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Self-organizing inter-cell interference coordination in 4G and beyond networks using genetic algorithms

Aasia Kashaf[a], Moazzam Islam Tiwana[a], Imran Usman[b] and Mohsin Islam Tiwana[c]

[a]Department of Electrical Engineering, COMSATS Institute of Information Technology, Islamabad, Pakistan; [b]College of Computing and Informatics, Saudi Electronic University, Riyadh, Kingdom of Saudi Arabia; [c]Department of Mechatronics Engineering, National University of Sciences and Technology, H-12, Islamabad, Pakistan

ABSTRACT

The design objective of the 4G and beyond networks is not only to provide high data rate services but also ensure a good subscriber experience in terms of quality of service. However, the main challenge to this objective is the growing size and heterogeneity of these networks. This paper proposes a genetic-algorithm-based approach for the self-optimization of interference mitigation parameters for downlink inter-cell interference coordination parameter in Long Term Evolution (LTE) networks. The proposed algorithm is generic in nature and operates in an environment with the variations in traffic, user positions and propagation conditions. A comprehensive analysis of the obtained simulation results is presented, which shows that the proposed approach can significantly improve the network coverage in terms of call accept rate as well as capacity in terms of throughput.

1. Introduction

The 4G and beyond mobile access technology promises to deliver high data rates from 100 Mbps to 1Gbps along with a high quality-of-service (QoS) provision for a variety of applications [1,2]. However, the increase in the size and the heterogeneity of these networks has given a strong impetus to the research in self-organizing networks [3]. Self-organization targets to reduce the capital expenditure (CAPEX) as well as operational expenditure (OPEX) of these networks. While at the same time, the QoS constraints on various telecom services in terms of coverage and capacity must also be satisfied. The autonomic self-organization functions comprise of self-configuration, self-optimization and self-healing. This work focuses on self-optimization where performance measurements from the network known as key performance indicators (KPIs) are used to optimize the radio resource management (RRM) parameters. This leads to an optimal network performance. Hence, autonomic self-optimization reduces OPEX of the network by reducing the workload of the site survey and network performance analysis teams.

The industry and academia have done some significant work on the self-optimization in radio access networks (RANs) during the last decade [4,5]. In spite of the early research work and industrial interest in self-optimization of GSM and UMTS [6–7], self-optimization was not included as a part of these standards. Later, the focus of research shifted towards self-optimization in heterogeneous networks using load balancing [8]. With the advent of Long Term Evolution (LTE), the research on LTE self-optimization involves RRM parameters like interference mitigation using inter-cell interference coordination (ICIC) [9,10], load balancing [11,12] and bandwidth allocation [13].

Recently, reinforcement (machine) learning technique of fuzzy Q-learning (FQL) has been used for the optimization of RRM parameters in LTE. FQL has been used for the optimization of mobility parameters of both GSM Edge Radio Access Networks (GERAN) [14] and LTE network [15]. More recently, FQL has been used for coverage/capacity optimization of LTE networks by adjusting the vertical tilt angle of the antenna employed at eNodeB (eNB) [16–18]. Despite the widespread use of FQL, all these works lack any discussion on the criteria when to switch from exploration to exploitation mode. This problem is known as exploration/exploitation dilemma. Furthermore, FQL algorithm is quite susceptible to trapping in local minima.

GA is a machine learning technique that has been used in many different fields to solve the complex optimization problems [19]. It is an efficient stochastic search technique that has the tendency to quickly attain optimal/near-optimal solution in large solution spaces. With appropriate fitness function defined and right parameters taken into consideration, this solution could be generalized. GA is an evolutionary algorithm that models the biological processes of evolution, through successive selective breeding over generations

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CONTACT Moazzam Islam Tiwana ✉ moazzam_islam@comsats.edu.pk

[20]. It is a gradient-free technique that is very robust against getting stuck in the local optima. Owing to these reasons, we choose GA to solve the LTE network optimization problem by optimizing the inter-cell interference mitigation parameters.

