Load Balancing in Self-Organized Heterogeneous LTE Networks: A Statistical Learning Approach

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***Abstract*—The continuous evolution of cellular communication networks into dense, dynamic and heterogeneous networks has posed new challenges for system configuration as well as coverage and capacity optimization, especially in areas with unequal user traffic distribution. In a mixed macro/small (or heterogeneous) cell scenario, load balance is one of those challenges since users typically select the base station with the highest received signal power. Hence, the higher transmit power of macro-cells causes difficulties in offloading a sufficient number of users to small cells. This paper propose a Self-Optimizing Cell Range Expansion Scheme based on a statistical learning approach for an LTE heterogeneous network. System level simulations show the effectiveness of this approach in dynamically expanding the small cell coverage according to traffic conditions, balancing traffic load, reducing cell congestion, and diminishing packet losses.**

***Keywords*– LTE systems; heterogeneous networks; self-organized; load balancing; cell range expansion.**

I. Introduction

The evolution of cellular networks has been characterized by the constant introduction of new technologies, devices and network architectures to keep up with the increase in users and the demand for high-bandwidth applications, leading to an increase in complexity of both configuration and optimization tasks [1]. To address this challenge, Self Organizing Networks (SON) functionalities have been introduced as one of the techniques in Next Generation Mobile Networks (NGMNs) [2] to optimize network performance while at the same time reducing network operational expenses (OPEX). Self-Organization (SO) is a concept inspired from nature, where certain biological systems exhibit an organized behavior in order to achieve a desired objective while autonomously and intelligently adapting to the dynamics of their environment. This concept has been used in several areas including electronics and computer science [3]. In the field of mobile communications, the 3rd Generation Partnership Project (3GPP) has identified the need to introduce these functionalities to its Long Term Evolution (LTE) and LTE-Advanced standards. The goal is to provide network intelligence, adaptability and management features in order to automate configuration (self-configuration), optimization (self-optimization) and recovery (self-healing) [4] functions, allowing mobile wireless networks to adapt to varying radio channel and traffic conditions. Over the last decade, SO in Radio Access Networks has attracted the interest of industry and academic communities, leading to several contributions in topics such as coverage/capacity optimization, load balancing and inter-cell interference coordination. In [5] Aliu and colleges provide a survey of the existing literature in SO cellular networks, comparing the strengths and weakness of existing solutions and highlighting the key research areas for further development. We focus in this paper on the relevance of the load balancing functionalities to deal with unequal distribution of traffic load over macro and small base stations. In the heterogeneous networks (HetNet) context, the main problem is the higher transmit power of macro-cells, which causes difficulties to offload sufficient amount of users from macro-to-small cells since the UEs will usually select the base station with the highest received signal power. Many contributions on load balancing in mobile networks are present in the literature [6], however most of these studies have addressed homogeneous scenarios, distributing traffic loads across multiple cells of similar coverage. In [7], Atayero et al. presented a neural-fuzzy model to adjust the hysteresis handover parameter to force UEs at the cell edge to reselect a less loaded cell. One of the main key performance indicators used in [7] to make the load adjustments is the Load Distribution Index, measuring the degree of load balance in the entire network, but with no relation to a quality of service metric. The problem of expanding this approach to the Heterogeneous scenario stems from the different power transmissions and coverage areas between the macro and the small cells (likely resulting from different number of UEs or traffic loads each is serving), which may cause premature handovers from Macro-to-pico cells highly interfered in their borders. In [8] Simao and colleagues, proposed an admission control algorithm to perform congestion control and interference avoidance in a 3GPP heterogeneous scenario employing femto-cells. The developed algorithms were based on integer linear programing and stochastic admission process to achieve load balance. Another approach in load balance techniques is to offload users from cellular networks into wireless local area networks (WLANs) [9] [10], exploiting the complementary advantages of each technology.

