

A User Centric Self-optimizing Grid-based approach for Antenna Steering Based on Call Detail Records

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Abstract— In this paper, we propose a user centric network parameter optimization approach that utilizes the information contained in subscriber call detail records generated in a cellular network. To be able to maximize average user throughput on a cell level, we perform optimization of sector azimuth angles based on user centric weighted grids. The grid pattern is formulated by identifying spatially distributed points that correspond to user activity quantified by user location and service utilization information obtained from the call detail records. In this study, we present numerical and cell level simulation over a system of 30 cells to evaluate the proposed solution. In comparison to an optimal brute-force method that takes into account the location of every user to optimize the azimuth angles in a cell, we show that the proposed grid based self-optimization approach yields matching results in performance with substantial reduction in computational complexity.

Keywords— (Self-optimization, Grid-based, SON, azimuth)

I. INTRODUCTION

As the path towards 5G evolves, it is envisioned that harnessing the vast amounts of underutilized data present in cellular networks can provide operators with valuable insights. These insights will have a profound effect on improving performance and reducing costs. Big data empowered Self Organizing Networks (BSON) [1], is a recently introduced paradigm that is envisioned to fundamentally change the way networks are operated, managed and maintained. The key idea in BSON is to exploit the deluge of data available in emerging and future cellular networks to create end-to-end network intelligence and then use that intelligence to empower the decision making process at the SON engine [1]. Building on the BSON framework, in this paper we propose a simple approach to improve the cellular system post-deployment optimization process, by exploiting one continually generated stream of data mainly used for billing purposes in cellular networks; subscriber call detail records (CDRs). We propose the extraction of location information from data records generated by subscriber activity and logged as CDRs. The location information is mapped onto spatially distributed points superimposed on a map of region of interest (ROI). The ROI is in turn divided into grids. Each grid is then assigned a weight proportional to the user density or capacity demand generated within that grid and inferred from the CDR data, thereby making the optimization solution user centric. The user centric weighted grids are then used to optimize selected network configuration parameters. The proposed CDR based Self Optimization approach is hereafter referred to as Grid-based Self Optimization using Data record (GSOD). We believe the

significance of GSOD is threefold. First GSOD makes the optimization process user centric by exploiting CDR data records present in any cellular network. The second advantage of GSOD is that the concept of dividing ROI into grids effectively reduces the complexity of the problem from having to optimize cell parameters while considering every user, to optimize for a far less number of grids in a cell. This simplification enables the implementation of GSOD in online fashion with lower signaling overhead and computational complexity. Since in GSOD the size of the grid offers a tradeoff between complexity of the solution and the potential performance gain, we present a method to determine optimal grid size for a given user distribution. Thirdly, GSOD serves as a framework which can be exploited for a variety of cell parameter optimization processes. In this paper, we use sector azimuth angle as a case study to evaluate the proposed framework solution. We compare the results attained for cell azimuth optimization using GSOD to results achieved by optimizing cell azimuth angles for every individual user in the cell, a method we hereafter refer to as the brute-force method.

The rest of this paper is organized as follows: In section II we present related work previously done in this domain to establish the novelty of this work. In section III, we present the system model, our assumptions and the mathematical formulation of the problem. In section IV, we evaluate the proposed GSOD framework solution numerically and by simulation for two cells. Finally, in section V we present results of implementing our proposed solution to all system cells and discuss the gain GSOD achieves. Section VI concludes the paper.

