability, but its implementation in an operational network will result in quality issues for the users. This is due to the fact that with each adaptation the cell boundaries change, forcing the users at cell edges to execute a handover.

In this paper, we consider the self-optimized adaptation of remote electrical tilt (RET) [1] for BS antennas and common pilot channel (CPICH) [2] power. Self-optimization is a functionality of self-organizing networks (SON) [4]. In such a network, each network element is responsible for its own parameter adaptation based on some global optimization goals. This *eliminates central control* and thus one point of failure. SONs are also highly *scalable*, as, they rely only on neighbor information for decision making. Additionally, their ability to perform local optimizations results in *reduced complexity* of optimization problem compared to global optimization.

Our focus is not only on the optimization algorithm, but to develop a complete optimization framework. The complexity of our problem increases at least by three factors [3]: the number of users, the frequency of the required adaptations and the size of the network. Among these factors, the number of users is not in our control; hence, we consider the last two factors. We controlled the frequency of adaptation by relating the optimization triggers to the network performance instead of traditional fixed timing-based triggers. Moreover, we introduced the concept of *Coupling Matrix* for complexity reduction, by considering local distributed optimizations instead of the centralized optimization of the network as a whole. For evaluation, we used a snapshot-based simulator. The results show remarkable performance gains in terms of network coverage and capacity.

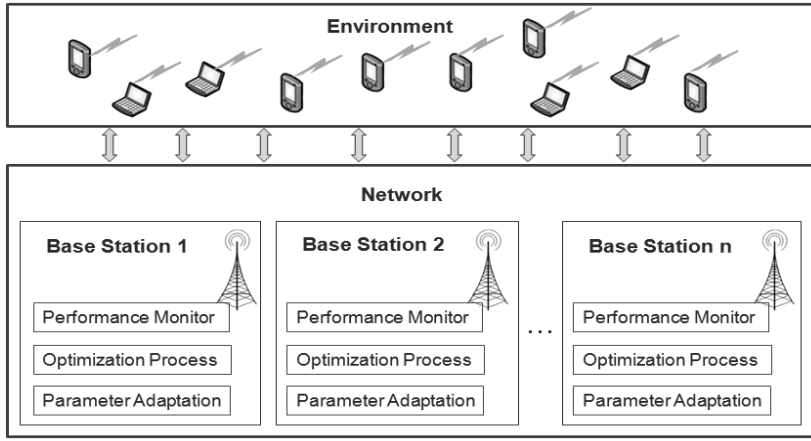


Figure 1: Optimization Framework

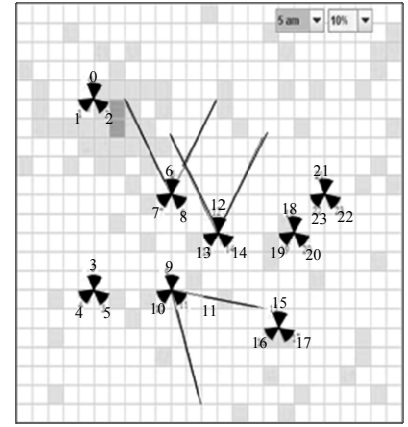


Figure 2: Sector Coupling

The rest of the paper is organized as follows. Section II describes our optimization framework in detail. Section III discusses the optimization problem at hand and the algorithm used to solve it. Section IV introduces the network topology and the simulation environment used for our study. Section V presents the simulation results and the advantages obtained by using our self-organized adaptation of antenna tilt and pilot power. Section VI concludes the paper and outlines ideas for further enhancements.

## II. OPTIMIZATION FRAMEWORK DETAILS

We present the components of our optimization framework in this section, as shown in Figure 1. Here the network environment consists of mobile users within the network coverage area. The network itself consists of a number of self-optimizing BSs. Each BS monitors the network performance, in terms of user satisfaction, in its own coverage area and triggers the optimization process whenever necessary. The optimal parameters are then calculated and the BS is adapted accordingly. The efficiency of the framework depends upon the chosen parameters for adaptation, the triggers that initiate the optimization and the optimization methodology. These factors are explained in the following sections.

### A. Adaptation Parameters

In our framework, we consider the antenna tilt and pilot power as the adaptation parameters for network optimization. Primary reason for their selection is the ease with which they can be adapted without any human involvement.