This paper proposes a dynamic Cell Range Expansion (CRE) scheme based on a Statistical learning approach. The main idea is to give the network the ability to learn and adjust dynamically the Small Cell Offset according to cell traffic conditions, balancing the traffic load between the Macro and the small cell, reducing the cell congestion, and diminishing packet losses.

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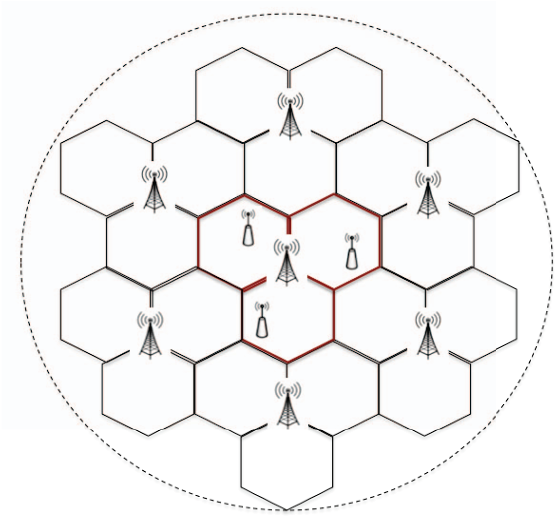

Fig. 1. Case study scenario

The paper is organized as fallows: Section II details the case study scenario and the concepts regarding the CRE technique for load balance in heterogeneous networks. Section III, presents the proposed scheme and the learning/selection methodology. In section IV simulation results are shown, and finally in section V conclusions and future perspectives are offered

II. System Model

A. Case Study Scenario

We consider a HetNet environment with 7 eNB sites with an Inter Site Distance (ISD) of 500 meters. Each site is composed of three hexagonal sectors with reuse factor 1, and one omnidirectional small cell per sector at the cell edge as shown in Fig. 1. In the deployed scenario, the center cell and small cells are the area of interest, while the rest consist of eNBs generating interference to target users (UEs). The UEs are dropped randomly throughout the region of interest and according to the traffic conditions, the Macro Sectors can activate the small cells (message over X2 interface) with specific offsets to enhance the load balance functions (as explained in the next subsection). Table I shows the main parameters and propagation losses models used for the E-UTRAN. These values were based on the baseline parame-ters defined by 3GPP for the simulation of heterogeneous systems, specifically for the case in Model 1 (Urban Macro cell + outdoor Hotzone cells, table A.2.1.1.2-3 in [11]).

B. Load Balance: Cell Selection and Virtual Cell Range Expansion Technique

HetNets and the use of Low power base stations (like small eNBs) are useful in optimizing coverage and capacity especially in unequal user traffic distribution areas and in hotspot areas. However, due to higher transmit power of macro-cells, in some cases, it is not possible to offload a sufficient number of users. This is because in the traditional cell selection method, UEs can select their serving cell by comparing the Reference Signal Received Power (RSRP) from macro eNBs and small eNBs. The Virtual Cell Range Expansion technique can be used to overcome this problem by compensating for the difference in transmit power between small and macro eNodeBs so that the coverage area of the small eNB can be increased. This is accomplished by adding an offset or bias to its RSRP during cell selection, as is depicted in figure 2. Here, UEs do not connect to a cell with highest RSRP but with the cell with highest RSRP plus Offset, allowing more UEs to be associated with the Small eNBs. The benefits of CRE, however, come at the cost of higher downlink interference for users on the edge of small cells especially when they are in a co-channel scenario with macro-cells.

