A Target-Following Regime using Similarity Measure for Coverage and Capacity Optimization in Self-Organizing Cellular Networks with Hot-Spot

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Abstract—**The Self-Organizing Network (SON) has been seen as one of the promising areas to save OPerational EXpenditure (OPEX) and to bring *real* efficiency to the wireless networks. Though the studies in literature concern with local interaction and distributed structure for SON, study on its coherent pattern has not yet been well-conducted. We consider a target-following regime and propose a novel approach of goal attainment using Similarity Measure (SM) for Coverage & Capacity Optimization (CCO) use-case in SON. The methodology is based on a self-optimization algorithm, which optimizes the multiple objective functions of UE throughput and fairness using performance measure, which is carried out using SM between target and measured KPIs. After certain epochs, the optimum results are used in adjustment and updating modules of goal attainment. To investigate the proposed approach, a simulation in downlink LTE has also been set up. In a scenario including a congested cell with hot-spot, the joint antenna parameters of tilt/azimuth using a 3D beam pattern is considered. The final CDF results show a noticeable migration of hot-spot UEs to higher throughputs, while no one worse off.**

Keywords-components; Self-Organization, Self-Organizing Network, Long Term Evolution, Global Pattern, Optimization, Simulated Annealing, Capacity, Similarity Measure

I. INTRODUCTION

The most important challenge for wireless operators is keeping pace with growing demands for streaming data. The remarkable growth of smart phones, and other devices as tablets and laptops in recent years, even worsens the situation. Figure 1 shows one of the recent predictions [1, 2] for this growth of data demand in the near future. To meet this demand several studies have recently been conducted. One of the promising areas is the concept of Self-Organization. The notion of self-organization has very old roots in literature [3], but its importance in science and technology has only recently been recognised. In fact, it is a process to maintain order in a complex dynamic system as such system has a distributed character, thus it is robust and resists perturbations. Ashby [3], for the first time, introduced principles for self-organizing systems; afterwards, these principles have been used in several areas of science and technology. Although the concept has been adopted from cybernetics, during the 1980s and the 90s the field was further fertilised by mathematical methods and theorems for complex systems and networks [4].

Due to the limited frequency reuse of modern cellular radio networks, the joint setting of the parameters of all cells with an irregular layout and coverage areas becomes a complex and challenging task. To this end, several research areas on different platforms have been initiated, investigated and implemented in academia and industry. Among them, Self-Organizing Network (SON) has been seen as one of the promising areas also to save OPerational EXpenditure (OPEX) to bring *real* efficiency to wireless networks. SON aims at network optimization, so the interaction of human (networker) can be reduced and the capacity of networks can be increased. Although there is no evidence of a unified framework in literature, self-organization has certain features as:

- global coherent pattern
- local interaction of nodes
- parallel and/or distributed structure

In this study, we investigate the first feature in SON and take the other two as given. This article includes 7 sections, which we present a literature review and state-of-the-art in section 2. Proposed methodology and formulation is presented in section 3 with a system model description in section 4. Desired scenario in SON-LTE/CCO is explained in section 5 with the simulation results in section 6. Also, the conclusion remarks are presented in section 7.

II. LITERATURE REVIEW

There are several use-cases, approved by 3GPP, included in different European projects. One of the most practical use-cases is considered to be Coverage & Capacity Optimization (CCO). It has been known for years that antenna has a high impact on the performance of cellular networks [5]. Some studies in the last decade have specifically been carried out on the optimization of wireless networks targeting the coverage and capacity. A work based on the multi-objective Tabu Search (TS) has been proposed [6] for optimizing the network performance at design stage, which introduces a service-oriented framework for an underlying network. As a trade-off between the capacity and coverage in cellular networks, it has been known that the Common PIlot CHannel (CPICH) and antenna parameters are effective while the power adjustments are less effective in a dynamic environment [7].
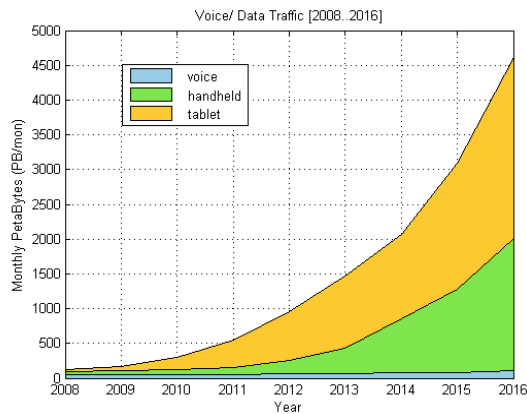
Figure 1: Data Access Demand Growth (reproduced from [1])

