Citation

Sharsheer, Mohammad; Barakat, Basel and Arshad, Kamran. 2016. ’Coverage and capacity Self-Optimisation in LTE-Advanced using Active Antenna Systems’. In: 2016 IEEE Wireless Communications and Networking Conference. Doha, Qatar 3 - 6 April 2026. [Conference or Workshop Item]

Persistent URL

https://research.gold.ac.uk/id/eprint/38195/

Versions

2016 IEEE Wireless Communications and Networking Conference WS 6 : IEEE WCNC'2016 Workshop on 5G & Vertical Industry - WS 11 : IEEE WCNC'2016 Workshop on The Tactile Internet: Enabling Technologies and Applications

Coverage and Capacity Self-Optimisation in LTE-Advanced Using Active Antenna Systems

Mohammad Sharsheer, Basel Barakat and Kamran Arshad
Department of Engineering Science,
Faculty of Engineering and Science,
University of Greenwich, United Kingdom
Email: {ms8822s, bb141, ak52}@greenwich.ac.uk

***Abstract*— In order to enhance the Long Term Evolution (LTE) network performance, the Third Generation Partnership Project (3GPP) introduced Coverage and Capacity Optimisation (CCO) in the context of Self Organising Network (SON). Antenna parameters (i.e. azimuth, electrical tilt etc.) play a key role in CCO and have a significant impact on the users' Quality of Service (QoS). In this paper, a novel metric, to evaluate the cells performance, that consider several performance indicators, is introduced. Furthermore, a distributed CCO algorithm is proposed which has three distinct phases. The first phase is to determine the target cell, the second phase adjust the antenna parameters for the target and neighbouring cells and in the last phase the optimum antenna parameters for the target and neighbouring cells is determined. The simulation results show significant improvement in the overall network performance with the proposed CCO algorithm. In particular, the target cell average performance can be improved by 16.75%.**

Keywords*— *Long Term Evolution Advanced; Self-Organising Network; Coverage and Capacity Optimisation; Performance Evaluating Metric.

I. INTRODUCTION

One of the biggest challenges facing the Mobile Network Operators (MNOs) is the exponentially increasing demand for the capacity and improved coverage. This motivates rapid improvements in the current communication network infrastructure. Several solutions have been proposed to address this issue, such as Femto Cells, Relays, Intelligent Distributed Antenna System (IDAS) etc. [1, 2]. However, most of the current network enhancement techniques increase the network complexity. Therefore, a trade-off between network performance and complexity is essential to keep the system more optimised and scalable [3].

The concept of SON is part of the 3GPP Release 8 to enhance the operability of a multi-vendor network. The SON functionality is used to improve the network operator targets, referred to as Key Performance Indicator (KPI). SON functions are categorised according to their region of interest, such as: self-configuration, self-healing, self-optimisation etc. [4]. Self-configuration functionality configure the base station (or eNodeB) to be compliable with the network configuration. Self-healing focuses on overcoming the incidence of an eNodeB failure or a similar fault by adjusting the neighbour eNodeB parameters. Self-optimisation ensures that all eNodeB operations are fully optimised. The cellular environment is highly dynamic and consistently changing (such as the users' density, traffic and the propagation characteristics), therefore self-optimisation plays a significant role in maintaining an acceptable QoS to the users [5].

One of the most promising self-optimisation functionalities is the antenna parameters optimisation. In the literature, optimisation of antenna parameters for LTE has been proposed from different perspectives. For instance, [6] proposed two models to optimise antenna parameters refereed as *statistical model* and *optimisation model*. The *statistical model* replaces the relationship between the KPI and the antenna parameters with a surrogate model, while the *optimisation model* searches for the optimal antenna tilt in an iterative manner using *Search and Poll algorithm* [6]. In [7], self-optimisation of antenna parameters were proposed by using *k-nearest neighbour (K-NN)* algorithm and referred as *Case Based Reasoning (CBR)* approach. However, these approaches applied to centralised network architecture increase the network operating complexity. In addition, another solution using *Golden Section Search (GSS)* algorithm has been proposed in [8], as a near optimal solution can be obtained using GSS algorithm which afterwards needs to be fine-tuned to an optimal value. However, the simulations in [8] do not reflect real world scenario, as it was assumed that the users' distribution in the cell was uniform, and it considered only three sectors in network layout. Therefore, this approach would not be able to consider the degradation in performance of the neighbour cells and the interference caused by them.