TABLE I. Simulation Parameters for the E-UTRAN

Parameter	Value
Inter Site Distance	500 [m]
Carrier Frequency	2 [Ghz]
Carrier BW	5 [Mhz]
Macro Cell Tx power	43 [dBm]
Small Cell Tx power	30 [dBm]
Macro Cell Path Loss	128.1+37.6*log10(R)
Small Cell Path Loss	140.7 + 36.7*log10(R)
Penetration Loss	20 [dB]

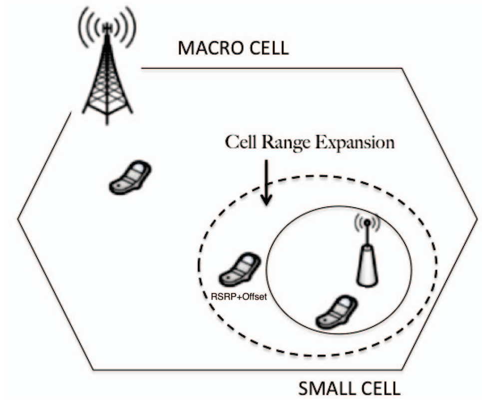

Fig. 2. Cell Range Expansion technique

III. Dynamic CRE offset learning and selection process

We adopt a statistical machine learning approach to improve the SON functionalities related with Load balancing and CRE techniques. The block diagram of the methodology selected is depicted in Figure 3. Here, we used an open-source system level simulator to generate the dataset with the Key per-formance indicators (KPI) and for testing the proposed mechanism. The process occurs in two phases: The learning and the CRE selection phase, as explained below.

A. Learning Phase

The objective of this phase is to extract for the particular scenario the relationship (model) between the KPIs and the offset value responsible of the small cell range expansion by learning from experiences (training examples). More precisely, we used a supervised learning methodology [12]

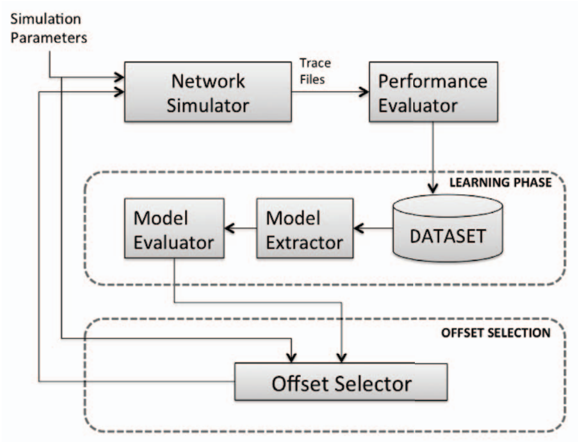

Fig. 3. Block diagram of learning/selecion process

called polynomial regression to estimate the association between a continuous outcome (dependent) variable and multiple predictors (explanatory variables) [13]. This phase was conducted following the classic supervised learning pipeline: 1) Obtaining Raw Data, 2) Feature Extraction, 3) Supervised learning for model extraction and 4) Evaluation.

1) Obtaining the Raw Data: In this step, we construct a training set where the learning is done. Commonly, this training set is built from observations that contain a sufficient amount of data points and also cover the whole region of interest. The challenge with this approach is to get diverse network measurements (to cover the region of interest) obtained from an operational network, since we have to test a large variety of offsets configurations (including relatively bad ones) on a network that is supposed to give satisfactory QoS to the customers. One of the solutions is to construct the training database from simulation samples. Once the tendencies are extracted, or relative behaviors are found, there is a need to perform a corrective mapping between simulation and measurements. In this case, the reliability of the predictions depends on the accuracy of the simulations as well as on the quality of the measurements. In this work, the dataset is generated using the NS-3 simulator [14] varying randomly the position and the number of UEs (between 15 and 40) to vary the traffic condition within the cell and the offset values (between 0 and 8 dB) used by the small cell to expand its coverage area.

2) Feature Extraction: Once obtained the raw data, we need to extract features/attributes from it. This step allow us to incorporate the domain knowledge when representing each of these observations via numerical values. From each experience (conducted simulations), the features extracted were: the specific cell traffic condition (amount of users), the small cell offset value and the Packet Loss Ratio (PLR) at the Packet Data Convergence Protocol (PDCP) LTE layer.