II. BACKGROUND

The pre-deployment planning and post deployment optimization process in emerging and future cellular networks are expected to be more user centric than their predecessors. A user centric approach is a key methodology of ensuring network design meets user's expectations and quality of experience requirements [2]. Accordingly, authors in [3] attempted to address the issue of tilt optimization suggesting a user focused framework that divides a cell into concentric semi-circles called regions, where a scheduler would select one out of a finite set of tilts and vertical half-power beam widths (HPBW) for a given user distribution attached to the base station depending on the received signal strength. Authors in [4] used the notion of Center of Gravity (CG) to simplify the representation of a given user distribution and user activity profile in a cell. They used their concept of CG in forming an

analytical framework for distributed self-organization of base station (BS) tilts. Another work involving user centric network parameter optimization is [5] where authors proposed a method to assist in handoff decisions using historical geo-tagged signal strength data and location information. In addition to studies that have used a user centric network parameter optimization approach, a number of studies that have optimized antenna parameters such as azimuth without particularly using a user centric approach are also relevant. For example, metaheuristic techniques such as simulated annealing [6] and Taguchi's method [7], as well as mathematical models such as in [8] have been used to find optimal values of azimuth angle for increased system capacity. However, emerging and future cellular networks differ from their predecessors in that future network operators can have access to accurate subscriber location information, in addition to numerous user specific data streams as enlisted in [1] and [9]. CDRs, which include an array of newly integrated fields in LTE and LTE-A, include user related information, which can be a valuable tool for optimizing cellular networks [1].

The novelty of this work is the utilization of user location information stored in CDRs that act as a basis for cell parameter optimization. Moreover, a new method has been proposed for implementing the optimization process, by substituting individual user locations mapped from CDRs, with corresponding weighted grid centroid locations and then optimizing accordingly. Furthermore, we propose a method to optimize grid size. This offers a tradeoff between computation complexity and gain of the optimization method. To the best of our knowledge this paper is first to present such an approach and implement it for sector azimuth angle optimization as a case study.

III. SYSTEM MODEL, ASSUMPTIONS AND PROBLEM FORMULATION

For this study, we consider a sectorized cellular network, where each BS has three sectors. The sector azimuths are initially set at 120 degrees apart. The rotation of one sector azimuth is independent of the other sectors in the cell. Hence, rotating any azimuth will affect the SINR experienced in all other sectors. Mechanical and electronic steering solutions can be used for remote rotation similar to [10]. As the CDRs are continually generated in accordance with subscriber activity, location points are added to a user map. This map is arranged into equal size square grids. Each grid is assigned a weight based on the number of users located inside it. Optimization of azimuth angles in a cell are based on grid weights, thus different grid sizes, yield different weights and in turn affect the optimization of the azimuth angles. We begin our proposed solution by optimizing the grid size.

A. Grid size optimization

The grid optimization problem is a trade-off between resolution and computational complexity. Decreasing grid area size increases resolution but also increases solution complexity. The term resolution refers to the ability of extracting detail from the gridded map formed of element location points. The smaller the grid size, the more individual location points can be discerned, thus, the higher the

resolution. However, a larger grid size reduces the number of points for the optimization process, thus, reducing the complexity. To solve this problem that has two contradicting objectives we introduce the following assumptions and formulation: Let A_{cell} represent the sectorized cell area for which the optimization problem is being solved, A_{sector} be the area of a sector and x represent the length of the side of the grid. Considering the distribution of user locations on the gridded map to follow a clustering operation where cluster child points (user locations) are geographically distributed according to a Poisson Point Process (PPP) Φ of intensity λ_s over \mathbb{R}^2 . According to [11], we define $G(\lambda_s, x) = e^{-\lambda_s x^2}$ as a resolution function. Maximizing this defined resolution function will decrease the grid area size x^2 , effectively increasing resolution. The complexity of the grid optimization problem is proportional to the number of grids. Accordingly, we define a complexity reduction function as $\frac{x^2}{A_{\text{cell}}}$. Maximizing the complexity reduction function, increases the area size of the grid x^2 , effectively reducing complexity. The grid optimization problem can now be given as the tradeoff between complexity and resolution as:

$$\Omega(A_{\text{cell}}, \lambda_s, x) = \frac{x^2}{A_{\text{cell}}} e^{-\lambda_s x^2}, \quad (1)$$

where $\lambda_s \left[\frac{\text{users}}{\text{m}^2} \right]$ is the intensity of child points (users) in the cluster. Given our assumption of a sectorized cellular network, we add a constraint that the maximum grid area size cannot exceed the area of a sector. Thus, the grid optimization objective function can be stated as:

$$\text{argmax}_{x^2 \in [0, A_{\text{sector}}]} \Omega(A_{\text{cell}}, \lambda_s, x) = \frac{x^2}{A_{\text{cell}}} e^{-\lambda_s x^2}. \quad (2)$$