#### 1) Antenna Tilt

Antenna tilt can be used to minimize the interference to the neighboring cells and therefore capacity enhancements in an interference limited system like WCDMA [8]. Antenna tilt can be adapted both mechanically and electrically. Doing it electrically, by shifting the signal phases of different antenna elements, has the advantage that both the main lobe and side lobes are tilted by same amount, whereas, with mechanical tilt the side lobes are not tilted as much as the main lobe [8]. Moreover electrical tilt can also be performed remotely making it more suitable for frequent adaptations. In

this paper the permissible range for antenna tilt is 0 - 8 degrees and can be modified in steps of 2 degrees.

#### 2) Pilot Channel Power

Pilot channel is used to define the boundaries of the cell and hence the load balancing among the neighboring cells. It is one of the major consumers of transmission power at the BS; hence, it is desirable to reduce its value, while maintaining the network service area requirements. Reducing pilot power also helps to minimize pilot pollution, where mobile stations perform frequent handovers due to the ambiguous cell boundaries. We consider pilot power levels between 20dBm and 32 dBm which can be changed in 2 dB steps.

### B. Optimization Triggers

A natural selection for optimization initiation is to have some periodic triggers throughout the day [3]. However, this may lead to under or over optimization in different load situations. We propose to make the optimization triggers dependent upon the network performance. We choose the user satisfaction as a metric to trigger network optimization. In this paper, we consider only dedicated channels, so, any user unable to access a channel either through blocking or dropping is considered as an unsatisfied user. This is a critical performance metric and defines the network quality from a users' point of view. Therefore operators want to ensure its highest possible value. For our work, we set a threshold of 90 percent user satisfaction as optimization trigger, so that whenever its value falls below 90 percent in any sector, we adapt our network to the current load situation.

### C. Optimization Methodology

We use a distributed optimization methodology for complexity reduction. Here, it is important to note, that the coverage and capacity problems we want to solve are highly localized in nature. Meaning, at a specific time, we have only a limited number of problematic areas that need network adaptation. In this paper, we introduce the concept of *Coupling Matrix* for a distributed optimization implementation. Using this approach we can localize the

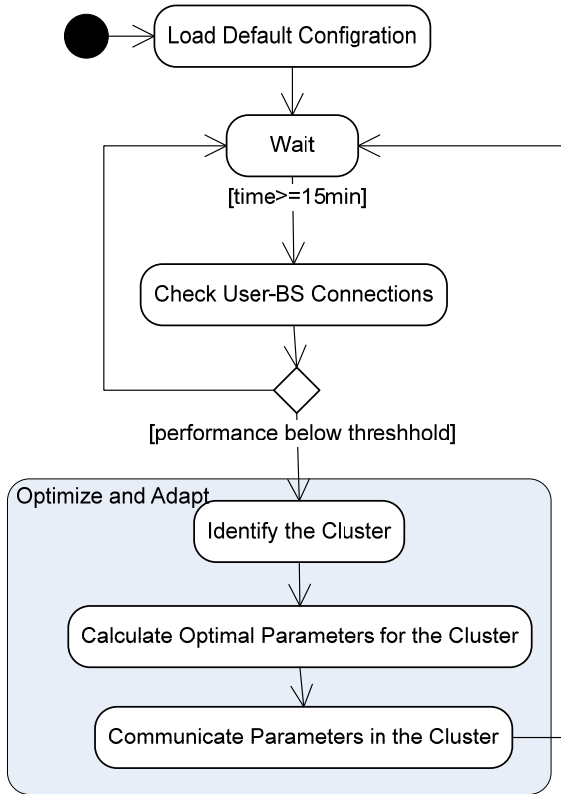
optimization problem to specific problematic areas and avoid the traditional complex whole network optimization.

#### 1) Distributed Optimization using Coupling Matrix

Modern cellular networks widely use sector antennas for interference reduction and hence capacity enhancement. This is achieved by directing the transmitted signals in a particular direction for example  $60^\circ$  in horizontal plane instead of complete  $180^\circ$ . Moreover, signal strength also decays with distance and hence becomes irrelevant after a particular distance. Taking into account both of these factors, we can easily assume that the signal of one BS interferes with different BSs in the network differently i.e. there is a varying degree of coupling between different BSs of a network. For example, Figure 2 shows a snapshot of our simulator with eight randomly distributed BSs with 3 sectors each. Here, it is clear that the signals of sector 12 affect the coverage area of sector 6 more than sector 11. Hence, any adaptation of antenna tilt and pilot power at sector 12 will affect the users in sector 6 more, than in sector 11.

sector number under observation and the remaining rows in a particular column represent other sectors in decreasing order of coupling from the sector under observation. For example, sector 0 in the second column is most coupled to sector 2 and least coupled to sector 10. One thing to notice here is that the top three most coupled sectors belong to the same BS as the sector under observation. This is due to the heavy dependence of the factors upon distance that we consider for calculating the coupling values. Therefore, for our optimization, we ignore the three most coupled sectors and form the cluster from the rest of the sectors.