3) Model Extraction: In this step, we used a supervised learning method called multivariate polynomial regression [15] to find the relationship between the cell traffic condition and the small cell offset (explanatory variables) with the PLR at the PDCP layer (dependent variable). Let z be the PDCP PLR, x the number of active UE and y the small cell offset. Thus, the PDCP PLR will be modeled by

$$z = \beta_0 + f(x, y) \tag{1}$$

As an example, a second order multiple polynomial Regression can be expressed as:

$$f(x, y) = \beta_{00} + \beta_{10}x + \beta_{01}y + \beta_{20}x^2 + \beta_{11}xy + \beta_{02}y^2 \tag{2}$$

Here the coefficients, β_{10}, β_{01} are called as linear effect parameters. β_{20}, β_{02} are called as quadratic effect parameters and β_{11} is called as interaction effect parameter

Then, from the collected experiences (Kwnoledge) $K_l = \{(x_1, y_1, z_1), (x_2, y_2, z_2), .., (x_m, y_m, z_m)\}$, the least-square method is used to calculate the β_{ij} coefficients in order to minimize the sum of the squares of residual errors. Thus,

$$S = \min_{\beta} \sum_{i=1}^{m} [z_i - f(x_i, y_i)]^2 \tag{3}$$

$$S = \min_{\beta} \sum_{i=1}^{m} \left[z_i - \left(\beta_{00} + \beta_{10}x + \beta_{01}y + \beta_{20}x^2 + \beta_{11}xy + \beta_{02}y^2\right)\right]^2 \tag{4}$$

Finally, to obtain the least square error, the unknown coefficients β_{ij} must yield zero first derivatives. Solving the resulting equations lead to the desired model parameters.

$$\forall i, j \frac{\partial S}{\partial \beta_{ij}} = 0 \tag{5}$$

In this work, the model extractor module test several degrees (between 1 and 4 for each explanatory variable) for the polynomial function and according to the evaluation process choose the one with the best fitting/learning results.

4) Evaluation: To evaluate the generated model, the goodness-of-fit statistics and how well it's performing (making prediction) with a test dataset (30% off the collected experiences) that wasn't used for training.

To examine the goodness of fit were calculated two metrics: the Sum square error (SSE) and the $R - square$. The SSE measures the total deviation of the response values from the fit to the response values:

$$SSE = \sum_{i=1}^{m} w_i(z_i - \hat{z}_i)^2 \tag{6}$$

On the other hand, $R - square$ measures how successful the fit is in explaining the variation of the data. Mathematically, $R - square$ is the square of the correlation between the response values and the predicted response values, and is defined as the ratio of the sum of squares of the regression (SSR) and the total sum of squares (SST). Thus, SSR is defined as:

$$SSR = \sum_{i=1}^{m} w_i(\hat{z}_i - \bar{z}_i)^2 \tag{7}$$

SST is also called the sum of squares about the mean, and is defined as

$$SST = \sum_{i=1}^{m} w_i(z_i - \bar{z}_i)^2 \tag{8}$$

where $SST = SSR + SSE$. Given these definitions, $R-square$ is expressed as

$$R - square = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{9}$$

$R-square$ can take on any value between 0 and 1, with a value closer to 1 indicating that a greater proportion of variance is accounted for by the model.

B. CRE offset selection

The small cell offset is determined dynamically following the extracted model to minimize the PDPC PLR according to the cell/sector traffic condition. Thus, the desired value will be determined by:

$$CRE_{\text{offset}} = \underset{y \;\;\epsilon\;\; [y_1, y_2]}{\text{argmin}} \; [f(X, y)] \tag{10}$$

Where X symbolizes the traffic condition and y the small-cell offset belonging to the interval of offsets used during the learning phase.

IV. Performance Evaluation

In this section we evaluate the proposed scheme for downlink transmissions of the heterogeneous LTE scenario described in section II (System Model), through system-level simulations (NS-3). We compared and analyzed the PLR at the LTE PDCP layer and the small-cell PRB utilization for three scenarios: a)Homogeneous network (without small cells), b) heterogeneous network without CRE techniques and c) HetNet with dynamical small cell offset selection (implementing the proposed scheme). For each scenario, the cell/sector traffic condition was varied by changing the number of users receiving a CBR UDP transmission of 512 Kbps.