There are two different approaches for a CCO use-case in SON, which are parameter-based and antenna-based. The parameter-based approach for optimization in a SON produces several problems, e.g: low received SINR in a load-balancing case. These problems can be avoided in an antenna-based SON.

In the Bell lab research [8] authors propose two different dynamic methods, including the closed-loop and open-loop approaches. Combes [9] has proposed a new method based on an α-scheduler for CCO in OFDM-based networks with Multiple Input Multiple Output (MIMO). They have also proposed a closed-form formula and Monte Carlo method for the desired network. The impact of antenna azimuth and tilt has been studied and its importance in the deployment phase of networks has been investigated [10]. In addition, it has been shown that a 10dB gain over large areas can be achieved by beam optimization [11]. The study on network parameter optimization has been started in 3G networks e.g. the optimization of parameters of UMTS as antenna beam and CPICH control. It is worth pointing out that as information from the environment is a necessary part of SON, many researchers have already proposed to use the intelligent methods from machine learning to neural networks, fuzzy systems [12] and game-theoretic approach [13]. Feng [14] has described the self-optimization algorithm in SON as an auto-tuning process of network, considering the measurements from User Equipment (UE) & eNodeB. Temesvary [15] has presented an approach for tilt configuration based on SINR, which is obtained from Channel Quality Indication (CQI).

Real time antenna optimization has recently attracted many interests from the industry, among them Remote Electrical Tilt (RET) and Remote Azimuth Steering (RAS) have been standardised. From the technical side, having standards for tilt/azimuth, the advances in Electrical Down Tilting (EDT) have enabled the adjustments of antenna patterns. Other techniques such as Continuously Adjustable Electrical Down Tilt (CAEDT) have enabled intelligent algorithms for self-optimization. Antenna Interface Standards Group (AISG) [16] has provided the main standards for CAEDT and RAS. AISG v2 is consistent with the 3GPP standards (TS25.460, TS25.463). These techniques have provided the feasibility for creating an adaptive network that is SON in our study. The optimization process will be carried out in eNodeB while the configuration control is for the parameter adjustments

whenever the final optimal results are obtained. As a history, CELTIC GANDALF [17] projects (2005-2007) are among the first European projects that addressed the potential of automating tasks in GSM, UMTS and WLAN. Thereafter, the MONOTAS project provided the adaptive algorithms for pilot power to combat the traffic load during the next two years. Also, projects as SOCRATES [18], ANA [19], BIONETS, 4WARD and UniverSelf, have been dedicated to SON development. The recent project called EARTH is concerned with the *"new concepts"* for dynamic optimization of wireless networks, such as self-optimization and/or self-configuration [20].