In this paper, a CCO algorithm is proposed to enhance users QoS by exploiting *Active Antenna Systems (AAS)*. The proposed algorithm increases cell capacity, users' throughput and improves coverage area for a LTE-Advanced (LTE-A) cell. We also define a novel performance evaluation metric that simultaneously considers several weighted KPIs. The proposed algorithm in its' first phase determines the cell with worst performance according to the proposed metric. All the possible antenna configurations are tested in its second phase. Finally, the last phase of the algorithm determines the optimum antenna parameters for the worst performing cell and it neighbour cells.

This paper is organised as follows: Section II introduces CCO and the relevant eNodeBs antenna parameters. The proposed CCO algorithm is presented in Section III. The model used in the simulations and the simulation parameters are presented in Section IV. Simulation results and discussion are also given in Section IV and Section V concludes this paper.

II. COVERAGE AND CAPACITY OPTIMISATION (CCO)

According to 3GPP, coverage and capacity optimisation is one of the most important SON functionalities for LTE [4]. The main advantage of CCO is to autonomously avoid interference among overlapping cells by detecting and eliminating coverage holes. Also, while the manual cells optimisation can cause high Capital Expenditures (Capex) and Operating Expenditures (Opex), CCO is able to minimize these costs effectively through operating: either centrally or locally (distributed) in a specific time frame [10]. This could vary from few hours to several days depending on network complexity and parameter elements considered in CCO.

3GPP designed CCO as a plug-n-play functionality and it can be used with any existing deployed network. CCO can be used by any eNodeB (such as multi-vendor networks) that needs extra optimisation to enhance its' coverage and capacity. However, CCO can be implemented in other possible ways as well [3]. For instance, it can be used in parallel with planning phase to make it faster by applying it on a new network after the initial rough planning. In addition, CCO can be utilised during reusing the existing Universal Mobile Telecommunications System (UMTS) network with LTE network [4].

In order to achieve the required coverage and capacity objectives, one possible way is to optimise antenna parameters (i.e. antenna tilt and azimuth) simultaneously. Antenna parameters play a crucial role in the cell performance as antenna radiation pattern and directivity is directly related with the received signal power, and hence Signal-to-Noise Ratio (SNR). The antenna parameters can be adapted either mechanically or remotely (autonomously). However, the mechanical adjustment is time consuming process and generally requires human effort. The remote electrical parameters, such as Remote Electrical Tilt (RET) and Remote Electrical Azimuth (REA), can be utilized autonomously using AAS. Therefore, in this paper we consider CCO using AAS.

III. PROPOSED CCO SON ALGORITHM

It is mandatory to design a CCO algorithm that is dynamic in nature and able to constantly and autonomously optimise the network performance. Our proposed self-optimisation algorithm is based on distributed SON approach and has three main phases. In the first phase, the cell with worst performance (referred to as Target Cell (α)) is determined. During the second phase, the algorithm modifies antenna parameters of the target cell and its first tier neighbours' in an iteration manner to obtain the possible solution space. In the third (final) phase, the algorithm determines the optimal iteration step (i.e. the one that gives the best performance in terms of the proposed performance metric) and adjusts the target cell and its neighbour cells' antenna parameters. The algorithm phases are explained in the subsequent sections. Fig. 1 shows the flow chart of the algorithm phases (i.e. search for target cell, test all the possible antenna parameters and determining the optimal antenna parameters).

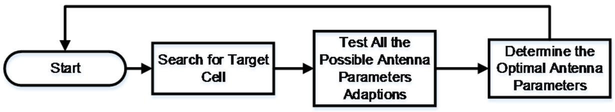

Fig. 1 Proposed Self-Organisation Algorithm flow chart.

A. *Phase 1: Search for a Target Cell*

The first phase in the proposed algorithm is to determine the target cell (the cell with the worst performance according to the performance evaluating metric) within a given network. The performance metric (γ) proposed in this paper considers following KPI elements: (i) Normalised cell average throughput (T), (ii) Spectral Efficiency (S), (iii) Average Energy per Bit (E), (iv) Resource Blocks occupancy (RB). It should be noted, that the cell average throughput is normalised by the highest achieved throughput by a cell in the network (T^{max}). Each element in the proposed metric is weighted with a weighing factor (W). In this paper, we consider the number of users' ratio to be the weight for T (W_T) and the normalised data transmitted in bits to be the weight for E (W_E). The proposed performance metric for the i^{th} cell in the Default scenario (D), ($\gamma_{i,D}$) is written as:

$$\gamma_{i,D} = (W_T \times T_i + W_S \times S_i + W_E \times E_i + W_{RB} \times RB_i)/4 \quad (1)$$

Where W_S and W_{RB} are the weights for S and RB respectively. Both W_T and W_E can be obtained by:

$$W_T = \frac{\eta_i}{\eta_{Max}} \qquad W_E = \tau_i \quad (2)$$

Where η_i is the number of users in cell i, and η_{Max} is the number of users in the most crowded cell in the network. The total data transmitted in the last Transmission Time Interval (TTI) for the i^{th} cell is referred as τ_i.