Using this coupling matrix, we can identify clusters of different sizes around a troubled sector, leaving out the sectors which are not heavily coupled to the problematic sector. In this way, we can localize our adaptation procedure to the chosen cluster and perform the parameter adaptation only for this cluster. Using a fixed cluster size for each optimization limits the solution space to a fixed value regardless of the size of the network. Our results show that



**Figure 3: Optimization Process**

We quantify this coupling among the BSs with equation (1). Here  $x$  stands for the sector under observation and  $y$  for any other sector with which the coupling is calculated. Using this relation we can calculate the coupling values for all the sectors, forming a square matrix of the order of the number of sectors in the network. The resulting values are presented in Table I. For space limitation only the partial values for the first four sectors are shown. Here the first row represents the

**Table I: Coupling Matrix (Partial)**

Sector Identity under Observation	0	1	2	3
Surrounding Sector's Identity in Decreasing Order of Coupling	2	2	2	5
	1	1	1	4
	0	0	0	3
	3	3	6	7
	6	9	9	10
	9	6	12	13
	12	12	7	1
	7	7	3	2
	22	13	13	19
	13	4	22	22
	19	10	19	9
	18	15	15	8
	21	8	18	0
	15	5	8	16
	8	16	21	11
	10	14	10	12

with a good choice of the optimal cluster size, we can avoid the unwanted global network optimization, while still achieving a performance close to the global optimization of the whole network. Figure 3 explains the optimization process which starts with the loading of the default configuration once the BS becomes active. During the operational state it continuously checks the user connections and monitors the sector performance in terms of user

$$C(x, y) = Pathloss_{x,y} * Antenna Gain_{x,y} * Antenna Gain_{y,x} * CPICH Power_y \quad (1)$$

satisfaction every 15 minutes. If at any of these checks the performance falls below the 90 percent threshold, the optimization and adaptation procedure is activated. This process then calculates and adapts the optimal antenna tilt and pilot power parameters throughout the cluster.

### III. OPTIMIZATION PROBLEM AND ALGORITHMS

Both of the optimization parameters under study are discrete in nature. Therefore, the optimization problem takes the form of a combinatorial optimization, where the optimal combination of antenna tilt and pilot power for all the sectors within a cluster needs to be calculated subject to some objective function. As we consider a WCDMA network which is interference limited [8], an obvious choice for the objective function is to minimize the interference which is directly related to the transmission power. Moreover, as we take the user satisfaction as the optimization trigger, this should also be a part of the objective function. In the chosen objective function (2) we want to minimize the total uplink and downlink transmission power as well as the outage probability. Here  $p$  represents the transmission power in uplink and downlink denoted by the direction of the arrow,  $u$  represent the number of active users in a pixel of the network map,  $g_{ij}$  is the link budget between a pixel  $i$  and BS  $j$ ,  $x$  is a binary variable that is 1 when a pixel  $i$  is assigned to BS  $j$  and 0 otherwise,  $\lambda$  and  $\beta$  are the weight factors for the different terms in the objective function,  $n$  is the number of active mobile users and  $m$  is the number of BSs. The link budget contains the antenna gain depending upon the user position in the 3D antenna beam pattern of each sector as well as the path loss using the Hata-Okumura model for urban scenario.

The objective function is subject to some constraints. Equation (3) represents the uplink power control condition and equation (4) is the equivalent for downlink. Using these

two inequalities, the transmission powers can be calculated so that a minimum Carrier to Interference (CIR) ratio is met. The downlink equation is different in the sense that it contains both the inter- and intra-cell interference in the denominator. Equation (5) and (6) represent the permissible range of transmission power per connection in uplink and downlink direction respectively with  $P_{\max}$  as the maximum value. Finally, equation (7) represents the total available power at a BS. The power control mechanism is performed in an iterative manner. With the addition of every new user into the network the power required to reach its target CIR is calculated. The power of all other existing users is then calculated again by taking into account the new user power levels to maintain the target CIR values.