III. METHODOLOGY

As the global pattern is one of the main SON features, in this study, target KPIs are considered as our global pattern and the similarity between target and performance parameters is measured by Similarity Measure (SM) [21]. Thereafter, for the optimization part, a Monte Carlo based optimization, a meta-heuristic algorithm, the Enhanced Adaptive Simulated Annealing (EASA) has been designed [22]. A pseudo-code of EASA is shown in figure 2. EASA has been proposed as optimization algorithm in our goal attainment approach. In this study the applicability of the proposed method in a mobile network is investigated, with a simulation towards a multi-cell multi-user model. As SON functionality is supported by LTE, we used LTE structure in our simulations. The pseudo-code represents the developed algorithm for self-optimization in simulated SON. The annealing function in EASA is based on Similarity Measure (SM), which will be discussed later in this section. The following procedure was designed to put coverage & capacity in an adaptive process. In the remainder of this article, two parts of *adjustment* and *update* are considered for network (soft) and antenna (hard) parameters as depicted in the flow diagram (figure 3).

```
begin procedure
    define objective function f(v), v:=(p₁, p₂, ..., pⱼ)
    begin initialization
        initialize Temperature T₀
        initialize initial guess v₀
        set final Temperature Tf
        determine max(Iteration):=N
    end initialization
    determine the similarity measure(S) between KPIs
    define cooling schedule T(S,t) as α(S)T(t); (0<α<1)
        while (T>Tf) and (n<N)
            set new parameters: vₙ₊₁
            calculate δ=fₙ₊₁(vₙ₊₁)-fₙ(vₙ)
            accept the new solution if better
                if not improved
                calculate β=exp{-δ/{KT(S,t)}}
                generate rand (0<rand<1)
                    if β>rand
                        accept the new solution
                    endif
                endif
            update the best v*, f*
        end while
        determine optimum parameters ζ̂:=v*
end procedure
```

Figure 2: Pseudo-Code for EASA Optimization Algorithm

Mathematically, we consider a maximization of performance as the main objective, therefore;

$$\max\{f(p_1, p_2, \ldots, p_j)\} \quad ; j \in K \tag{1}$$

where K is the number of cells, p is the performance measure and f is the objective function, so our optimum parameters can be formulated as:

$$\{\hat{\zeta}_1, \hat{\zeta}_2, \ldots, \hat{\zeta}_j\} = \frac{\arg\max\{f(.)\}}{\zeta_1, \zeta_2, \ldots, \zeta_j} \tag{2}$$

which is combination of $\zeta_1, \zeta_2, \ldots, \zeta_j$ network parameters within K cells. As a Multi-Objective Optimization (MOO) has been set up in our study, the performance measure is defined based on similarity between measured KPIs and target KPIs. KPIs from all involved cells are considered, as:

$$\text{KPI: } \{KPI_{ij}\} \quad ; i^{th} \text{ KPI in } j^{th} \text{ cell} \tag{3}$$

As the network operator may consider different patterns for different cells, a measure using all parameters is considered. If target KPI is denoted by $KPI^{(t)}$:

$$\sum_i \sum_j w_{ij} \left\| KPI_{ij}^{(m)}, KPI_{ij}^{(t)} \right\| \tag{4}$$

is the general form of performance measure in our approach and w_{ij} is weight for i^{th} KPI in j^{th} cell and $KPI^{(m)}$ is measured KPI and $\|.\|$ denotes a measure. The best weights can also be selected through the optimization process, however, they are initially set up by the network operator in our approach.

In that case, each cell may have its own performance; in the first step, the overall performance measure of p_j is considered for cell j. We evaluate each step of optimization by measuring a distance (*similarity*) among KPIs. Mostly to measure a distance between any two sets of parameters, a measure in Euclidean space is used that measures *farness*. However, this measure does *not* provide any holistic view of real similarity between measured and target vectors. To this end, we considered similarity between KPIs, so the formulation for similarity measure of jth cell is:

$$SM_j\left(KPI_{ij}^{(m)}, KPI_{ij}^{(t)}\right) = \left\{\sum_{i=1}^{l} S^q\left(KPI_{ij}^{(m)}, KPI_{ij}^{(t)}\right)\right\}^{1/q}$$
$$S(\mathbf{x}, \mathbf{y}): \text{similarity between vectors } \mathbf{x}, \mathbf{y} \tag{5}$$