As weights are assigned to each grid, we define a weight variable for grid $g \in \mathbb{G}$; the set of all grid centroid points as:

$$w_g = \frac{\Lambda_g(n \in N)}{N}, \quad (3)$$

where N is the total number of users in the cell, and $\Lambda_g(n)$ is a counting operator for the number of users in g^{th} grid. The defined weight variable will subsequently be used in azimuth angle optimization introduced in the next subsection.

B. Azimuth angle optimization

Let B denote the set of points corresponding to all transmission antenna locations in a cell and A denote the set of all azimuths in a sectorized cell. The geometric SINR for grid centroid $g \in \mathbb{G}$ associated with sector $b \in B$ can be given as:

$$\gamma_g^b = \frac{P^b G_g^b G_g \delta_g^b \alpha (d_g^b)^{-\beta}}{TN + \sum_{b' \in B/b} P^{b'} G_g^{b'} G_g \delta_g^{b'} \alpha (d_g^{b'})^{-\beta}}, \quad (4)$$

where TN is the thermal noise, $\{/\}$ is an exclusion operator i.e. B/b means all sectors in set B excluding sector b . α and β are respectively the path loss coefficient and exponent used to model a generic path loss model. δ_g^b , $\delta_g^{b'}$ are shadowing coefficients at point g from the respective sectors b and b' .

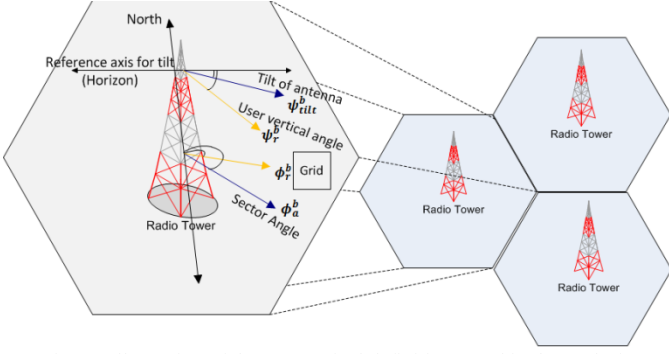


Fig. 1 - Illustration of the geometrical definitions used in the analysis.

G_g^b is the antenna gain perceived at the g^{th} grid from the b^{th} sector. Respectively, for 3GPP LTE the three dimensional antenna pattern can be modeled as in [12]. Thus the perceived antenna gain at location (g) is expressed as

$$G_g^b = 10 \left(\begin{array}{l} \lambda_v \left(G_{\max} - \min \left(12 \left(\frac{\psi_g^b - \psi_{\text{tilt}}^b}{B_v} \right)^2, A_{\max} \right) \right) + \\ \lambda_h \left(G_{\max} - \min \left(12 \left(\frac{\phi_g^b - \phi_a^b}{B_h} \right)^2, A_{\max} \right) \right) \end{array} \right). \quad (5)$$