#### A. Heuristic Algorithm

We rely on heuristic algorithms to quickly find a near optimal solution. The parameter adaptation needs to be performed frequently to match the changing traffic load situation. Therefore time required to find the optimal solution is critical. On the other hand, the solution space consisting of the possible combinations of antenna tilt and pilot power grows exponentially with every new sector considered by the optimization procedure. Heuristic algorithms are useful to address both of these factors. These algorithms do not guarantee optimality, but still, can calculate near optimal solutions in a very short time.

In our work we have used a randomized variant of Tabu Search (TS) to explore the solution space for the optimal solution. Tabu search maintains a tabu list of previously considered solutions and prohibits them to be considered again for some time. By maintaining this list of already explored solutions, it ensures the exploration of a large portion of the solution space without getting stuck in local

$$\min \left\{ \lambda^{\uparrow} \sum_{i=1}^n \sum_{j=1}^m u_i p_i^{\uparrow} g_{ij} x_{ij} + \lambda^{\downarrow} \sum_{i=1}^n \sum_{j=1}^m u_i p_i^{\downarrow} g_{ij} x_{ij} + \beta \left[ 1 - \frac{\sum_{i=1}^n \sum_{j=1}^m u_i x_{ij}}{\sum_{i=1}^n u_i} \right] \right\} \quad (2)$$

$$\frac{p_i^{\uparrow} g_{ij}}{\sum_{h=1}^n \sum_{t=1}^m u_h g_{ht} p_h^{\uparrow} x_{ht} - p_i g_{ij} + \eta} \geq CIR_{tar}^{\uparrow} x_{ij} \quad (3)$$

$$\frac{p_i^{\downarrow} g_{ij}}{\alpha \left( \sum_{k \text{ assigned to } j} u_k \frac{g_{ij}}{g_{kj}} p_k^{\downarrow} x_{kj} - p_i^{\downarrow} \right) + \sum_{\substack{l \in S \\ l \neq j}} \sum_{k \text{ assigned to } l} u_k \frac{g_{il}}{g_{kl}} p_k^{\downarrow} x_{kl} + \eta} \geq CIR_{tar}^{\downarrow} \quad (4)$$

$$0 \leq p_i^{\uparrow} \leq P_{\max}^{\uparrow} \quad (5)$$

$$0 \leq p_i^{\downarrow} \leq \sum P_{\max}^{\downarrow} g_{ij} x_{ij} \quad (6)$$

$$\sum_{i \in I} \frac{p_i^{\downarrow}}{g_{ij}} x_{ij} \leq P_{tot} y_j \quad (7)$$

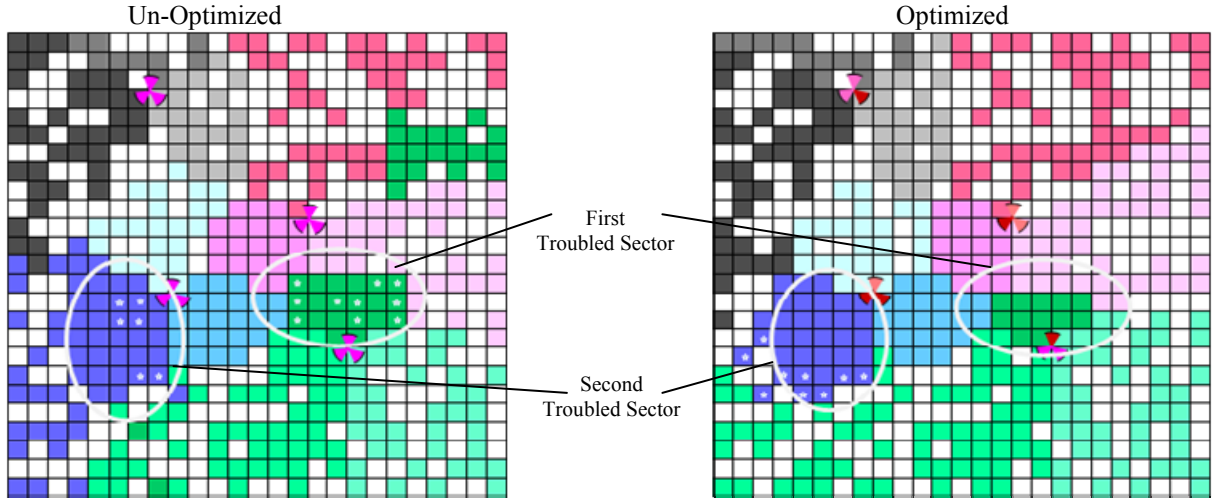


Figure 4: Load Balancing using Parameter Adaptation

minima. At every troubled sector, the algorithm starts with an initial solution for the chosen cluster around that sector and puts it into the tabu list. After that a neighbor solution is calculated by modifying the optimization parameters by a small value and its optimality is checked by calculating the objective function. Depending upon the objective function value, this neighboring solution can be ignored or picked as the optimal solution and then inserted into the tabu list. The process continues for some fixed number of iterations and the last optimal solution is communicated within the cluster for parameter adaptation.