A. Extracted Model

The extracted model reflects the relationship between the cell traffic condition and the small cell offset with the PLR at the PDCP layer (for the target scenario studied in this paper). Here, the resulting model was characterized by a quadratic polynomial function (equation 2) with coefficient values: $\beta_{00} = 0.87$, $\beta_{10} = 1.478$, $\beta_{01} = 1.315$, $\beta_{20} = 1.052$, $\beta_{11} = -1.312$, $\beta_{02} = 1.735$ and $R - square = 0.72$, as shown in Fig. 4 (3D plot) and Fig. 5 (contour plot). From these figures, it can be observed how the model predicts small-cell offset values that reduce the average PLR. This is done by expanding the coverage area of the small eNB and, consequently, offload traffic from the macro to the small-cell. However, it is also posible to observe limits for the offset value. This is because if the coverage small eNB increase beyond some point, the Macro-to-small cell interference will affect strongly to the UEs in the small-cell edges.

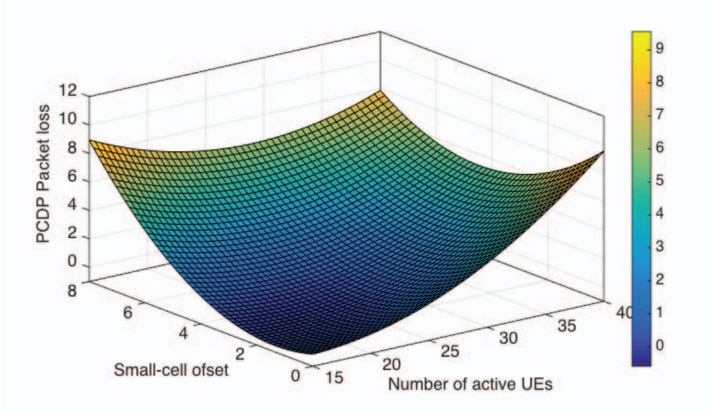

Fig. 4. Extracted model - 3D plot

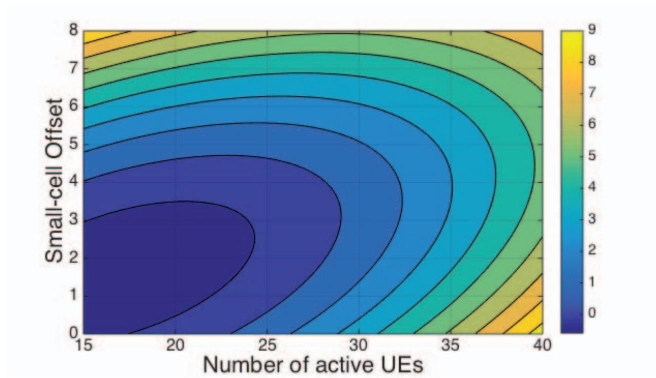

Fig. 5. Extracted model - contour plot

B. PDCP Packet Loss Ratio Results

Fig. 6 shows the relationship between the average PDCP PLR and the number of active UE within the cell (Macro + Small) for the three proposed cases. It can be seen that PLR increases with the number of users due to an increment in network load, as expected. Fig. 6 also shows how intruducing an heterogeneous environment benefits the average cell performance. By implementing dynamic offset selection, PLR is decreases due to more UEs being connected to the small cell, despite stronger RSRP values in the macro-cell. Fig. 7 illustrates the empirical cumulative distribution function (CDF) when the cell is heavily congested (40 UEs). In this case, the three scenarios experience considerable losses because there are not enough resources to meet the traffic demand. However, it is possible to observe how the proposed scheme can improve the network performance.