As shown in Fig. 1, ψ_g^b is the vertical angle at the b^{th} sector in degrees from the reference axis (horizon) to the grid point g. ψ_{tilt}^b is the tilt angle of the b^{th} sector. ϕ_g^b is the angle of the g^{th} grid from the horizontal reference axis (north) at the b^{th} sector. B_h and B_v represent the horizontal and vertical beam widths of the sector antenna respectively, and λ_h and λ_v represent weighting factors for the horizontal and vertical beam pattern of the antenna in the 3D antenna model. G_{\max} denotes the maximum antenna gain in dB at the bore sight of the antenna while A_{\max} denotes the maximum antenna attenuation in dB at the sides and back of the bore sight of the antenna. Values of G_{\max} and A_{\max} are the same for the horizontal and vertical radiation pattern. We further simplify this model without the loss of generality by omitting A_{\max} and assuming G_{\max} is 0 dB. *Nevertheless, this assumption will be removed in the simulation and numerical analysis parts.* The simplified antenna model can be written as:

$$G_g^b = 10 \left(\begin{array}{l} \lambda_v \left(\frac{\psi_g^b - \psi_{\text{tilt}}^b}{B_v} \right)^2 + \\ \lambda_h \left(\frac{\phi_g^b - \phi_a^b}{B_h} \right)^2 \end{array} \right). \quad (6)$$

We assume our network is operating at full load with frequency reuse reducing out-of-cell interference. Power allocation across all subcarriers is equal and cell sector antennas are collocated on a center mast. This analysis can be extended to mmWave future networks by applying mmWave path loss models and massive (user-specific) beamforming. For ease of expression, we will use the following contractions:

$$\left\{ \begin{array}{l} \varphi_g^b = \frac{B_h^2 \lambda_v}{B_v \lambda_h} (\psi_g^b - \psi_{\text{tilt}}^b)^2 \\ \kappa = \frac{-1.2 \lambda_h}{B_h^2} \end{array} \right\}. \quad (7)$$

With the aforementioned assumptions taken into consideration, the SINR in (4) can now be approximated as a SIR function of azimuth angles as follows:

$$\gamma_g^b(\phi_a^b) = \frac{10^{\kappa(\varphi_g^b + (\phi_g^b - \phi_a^b)^2)}}{\sum_{\forall b' \in B/b \forall a' \in A/a} 10^{\kappa(\varphi_g^{b'} + (\phi_g^{b'} - \phi_a^{b'})^2)}}, \quad (8)$$

where ϕ_a^b refers to the azimuth angle for sector b currently serving the grid centroid (g). $\phi_a^{b'}$ are the azimuth angles of all other sectors $b' \in B/b$ causing interference. Our objective is to find the optimal azimuth angles for all sectors that yields the maximum average user throughput for all subscribers in a single cell simultaneously. $\forall g \in \mathbb{G}, \forall b \in B$, mathematically we express this as a function of all azimuths of all sectors, for every individual grid g covered by sector b, given as follows:

$$\underset{\phi_a^b}{\operatorname{argmax}} \eta(\phi_a^b) = \sum \mathcal{H} w_g \log_2 \left(1 + (\gamma_g^b(\phi_a^b)) \right), \quad (9)$$

where \mathcal{H} refers to the bandwidth. The SIR expression in (8) is a function of azimuth angles of all sectors in the cell. The formulation in (9) is a nonlinear multi variable optimization problem. Maximization of the objective function is to be solved simultaneously for all sectors in a cell for every grid point g.

IV. OPTIMIZATION FRAMEWORK EVALUATION

Evaluating the performance of the proposed solution using simulation and the mathematical objective functions presented in section III, we compare our proposed GSOD method with the aforementioned heuristic brute-force approach collectively for grid and azimuth optimization. For simulation, a MATLAB[®] program has been written to generate user voice and data CDR's. Users are scattered based on a Matern cluster point process (MCP) [13]. We begin by optimizing the grid size, and then illustrate azimuth angle optimization for two separate cells. While the azimuth optimization results do not yet reflect the entire system of cells considered, they are readily obtainable from the aforementioned formulas and serve the purpose of aiding the validation of our proposed solution.