#### B. Neighborhood Search and Solution Vector

As we have a combinatorial optimization problem to solve, the solution vector consists of a combination of antenna tilt and pilot power values for all the sectors within the cluster and is depicted in Table II. Neighbor solutions are created by randomly selecting one of the sectors from the cluster which is not part of the tabu list and was not modified in the last iteration and changing its antenna tilt by  $\pm 2$  degrees and its pilot power by  $\pm 2$  dB.

Table II: Solution Vector

Sector 1	Sector 1	Sector 2	Sector 2	...	Sector n	Sector n
Tilt 1	Pilot 1	Tilt 2	Pilot 2	...	Tilt n	Pilot n

Table III: Mobility Parameters for Gauss-Markov Users

Simulation Time	00:00-06:00	06:00-18:00	18:00-24:00
Pause Probability	0.8	0.2	0.6
Pause Time [hrs]	3:00-6:00	0:00-3:00	2:00-4:00

Table IV: Mobility Parameters for Hotspot Users

Simulation Time	00:00-06:00	06:00-18:00	18:00-24:00
Number of Hotspots	1	3	2
Standard Deviation [m]	100	40-80	100

#### IV. NETWORK TOPOLOGY AND SIMULATION ENVIRONMENT

To evaluate our framework for distributed self-optimization we performed a snapshot analysis. The simulated network consisted of a 1 km<sup>2</sup> area and contained eight BSs with three sectors each. The position of the BSs remained fixed throughout the simulations. Mobile users were created with a defined mobility and traffic model for the complete 24 hours of the day. These users could be in active or non-active state and could move with a speed of 0-16 km/h. Half of the users moved according to a Gauss Markov Mobility Model (GMMM) to generate a uniform distribution of users, while the other half moved in a hotspot pattern to generate highly loaded areas. The position and activity of the users were updated once every second and snapshots of the network were taken at regular intervals of 15 minutes. The whole day was divided into three regions of low-load (0000-0600 hrs), medium-load (0600-1800 hrs) and high-load (1800-2400 hrs).

##### A. Moving Hot-Spot Mobility Model

A layered mobility model was used to generate non-homogenous user distribution. Half of the users moved with GMMM to generate a homogenous distribution of users throughout the simulation area. GMMM initializes the users with a certain speed and direction. After that once every second new values for speed and direction were calculated depending upon the last values using equations (8) and (9). Finally the new coordinates of the user were calculated with the equations (10) and (11).

$$s_t = \alpha s_{t-1} + (1 - \alpha) \bar{s} + \sqrt{(1 - \alpha^2)} s_{x_{t-1}} \quad (8)$$

$$d_t = \alpha d_{t-1} + (1 - \alpha) \bar{d} + \sqrt{(1 - \alpha^2)} d_{x_{t-1}} \quad (9)$$