The target cell to be concerned in the optimisation process is the cell experiencing the worst performance. Therefore, to determine the target cell, condition in (3) must be satisfied.

$$\gamma_{\alpha,D} = \min(\gamma_{i,D}) \quad (3)$$

Where $\min(.)$ operator refers to the minimum function. The target cell α corresponds to the cell with $\gamma_{\alpha,D}$ value calculated in (3).

B. *Phase 2: Test all possible antenna parameters adaptions*

The target cell (i.e. α) is determined in Phase 1. Now phase 2 tests all the possible antenna parameters for target and neighbouring cells. In particular, in this step, two main operations are accomplished (i.e. adjusting α's antenna tilt (θ) and the set of neighbour cells B's azimuth (ϕ)). These parameters sweep for all possible values (pre-defined) so that in the next phase the algorithm could choose the optimum. It should be noted that while the cells change their antenna parameters, they simultaneously keep record of their γ value.

The number of iteration steps to be considered rely on the given antenna specifications (each type of antenna has its specific range of title (Θ) and azimuth (Φ)) and step size between antenna parameters values. For instance, a step size of

2° and ±30° is considered for Θ and Φ respectively, as follows:

$$\gamma_{\alpha,j} = \gamma_{\alpha}(\theta) \quad , \theta \in \Theta \tag{4}$$

$$\gamma_{\beta,j} = \gamma_{\beta}(\phi) \quad , \phi \in \Phi ; \beta \in \mathrm{B} \tag{5}$$

where j refers to the iteration number and β refers to the neighbour cell number.

C. Phase 3: Determine the Optimal Antenna Parameters

In this phase, the optimal antennas parameters i.e. optimal target cell antenna tilt (θ^{opt}) and each neighbour cell azimuth (ϕ^{opt}), are determined according to the performance evaluating metric. Firstly, the algorithm discards the iteration steps in which the performance did not exceed the objective required performance (δ). The algorithm then determines the iteration number that represents the optimum performance (i.e. the optimum antennas parameters). This can be achieved by determining an overall performance metric ($\grave{\gamma}$) as follows:

$$\grave{\gamma}_j = \gamma_{\alpha,j} + \sum_{\mathrm{B}} \gamma_{\beta,\mathrm{j}} \tag{6}$$

From (6), the optimum performance indicator for the target cell and its neighbours can be obtained by:

$$\grave{\gamma}_{\mathrm{opt}} = \max(\grave{\gamma}_j) \tag{7}$$

Consequently, the algorithm adjusts the target cell antennas to the optimum antennas parameters (i.e. θ^{opt} and ϕ^{opt}). The adjustment is done by RET and REA using X2 and X1 interfaces [11]. Afterwards, the algorithm restarts to optimise the performance of the new target cell.

IV. SYSTEM MODEL AND SIMULATION RESULTS

In this section, the simulation system model and simulation parameters are described. In order to simulate the proposed algorithm the approach mentioned in [9] is used. In the simulation, the users are assumed to be randomly distributed. The network contains seven sites each attached with three eNodeBs, with inter-cell distance of 500 meters, as shown in Fig. 2. The key simulation parameters are summarised in Table 1.