C. Small-Cell resources utilization

Fig. 8 compares the Small Cell Physical Resource Block utilization with and without the proposed dynamic offset selection technique (for the heterogeneous scenario) under different traffic conditions. It can be seen that dynamic CRE offloads more macro eNB traffic to the small cell, increasing its resource utilization without overloading it.

V. Conclusion

This paper has proposed a Self-Optimizing Cell Range Expansion Scheme based on a statistical learning approach

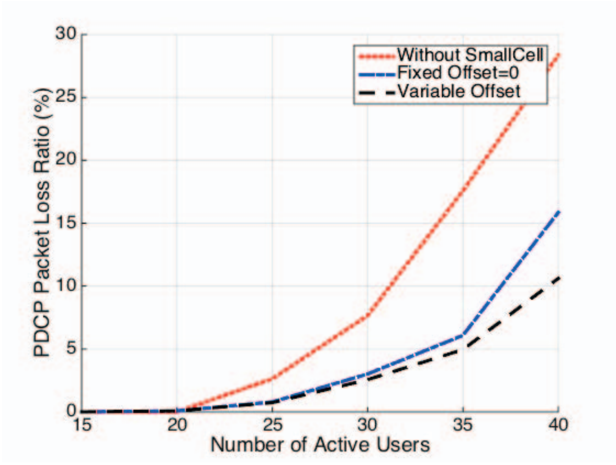

Fig. 6. Average PDPC Packet Loss Ratio Vs Number of Active UEs

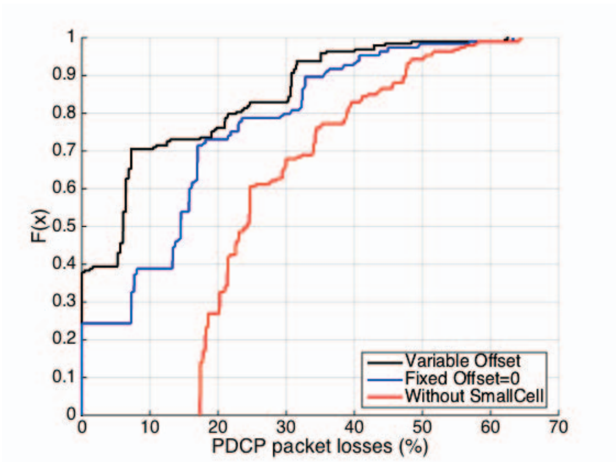

Fig. 7. Empirical CDF for PDPC Packet Loss Ratio (40 UEs)

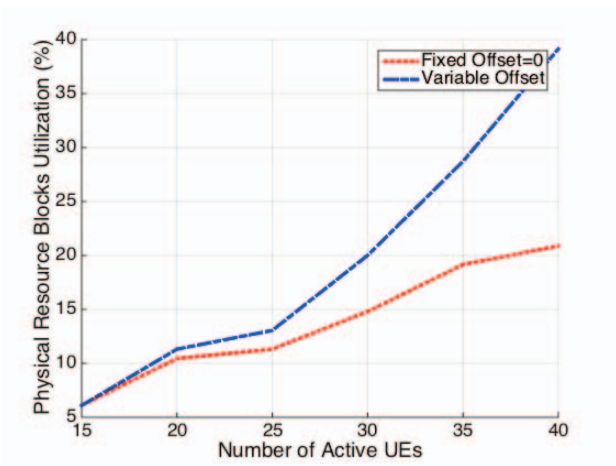

Fig. 8. Small Cell - PRB Utilization

for an LTE heterogeneous network. The extraction of a model from previous "network" experiences reflected the relationship between the cell traffic condition and the small cell offset with the packet loss ratio at the PDCP layer, allowing the network to anticipate its performance under specific circumstances. Simulations results showed the effectiveness of this approach in dynamically expanding the small cell coverage according to the traffic conditions, balancing the traffic load and diminishing packet losses. As next step in this work we intend to consider a mixed traffic environment with Quality of Service metrics constrains and developments in inter-cell interference coordination schemes.

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