$$x_t = x_{t-1} + s_{t-1} \cos d_{t-1} \quad (10)$$

$$y_t = y_{t-1} + s_{t-1} \sin d_{t-1} \quad (11)$$

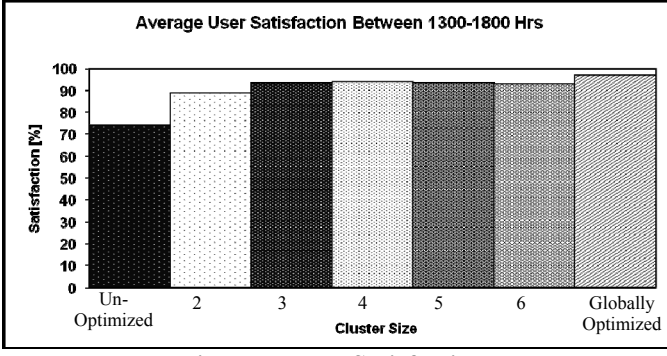


Figure 5: User Satisfaction

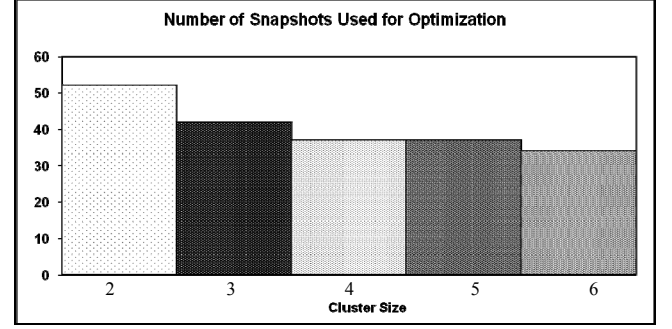


Figure 7: Snapshots Used for Optimization

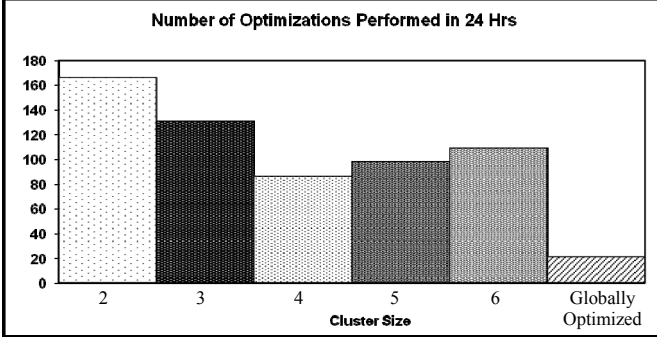


Figure 6: Optimizations Performed in 24 Hrs

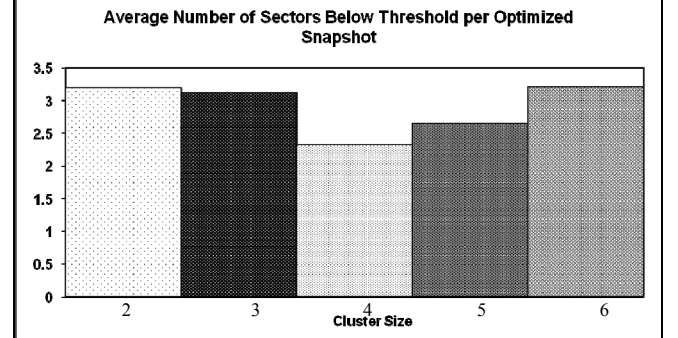


Figure 8: Average Number of Sectors below Threshold

In the above equations,  $s$  is the speed of the user,  $d$  the direction,  $t$  the time instant,  $x$  and  $y$  the Cartesian coordinates,  $\bar{s}$  the mean value of speed as  $t \rightarrow \infty$ ,  $\bar{d}$  the mean value of direction as  $t \rightarrow \infty$ ,  $s_{x_{t-1}}$  and  $d_{x_{t-1}}$  are two Gaussian distributed variables with mean 0 and standard deviation 1, and  $\alpha$  is a tuning parameter for randomness and can have values between 0 and 1.

For a realistic user behavior implementation the GMMM was enhanced to have a pause time parameter as well. This parameter represents the time for which a user would be stationary. Its value depends upon the time of the day and is given in Table III

The remaining half of the users is simulated with attraction point model to generate hotspots in the network. Attraction point model creates users around a central point, where the distance between the user and the center point is a two dimensional Gaussian distribution whose center is the central point and standard deviation is the radius of the hotspot area. The parameters for the simulated hotspots are summarized in Table IV.

## V. RESULTS AND DISCUSSION

For the evaluation of our framework, we simulated different scenarios and the results are discussed in this section.

### A. Parameter Optimization and Load Balancing

Antenna tilt and pilot power optimization results in better load balancing between the neighboring cells and thus

improved user satisfaction. Figure 4 shows this effect for a snapshot in our study. Each colored square represents the users served by one of the sectors, while the white squares means no active user in this area. The white stars within the squares represent some unsatisfied users. The color of the sector antenna represents the antenna tilt value: the darker the color is, the more down-tilted the antenna is.