where S is first-order (q=1) similarity measure and l is the number of KPIs in each cell. In this study, normalized inner product which complies with similarity measure [21] has been selected. The motivation for considering the similarity is establishing effective self-organization towards the target pattern, and a meaningful measure for performance evaluation in EASA. We will compare the results with Multi-Objective Simulated Annealing (MOSA) which together with Multi-Objective Genetic Algorithm (MOGA) are among conventional MOO methods, which in latter a genetic algorithm is exploited for optimization purpose, instead.
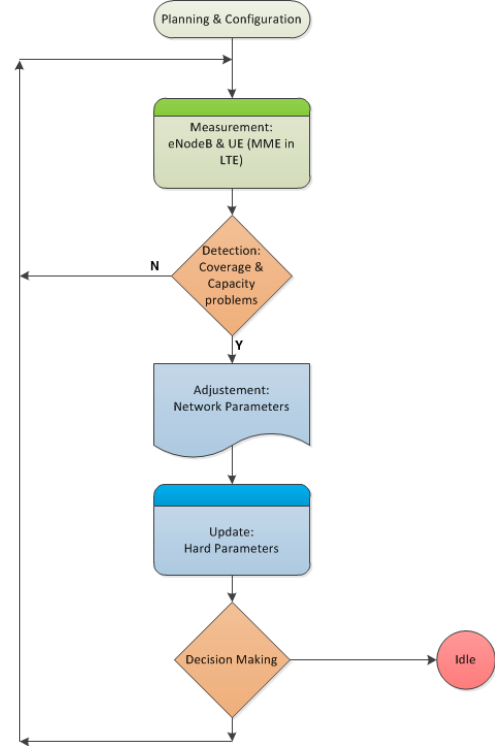

Figure 3: Flow Diagram of proposed Goal Attainment Approach

IV. SYSTEM MODEL

A scenario in LTE was set up and an analytical model for downlink was developed. An unbalanced load as a hot-spot in the first cell is considered and each cell may have its own parameters. The shadowing of log-normal distribution is utilised with correlations among users who are served by the same eNodeB and their distances are less than a pre-defined value (50m in the simulation). Path loss, penetration loss and thermal noise are added to our final model. Throughput and fairness are formulated as multiple objective functions, which are used in the optimization process. The PRB bandwidth (180 KHz) has been applied to each user in j^{th} cell. Also, including both antenna parameters (tilt & azimuth), the optimization algorithm of EASA is considered and a complete set of measurements and indicators are supposed for all cells, as well as traffic load information. A simulation was started from the largest set of values. The pair parameters to be adjusted are considered as:

$$\boldsymbol{\zeta} = \{(\theta_1, \Phi_1,), (\theta_2, \Phi_2)\ldots (\theta_j, \Phi_j)\} \tag{6}$$

which θ is tilt declination and Φ is azimuth orientation angles, with slight changes in angles we will have:

$$\boldsymbol{\zeta}' = \{(\theta_1', \Phi_1'), (\theta_2', \Phi_2')\ldots (\theta_j', \Phi_j')\} \tag{7}$$

To accept the changes, an evaluation based on similarity measure is carried out. Suppose β is the acceptance probability and then we will have:

$$\beta = \exp(-\delta/KT(S,t)) \quad ; \beta: \text{ff}(\delta, S), \delta = f(\boldsymbol{\zeta}) - f(\boldsymbol{\zeta}') \tag{8}$$

S in the similarity measure, $f(.)$ is the objective function and *ff* denotes "*function of*". K is Boltzmann constant and $T(S,t)$ is defined as:

$$T(S, t) = T_0 \cdot \alpha^t(S) \qquad ;\alpha(S) = \alpha_1 + \alpha_2 S \qquad (9)$$

is the annealing function in EASA with t as time and T_0 is the initial value for T. α_1, α_2 are determined empirically during optimization process, subject to: $0 < \alpha < 1$. As the probability function is exponential, so a decrease in S makes new pairs of $(\boldsymbol{\theta}, \boldsymbol{\varphi})$ acceptable even though the objective function becomes worse. However, a probability of rejection is always present unless $S=1$ (the exact match between *KPI*s). The self-optimization algorithm for self-optimization tasks is used which can adaptively update pair parameters of the cells.