A. Grid optimization

Evaluating the optimal grid size attained from equation (2), a comparison of the side length x of the grid found numerically using the analytical expression, to a heuristic approach that searches for the optimum grid side length in a cell was done. Cells are assumed hexagon in shape with side length of 150m. MCP cluster radius is assumed 30m. User intensity $\lambda_s = 0.001 [\text{users}/\text{m}^2]$. Solving (2) for our hexagon shaped cells, the solution confirms a grid side length of 26.59m representing the optimum grid side numerically.

The heuristic search followed. Intuitively, continually minimizing the grid area x^2 increases resolution as previously described. Once the variance between grid weights becomes smaller than a defined threshold, the process stops and the grid size is chosen. The threshold was chosen as the intensity λ_s of child points in a cluster multiplied by the number of clusters in a cell. This is defined as:

$$\operatorname{var}(w_g) \geq \lambda_s \times \frac{\text{Total area covered}}{\text{Cluster area}} \quad (10)$$

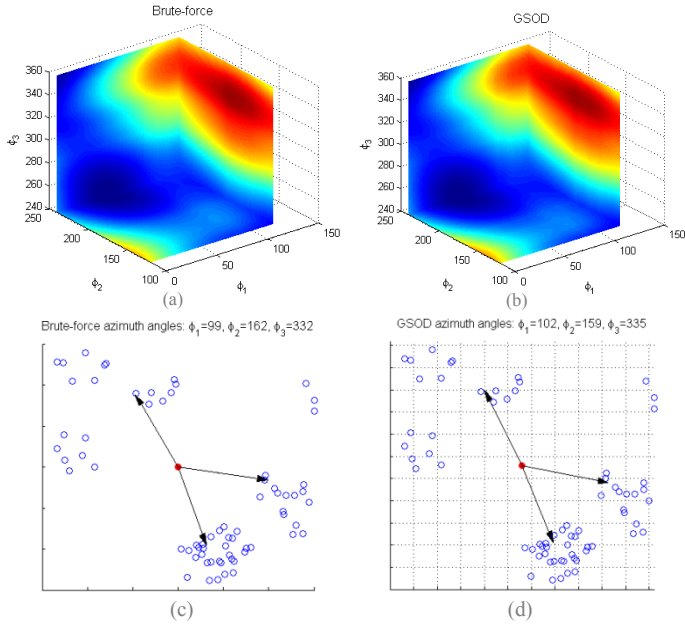


Fig. 2 – GSOD and Brute-force azimuth optimization (Cell #6)

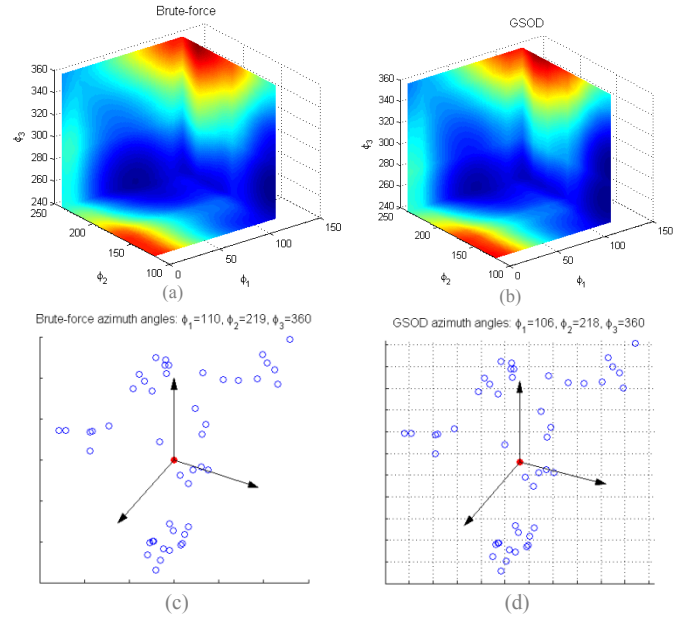


Fig. 3 – GSOD and Brute-force azimuth optimization (Cell #26)

The heuristic search was done thirty times on 30 system cells all with the same λ_g . The smallest grid side found in the search was 25m corresponding to cell #6. The largest grid side found in the heuristic search was 27.27m, corresponding to cell #26. The average heuristic grid side found over all 30 cells was 26.664m. This confirms the numerical result calculated. Testing the effectiveness and accuracy of this value as grid length, it was adopted throughout all subsequent azimuth optimization processes carried out.