In the un-optimized case all the sector antennas are initialized with 0 degree tilt, whereas, after the optimization we have different tilt values for different sectors of the BSs. Down-tilting the antenna results in reducing the coverage area of the troubled sector and shifting the cell edge users to neighboring sectors. Moreover, down-tilting also improves the signal gain in the vicinity of the BS, which results in better SINR values and thus improved capacity in a WCDMA network. As a result, in the optimized case, most of the unsatisfied users within the coverage area of the initially troubled sectors are now successfully connected to the network. This especially holds for the overload area on the right. However, some unsatisfied users can still be observed within the overloaded sector on the left. This is because; this sector has a large coverage area with no other BS to accommodate its cell-edge users. However, there still is an improvement which lies in the fact that in the optimized case only the cell edge users are unsatisfied, whereas in the un-optimized case, even the users very close to the BS are unsatisfied.

### B. Optimal Cluster Size and Complexity

The performance and complexity of our distributed optimization algorithm depends upon the size of the selected cluster. Different cluster sizes have been studied. Figure 5



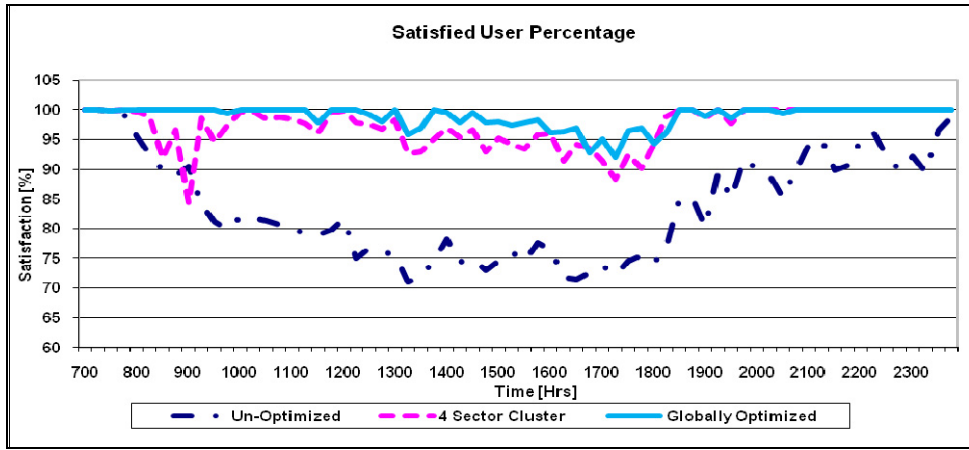


Figure 9: User Satisfaction throughout the Day

shows the average user satisfaction achieved during high-load times. In the un-optimized scenario an average satisfaction of only 74 percent is achieved, whereas its value increases to 97 percent by performing a global optimization which considers all the sectors in the optimization procedure. Both of these values serve as a reference to measure the performance improvement of our distributed algorithm. Using distributed optimization, the user satisfaction increases directly with the cluster size up to the cluster size of 4 and attains a value of 94 percent. Since, with the increasing cluster size we are more flexible to choose the parameters; therefore the performance increases with the cluster size. Any further increase in the cluster size actually degrades the achieved user satisfaction, unless we consider the whole network optimization at once. The coverage and capacity problems are localized in nature. Therefore, considering very large cluster size, actually results in parameter adaptation of many sectors, which are not directly involved in the load balancing of the troubled areas. This sometimes results in performance degradation of those sectors even below the un-optimized scenario. The optimal value for the cluster size is believed to depend upon the BS density and therefore may change in other scenarios accordingly.

The complexity also varies with the varying cluster size. The total number of optimizations performed within 24 hours is shown in Figure 6. Conversely, it shows the number of sectors that are below the performance threshold and that need parameter adaptation during a 24 hour simulation. Its value decreases to almost one-half as we increase the cluster size from 2 to 4. But again as we further increase the cluster size, the executed optimizations starts to increase again due to the unwanted parameter adaptation of sectors far away from the trouble areas.

Figure 7 represents the number of snapshots that required optimization to be performed out of a total of 96 snapshots (one per every 15 minutes) for the complete day. Here, the value decreases with the increase of the cluster size. But if we look at it in combination with Figure 8 it is clear that although the number of relevant snapshots is decreasing, the complexity in terms of sectors that are below the threshold per snapshot starts to increase beyond a cluster size of 4. As a

result, the overall number of optimizations performed starts to increase as well.