V. SCENARIO

The BS transmit power is 43dBm, the noise power is considered as -114dbm per PRB, an antenna pattern is assumed for BSs and antennas always have a relative gain. The beam pattern can be calculated based on:

$$B_{\theta_j} = 12\left(\theta_j - \Theta_j\right)^2 / \Delta\theta^2, \; B_{\varphi_j} = 12(\varphi_j - \Phi_j)^2 / \Delta\varphi^2 \qquad (10)$$

which $B_{\theta_j}, B_{\varphi_j}$ are the antenna beam patterns of the tilt and azimuth for j^{th} cell, also $\Delta\theta$ and $\Delta\varphi$ are vertical and horizontal half power beam-width, respectively. Pairs of $(\boldsymbol{\theta}, \boldsymbol{\varphi})$ are selected as in (6), also Θ_j, Φ_j denote tilt/azimuth of the antenna. Therefore, the 3D model of the antenna pattern can be obtained. Also, it is assumed that all cells have the same resource of bandwidth and then a fixed number of PRBs. The *best-effort* model for traffic is considered, however, Constant Bit Rate (CBR) model is not in line of our study. The width of the cell in the initial conditions is equal to 1Km. In addition, there is fair scheduling for PRBs. Values for parameters of the shadowing and path loss are based on 3GPP recommendation (Table A.2.1.1-3 in [23]) and for the shadowing effect, user correlations are also considered. The path loss (L) model is based on Okumura-Hata, thus with a penetration loss of 20dB, we have:

$$L=128.1+37.6\log(d)+20 \; (dB) \qquad (11)$$

which $d(Km)$ is the distance between the base stations and UEs. As the height of antenna can be 20-70m as per recommendations, in this study, the difference with UE is supposed to be 35m. To conduct an accurate shadowing model in our study, the two-dimensional shadowing is exploited in the simulation. Also, standard deviation is 8dB, $\mu=0$ [23] for log-normal distribution with spatial dependency. Therefore, the received power after total loss and total gain of antenna and beam pattern with transmit power of P_{Tx} is:

$$P = P_{Tx} - LOSS \quad \rightarrow \quad P_j = P_{Tx,j} - LOSS_j \qquad (12)$$

where P is the received power in the desired cell and P_j is the received power from the other cells in the area. Details of the initial setting for the network parameters can be found in table 1 for the scenario depicted in figure 4. The set up is based on SON-LTE with interference-limited scenario.

Reporting interval in this table represents how many times the UE and traffic measurements are collected. For coverage, the corner of each cell must receive at least power greater equal than the threshold from one of three neighbours. That is the same method as when a cell outage happens and the self-healing function of SON is enabled to recover the problem. Finally, two objective functions been considered using SINR which are throughput (TH) for i^{th} UE in j^{th} cell and Jain's Fairness Index (JFI) as:

$$SINR_{ij} = P_j \Big/ \left(N_i + \sum_{k, k \neq j} P_k\right) \qquad (13)$$

$$TH_{ij} = \rho_1 W \log\left(1 + SINR_{ij}/\rho_2\right) \qquad (14)$$

$$JFI_j = \sum_i^2 TH_{ij} \Big/ \left(M_j \sum_i TH_{ij}^2\right) \qquad (15)$$

which ρ_1, ρ_2 are the efficiency parameters for the Bandwidth (W) and SINR, respectively. M_j is number of UEs in j^{th} cell.
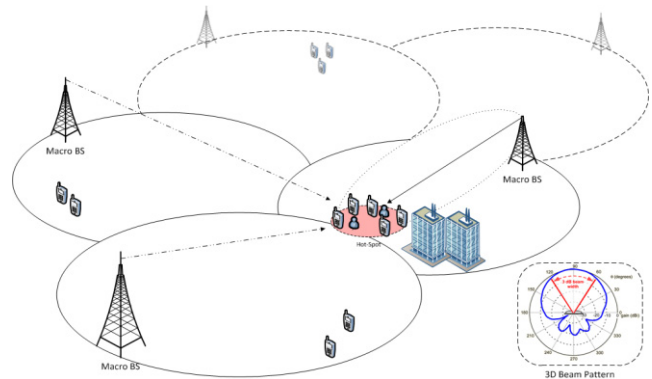