B. Azimuth optimization

Table I shows the parameters that were used to solve equation (9) for azimuth optimization. The numerical grid side length of $x = 26.59m$ was used for the analysis. Both aforementioned cells (6 & 26) were chosen for illustration of azimuth optimization as they correspond to the largest and smallest heuristic grid side length found. For every user in the case of the brute-force method, and every grid for GSOD, all possible azimuth values and resultant SIRs were calculated. This is illustrated in Fig. 2.a and 2.b for cell #6, and Fig. 3.a and 3.b for cell #26 as 4D slice plots. The volume of the plot represents the SIR, and the three axis's correspond to the azimuth angles ϕ_1 , ϕ_2 and ϕ_3 , respectively. The azimuth angles of both methods superimposed over maps with users in place are shown in Fig. 2.c and 2.d for cell #6, and Fig. 3.c and 3.d for cell #26. We find that running the same algorithm with the same grid length of $x = 26.59m$ on cell#6, the azimuths differ by 3° for ϕ_1 , ϕ_2 and ϕ_3 . Also, for cell #26 the azimuths differ by 4° for ϕ_1 , 1° for ϕ_2 and match for ϕ_3 . The normalized average user throughput for cell #6 was found to be 0.65287 using brute-force, and using GSOD it was 0.64674. Moreover, the average user throughput for cell #26 was found to be 3.3634 using brute-force and was 3.3549 using GSOD. This confirms that for these two cells the results of GSOD nearly match brute-force in terms of throughput achieved.

TABLE I. SYSTEM LEVEL SIMULATION PARAMETERS

Parameters	Values
User antenna gain	0dB (Omni directional)
B_h, B_v	$70^\circ, 10^\circ$
λ_v, λ_h	0.5
G_{max}, A_{max}	18dB, 20dB
Tilt	10°
Frequency	2 GHz

V. SYSTEM RESULTS AND DISCUSSION

To illustrate the proposed solution gain, a network system implementation of users distributed over 30 cells was simulated and tested for comparison. Optimization of azimuth angles of all cells using both methods was performed. Blind brute-force azimuth optimization was applied taking into account the location of every user in the cell. The term blind means users were not weighted according to services used, or according to priority levels. GSOD was applied using the same grid side length calculated in the previous section; (26.59m). Grid weights were calculated according to (3); based on the number of subscribers located inside the grid to the total number of subscribers in the cell. No weights were given to differentiate among user services or types of users. Fig. 4 shows a comparison of the achieved normalized throughput for all cells. The results achieved using GSOD matched those using the brute-force method in nearly every cell. This is confirmed in Fig. 6, which shows a comparison of the average user throughput CDF for the entire system of cells for both methods. Table II shows summary statistics of the average user throughput obtained for both methods over all cells. In terms of complexity, Fig. 5 shows the number of iterations executed per method, per cell (a) and over all cells (b). It confirms; GSOD is able to achieve the same amount of throughput for nearly all cells with a 41% reduction in iterations from 1363 to 807. Concluding, GSOD greatly reduced the complexity and computation time required.