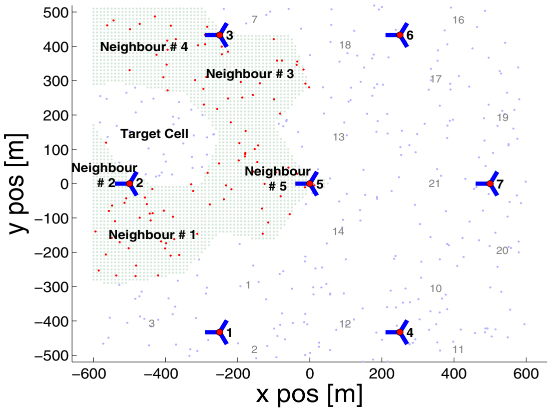

Fig. 2 The target eNodeB and its neighbour cells layout.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Transmission Bandwidth	20 MHz
Carrier Frequency	2.1 GHz
Number of eNodeBs	One Ring (7 sites)
Network Geometry	Hexagonal Grid
Number of cells	21
Simulation Interval	1000 Transmission Time Interval
Number of Users per network	400
Users Distribution	Random
Users Speed	1.388 m/s
eNodeB Transmission Power	40 dB
Scheduling Algorithm	Round Robin
Antenna Type	SISO
Antenna Gain Pattern	TS 36.942 3D [10]
Coupling Losses	70 dB [10]
Macroscopic Pathloss Model	Okumura Hata Model
Macroscopic Pathloss Model Environment	Urban
Noise Figure	9 dB
Noise Density	-174 dBm/Hz
Number of neighbour cells considered (B)	5
Antenna tilt range (Θ)	8-20°
Antenna tilt iteration step	2°
Spectral efficiency weight (W_S)	1
Resource Blocks occupancy weight (W_{RB})	1
Antennas azimuth range (Φ)	±30
Objective performance (δ)	0.8

The first phase was only considered with determining the target cell. As previously stated, the performance evaluating metric considers different elements of the KPI (i.e. average throughput, Spectral efficiency, average energy per bit and resource block occupancy). Fig. 3 presents the normalised default values for the considered KPI elements multiplied with its weight for each cell and the number of users in each cell.

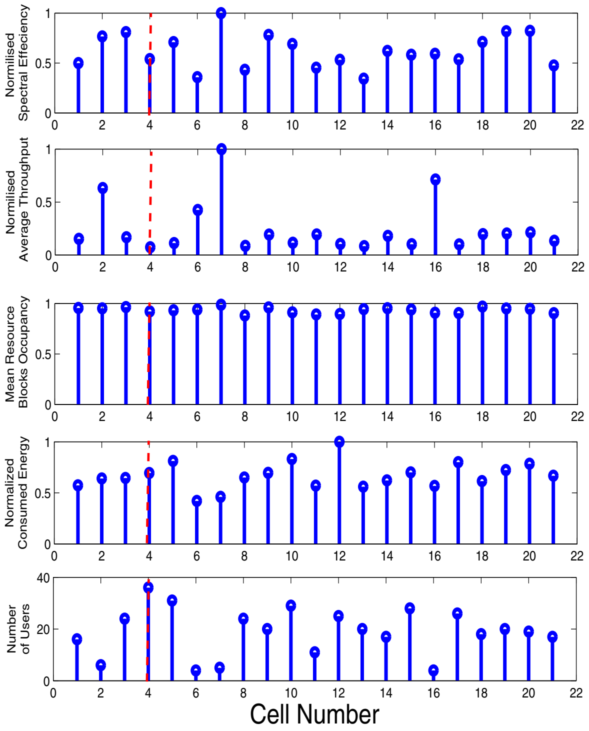

Fig. 3 The default value of each weighted normalised KPI element.

As shown in Fig. 3, the cell number four has a very low average throughput and also the other KPI elements of cell number four are relatively low. Moreover, the cell has a considerable number of users. Therefore, during the first phase the algorithm chooses cell number four as the target cell and choose the neighbouring cells to modify as shown in Fig. 2.

Moving to the second phase, the algorithm changes the antenna parameters for the considered cells (i.e. target and neighbour cells). The performance of the target cell according to the evaluation metric is presented in Fig. 4.

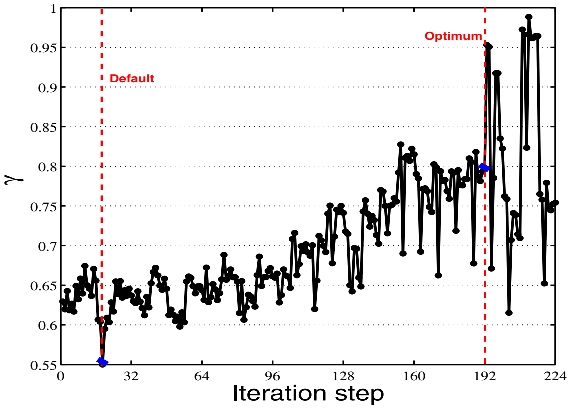

Fig. 4 Performance of the Target with respect to the iteration step number shown the default and optimum iteration steps.

As illustrated in the figure, the performance fluctuates closely to default value with the changing of the iteration step number until reaching iteration step number 96. However, afterwards the slope of the fluctuation starts increasing until it reaches the performance of the optimum solution point. Optimum antenna parameters are selected after considering all the surrounding five neighbouring cells' performance evaluation. For instance, Fig. 5 shows the performance of the first neighbour cell according to same evaluation metric. The figure shows how the performance drops periodically in almost the same performance levels for the first five stages. However, each iteration (i.e. starting from 0 until 32) represents different target cell's antenna tilt with different value of neighbour cells antennas' azimuth.