Figure 4: CCO use-case with Hot-Spot and Antenna Beam Pattern

Table 1: Set-Up Parameters in SON-LTE Scenario

Parameter	Value/ Setting
Height Difference <UE,eNodeB>	35m
Noise Figure	9dB
PRB (**W**)	180KHz
Antenna Gain	10dBi
eNodeB Tx Power (**P_Tx**)	43dBm
Cell Radius	1Km
Bandwidth Efficiency Coeff. ($\boldsymbol{\rho_1}$)	0.9
Max Number of UE in Cell (**M**)	50
Vertical half power Beam-width ($\Delta\boldsymbol{\theta}$)	10°
Horizontal half power Beam-width ($\Delta\boldsymbol{\varphi}$)	60°
Path Loss model: *Okumura-Hata* (L)	128.1+37.6log(d)
Thermal Noise (**N**)	-114dB
Traffic Model	best-effort
SINR Efficiency Coeff. ($\boldsymbol{\rho_2}$)	1.2
Shadowing Decorrelation Distance	50m
Shadowing Distribution Parameters ($\boldsymbol{\sigma, \mu}$)	8dB, 0
Antenna Azimuth Initialization	0, 120°, -120°
Reporting Interval	2sec
LTE Signal Bandwidth	20MHz
Penetration Loss [ref. 23]	20dB
Number of Cells/Sectors	19/57

VI. SIMULATION RESULTS

To investigate the proposed method, firstly, a homogeneous network is considered and the azimuth orientations are set at 0°, 120° and -120° as default for antennas in each cell. The scenario setup includes 19 cells

and 50 UEs distributed with a random hot-spot in the first cell. The fact that the path losses for UEs within the hot-spot are noticeably the same, is the main key for a represented system model, whereas most loss in this scenario caused by the path loss. The CDF results for the final epoch have been illustrated in figure 5. Each epoch in this study is the duration of certain steps in the optimization process. As we can see in this figure, the CDF of UE throughput has been improved as most UEs had lower throughputs before the optimization. Yet, we can still find few UEs with low throughput; most UEs have access to higher throughput. Effect of hot-spot UEs on CDF can be seen in figure (5). The final CDF results show a noticeable migration of hot-spot UEs to higher throughputs, while no one *worse off*.

Figure 6 (a) and (b) show convergence of EASA and MOSA and 10%-top UE throughput and fairness, respectively, based on (14), (15). The other methods as MOGA has also been known for MOO [24], however, while MOGA can also reach optimal solution, SA-based algorithms are based on local-search. In this study we considered two different SA-based algorithms to investigate the effect of SM. In this figure, results for one optimization of throughput and fairness are shown. Both methods are convergent in this scenario, however, EASA is faster than MOSA in terms of convergence. The optimization process affects the UE allocations as some UEs from neighbour cells have temporarily been reallocated until next optimization epoch and permanently reallocated after the process which is trigged by the detection module in figure 3. The JFI in (15) is calculated for UEs of underlying cell which is cell with the hot-spot for the result in figure 6(b), however, the reallocation has produced noticeable fluctuations, e.g. after epoch 20.

Figures 7 (a) and (b) show variations in tilt angles and azimuth orientations, converging to the final values of optimal states. It can be seen that the tilt of the antenna in first cell with hot-spot has been changed. In this figure the final values of azimuths show less noticeable changes while there are more changes in tilt angles as we may infer the optimization intends to decrease the interference while power is limited. In figure 7, tilts and azimuths are shown that cover the intersection of three adjacent cells, including the first cell with hot-spot. This scenario for hot-spot has already been shown in figure 4 in this article. In figure 7, epoch is defined as before and for consistency a specific range of angles between [-12°, 12°] has been considered.