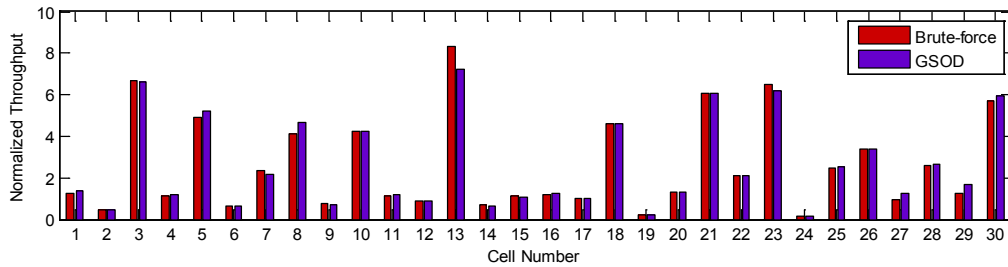


Fig. 4 – Throughput comparison between the proposed GSOD solution and the brute-force method for all system cells.

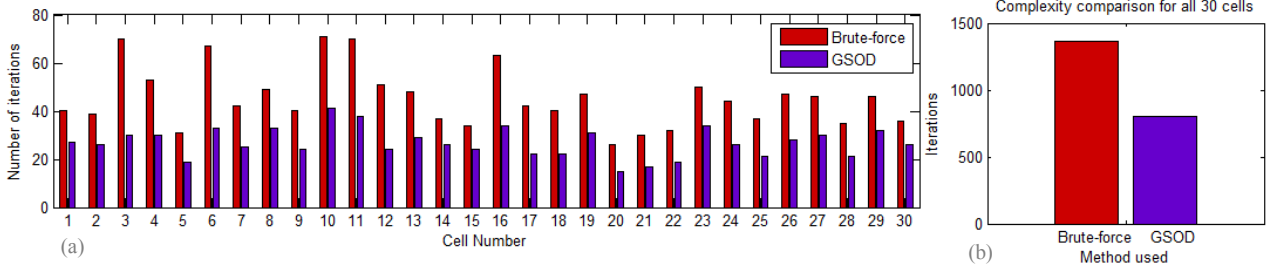


Fig 5- Complexity comparison between the proposed GSOD solution and the brute-force method for every cell (a) - all cells combined (b).

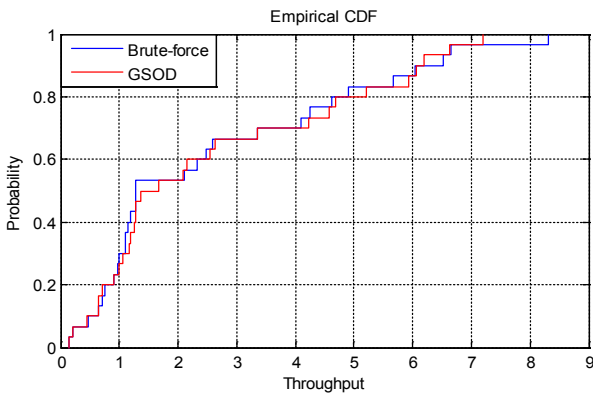


Fig. 6 –Average user throughput CDF comparison of Brute-force and GSOD.

TABLE II. SYSTEM LEVEL SUMMARY STATISTICS FOR THROUGHPUT

Parameters	Brute-force	GSOD
min	0.13615	0.14449
max	8.312	7.1974
mean	2.6056	2.6163
std	2.2736	2.1921

VI. CONCLUSION

A new user centric grid-based approach that utilizes location information retrieved from subscriber CDRs as a basis for cell parameter optimization, referred to as GSOD, has been presented. In addition, a method to determine an optimal grid size for a given user distribution has been shown. A case study of cell azimuth optimization using the proposed method was conducted. A comparison study between GSOD and brute-force optimization for all users in a cell was done. Simulation results for a 30 cell system show the proposed GSOD method matches the achieved throughput of the brute-force method for nearly all 30 cells. A total reduction of 41% in terms of the required iterations and subsequently execution time was achieved. The results confirm that the proposed grid based approach is an effective and efficient method for cell parameter optimization. Furthermore, the proposed method

has the potential for real time application considering the time scale of population displacement requiring cell azimuth adjustment is larger than a few seconds. Finally, this method forms a framework for other cell parameter optimization processes such as tilt and beam width optimization.

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