### C. Snapshot Analysis

We used snapshot-based optimization to analyze the benefits of self-optimization. Network snapshots were taken every 15 minutes for one complete day of 24 hours. These snapshots contain information about user location and activity. All the snapshots are then used consecutively to identify the BS-user connections and therefore the troubled sectors that require parameter adaptation. Figure 9 shows our results for such snapshots in three cases of un-optimized, distributed optimization using a cluster size of 4 and finally the global optimization of the whole network at once. Our distributed optimization produces significant performance gains in terms of user satisfaction as compared to the un-optimized case. Moreover, its performance is highly comparable to the global optimization. This means that we can avoid the signaling and single-point-of-failure characteristics of the traditional global optimization techniques while still achieving comparable performance gains by using our distributed self-organized optimization techniques.

## VI. CONCLUSION

In this paper, we introduced a framework for self-optimized antenna tilt and pilot power adaptation. We used network performance metric, as the triggers to the optimization procedure instead of traditional fixed time-based triggers. For complexity reduction of the optimization problem, we introduced the concept of Coupling Matrix. This helps to localize the optimization problem to specific problematic areas and avoids the traditional global optimization. Additionally, our localized optimization approach limits the solution space to a fixed value despite the growing network size. For the evaluation of our framework we have implemented a snapshot-based simulator. Our simulation results show that with the selection of an optimal cluster size in the distributed optimization, we can achieve significant performance gain, nearly equivalent to the global optimization while making the optimization procedure highly scalable. However the gain depends upon the chosen cluster



size and the issue is, whether there is an optimal cluster size for all scenarios. In our future work, we intend to investigate the relationship between BS density and the optimal cluster size. Moreover, we will extend our framework to handle OFDM systems as supported by LTE.

#### REFERENCES

- [1] Remote Control of Electrical Tilting Antennas, TR 25.802, Available at: <http://www.3gpp.org>
- [2] Technical Specification Group Radio Access Network: Physical layer procedures (FDD), Release 7, 3gpp TS 25.214 v.7.5.0, May 2005, Available at: <http://www.3gpp.org>
- [3] R. Abou-Jaoude, C. Hartmann, "Radio Parameters Frequent Remote Adaptation: Antenna Tilt and Pilot Power for Dedicated Channels", IEEE Vehicular Technology Conference (VTC)-Fall, 2009
- [4] L.C. Schmelz et al., "Self-configuration, -optimization and -healing in wireless networks", Wireless World Research Forum, 2008
- [5] M. Garcia-Lozano and S. Ruiz, "Effects of downtilting on RRM parameters," in Proc. 15th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC '04), vol. 3, pp. 2166–2170, Barcelona, Spain, September 2004
- [6] Per Zetterberg, "Performance of Antenna Tilting and Beamforming in an Urban Macrocell," Available at: <http://www.ee.kth.se>, 2006
- [7] E. Amaldi, A. Capone, F. Malucelli, "Radio planning and coverage optimization of 3G cellular networks", ACM Wireless Networks, 2008
- [8] J. Niemela, T. Isotalo, J. Lempiainen, "Optimum Antenna Downtilt Angles for Macrocellular WCDMA Network" EURASIP Journal on Wireless Communications and Networking, May 2005
- [9] I. Siomina, P. Värbrand, and D. Yuan, "Automated optimization of service coverage and base station antenna configuration in UMTS networks", IEEE Wireless Communications, vol. 13, pp. 16–25, 2006
- [10] A. Wacker, K. Sipilä, and A. Kuurne, "Automated and remotely optimization of antenna subsystem based on radio network performance," in Proc. 5th International Symposium on Wireless Personal Multimedia Communications (WPMC '02), vol. 2, pp. 752–756, Honolulu, Hawaii, USA, October 2002
- [11] M. Garca-Lozano, S. Ruiz, J. J. Olmos, "UMTS Optimum Cell Load Balancing for Inhomogeneous Traffic Patterns", IEEE Vehicular Technology Conference (VTC)-Fall, 2004
- [12] U. Türke, M. Koonert, "Advanced Site Configuration Techniques for Automatic UMTS Radio Network Design", IEEE Vehicular Technology Conference (VTC)-Spring, 2005
- [13] A. Gerdenitsch, S. Jakl, Y. Y. Chong, M. Toeltsch "A Rule Base Algorithm for Common Pilot Channel and Antenna Tile Optimisation in UMTS FDD Networks", ETRI Journal, Vol. 26, No. 5, Oct. 2004
- [14] M. Pettersen, L. E. Bråten, and A. G. Spilling, "Automatic antenna tilt control for capacity enhancement in UMTS FDD," in Proc. IEEE 60th Vehicular Technology Conference (VTC '04), vol. 1, pp. 280–284, Los Angeles, USA, September 2004.