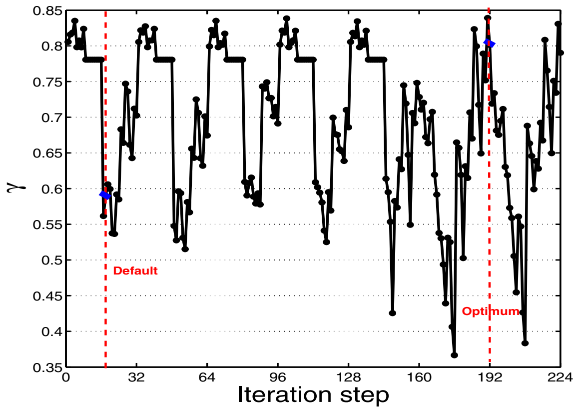

Fig. 5 Performance of the first neighbour cell with respect to the iteration step number shown the default and optimum iteration steps.

For each iteration step, all the evaluating metric of the considered cells has to achieve at least objective value of δ plus achieving the maximum of these values in order to find the optimum solution. The archived performance improvements are 25 %, 21%, 20.5%, 7%, 17%, and 10% for target cell, neighbour one, neighbour two, neighbour three, neighbour four, and neighbour five respectively. Therefore, the average improvement in the considered cells is equal to 16.75%.

V. CONCLUSION

In this paper, a performance metric that considers several KPIs simultaneously has been introduced. Additionally, a SON CCO algorithm that enhances the overall network performance in distributed manner has been proposed. The performance of the proposed algorithm has been validated using a standard compliance simulator. The proposed algorithm updates antenna parameter that has main influence on the coverage and capacity. In the first phase of the proposed algorithm it determines the target cell (the cell with the worst performance). The second phase tests all the possible adaptations and save their performances. Finally, the third phase chooses the optimum solution according to optimum performance indicator for all the examined cells. The results showed a significant improvement for the target cell and its neighbour cells, as the average performance improved by 16.75 %.

REFERENCES

[1] S. A. Hejazi and S. P. Stapleton, "Self-optimising intelligent distributed antenna system for geographic load balancing," Communications, IET, vol. 8, pp. 2751-2761, 2014.

[2] Zahir, T.; Arshad, K.; Nakata, A.; Moessner, K., "Interference Management in Femtocells," in Communications Surveys & Tutorials, IEEE , vol.15, no.1, pp.293-311, First Quarter 2013, doi: 10.1109/SURV.2012.020212.00101.

[3] O. Sallent, Pe, x, J. rez-Romero, Sa, G. nchez, et al., "A roadmap from UMTS optimization to LTE self-optimization," Communications Magazine, IEEE, vol. 49, pp. 172-182, 2011.

[4] 3GPP, “Self-Configuring and Self-Optimizing Network Use Cases and Solutions,” Tech. Rep. TR 36.902 v. 9.3.1, May 2012.

[5] 3GPP, “LTE; Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Self-configuring and self-optimizing network (SON) use cases and solutions,” Tech. Rep. TR 36.902 v.1.2.0, May 2009.

[6] 3GPP, “LTE; Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Self-configuring and self-optimizing network (SON) use cases and solutions,” Tech. Rep. TR 36.902 v.1.2.0, May 2009.

[7] Y. Khan, B. Sayrac, and E. Moulines, "Active antenna systems for centralized self-optimization of capacity in LTE-A," in Wireless Communications and Networking Conference Workshops (WCNCW), 2014 IEEE, 2014, pp.

[8] O. C. Yilmaz, J. Hämäläinen, and S. Hämäläinen, "Optimization of adaptive antenna system parameters in self-organizing LTE networks," Wireless Networks, vol. 19, pp. 1251-1267, 2013/08/01 2013.

[9] Ikuno, J.C.; Wrulich, M.; Rupp, M., "System Level Simulation of LTE Networks," in Vehicular Technology Conference (VTC 2010-Spring), 2010 IEEE 71st , vol., no., pp.1-5, 16-19 May 2010

[10] 3GPP TS 36.942, "Evolved Universal Terrestrial Radio Access (E-UTRA): Radio Frequency (RF) System Scenarios," V10.2.0, 2011.

[11] Hämäläinen, S., Sanneck, H. & Sartori, C., 2012. LTE self-organising networks (SON) : Network Management Automation for Operational Efficiency. illustrated, reprint ed. West Sussex: John Wiley & Sons Ltd.