VII. CONCLUSION REMARKS

The Similarity Measure (SM) was integrated into the self-optimization process of SON, which was designed based on simulated annealing, as Enhanced Adaptive Simulated Annealing (EASA) algorithm. The goal attainment approach with the proposed algorithm of EASA was investigated with a scenario of CCO use-case in SON-LTE with hot-spot. This is usually the case, as an effect of dynamic behaviour in the networks. The final results of UE throughput show that the proposed method outperforms the performance in terms of desired KPI. In comparison with the conventional method, a simulation was also considered. In a scenario including a congested cell with a hot-spot, the antenna parameters of tilt/azimuth were considered with throughput and fairness as

objectives. Based on the input measurements from UEs and the cells, optimizations were carried out which finally enhanced the CDF of UE throughput. The antenna parameters of tilt/azimuth were updated based on the final optimization process. The process was initiated after detection of coverage or capacity problem in cell/cells. It can be concluded that EASA outperforms the conventional method in SON-LTE with the application of CCO use-case. An extension of self-optimization approach to the Het-Net with dead-spot in a multi-tier single-RAT scenario (figure 8) is considered for future work.
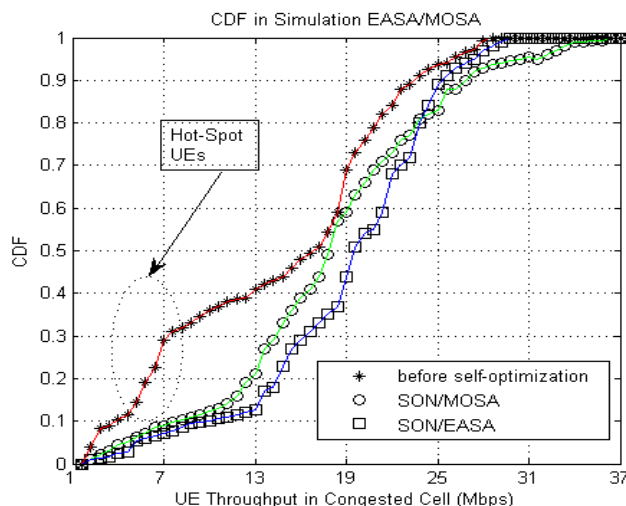

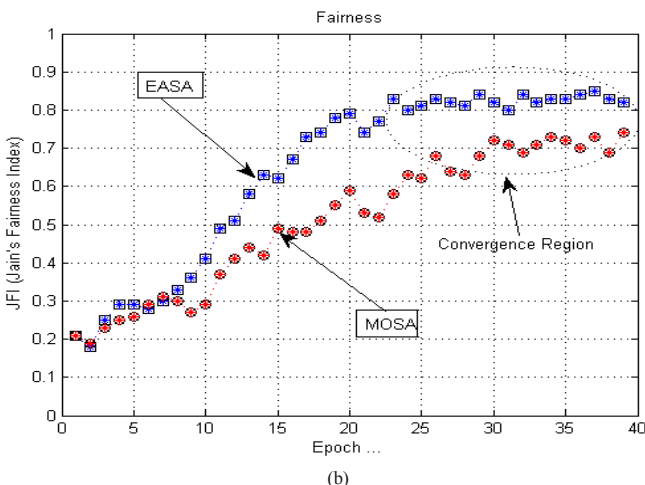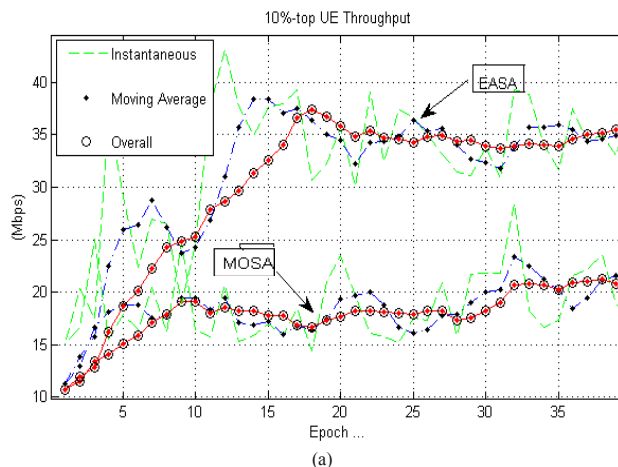Figure 5: CDF in Simulation: EASA and MOSA Methods

(a)

(b)

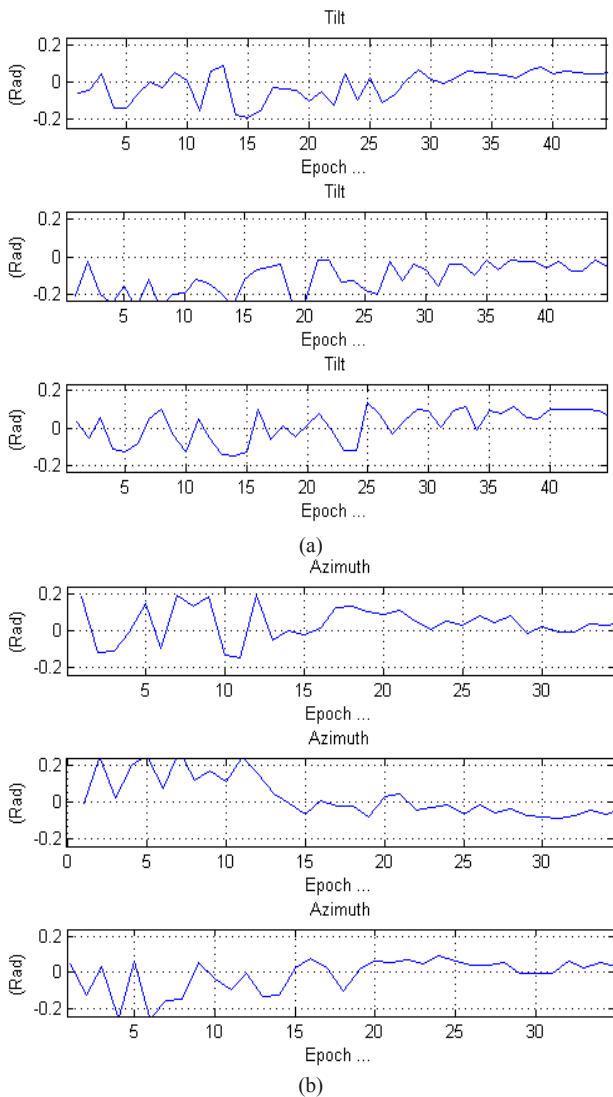Figure 6: UE Throughput (a) and Jain's Fairness (b) Results in EASA and MOSA

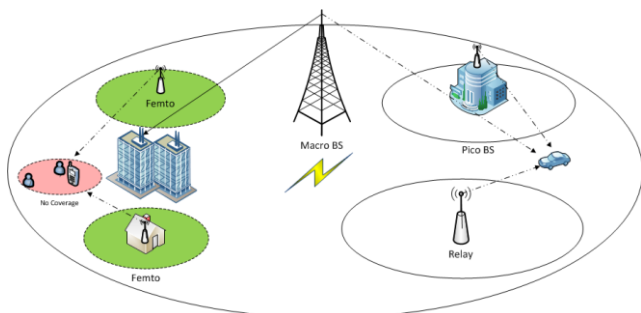Figure 7: Tilt (a) Azimuth (b) Results for 3 Sectors of Congested Cell

Figure 8: Multi-Tier Single-RAT Scenario with Dead-Spot in Het-Net

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