The proposed scheme is valid both for LTE as well as LTE-Advanced (LTE-A) as it is implemented in the management plane of the network. The basic network architecture of LTE and LTE-A is the same apart from some new features in LTE-A-like carrier aggregation, enhanced MIMO and Co-ordinated Multipoint (CoMP) Transmission. The self-optimization algorithms can be implemented in the operation and maintenance centre (OMC) of a network. In the paper, an eNB and a base station represent one and the same thing, and will be used interchangeably.

The paper is organized as follows: Section 2 presents LTE ICIC model used in our case study. Section 3 presents the proposed GA-based self-optimization framework. Section 4 deals with the simulation environment and provides the numerical results of the proposed scheme. Section 5 concludes this paper by presenting conclusion and future directions.

2. System model

Consider a downlink OFDMA-based cellular network with ICIC. The system uses a frequency reuse factor of 1. Hence, all the available bandwidths are reused in each cell. Physical resource block (PRB) is the smallest time-frequency resource unit that can be allocated to a user.

Figure 1 presents a seven-adjacent-cell layout. The frequency in each cell is subdivided into three sub-bands. One is the edge band and the other two are the centre bands. The users with worst channel quality are allocated at the edge band/protected band. These users are mostly located at cell edges but could also be closer to the base station and experiencing deep fading conditions. If the edge band of a cell is completely occupied, the remaining users are allocated PRBs in the centre bands. As evident from Figure 1, the main interference is between the edge band users of a cell with centre band users of the neighbouring cells. P is the maximum transmit power for each sub-carrier. However, the transmit power in the centre band is reduced to αP, in order to reduce interference with the neighbouring edge bands. A priority scheme is used to allocate the PRBs to the users on the edge band. This priority scheme is based upon the calculation of a quality metric as explained here. For a user u with the serving base station b, the quality metric h_u is calculated using pilot channel signal strengths:

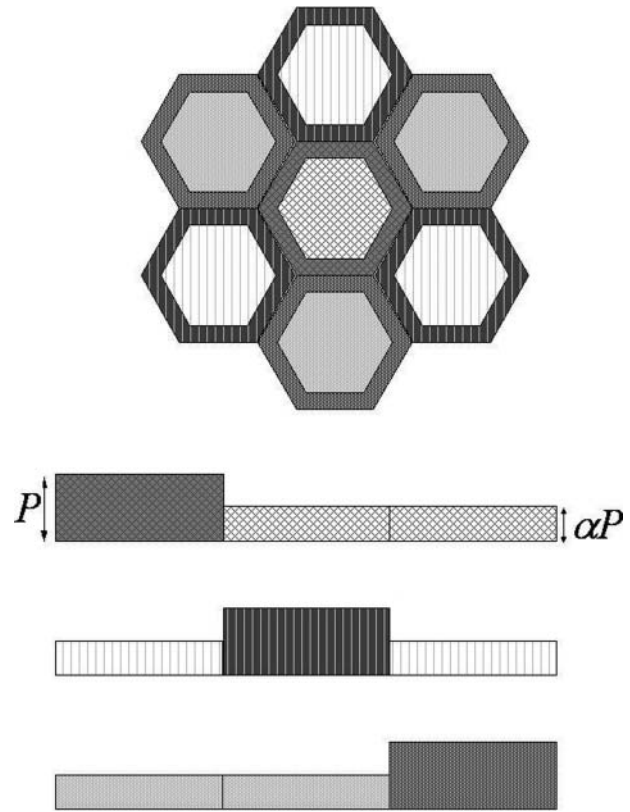$$h_u = \frac{Pr_{bu}}{\sum_{b' \neq b} Pr_{b'u} + \sigma_n^2} \qquad (1)$$

Figure 1. System model.

where Pr_{bu} and $Pr_{b'u}$ represent the mean pilot signal power received by u from the base stations b and b', respectively. The users with the worst quality metric h_u are allocated resources from the edge band, and hence they get benefit of maximal transmission power P of base stations. When the edge sub-band is full, the users are allocated resources from the centre band. The handover for the users from one base station to the other is dependent on the received power-level difference between the two base stations. For a user u, hard handover will be performed to move from the serving base station b to b', if the following condition is satisfied:

$$Pr_{b'u} - Pr_{bu} > T_{\text{hyst}} \qquad (2)$$

where T_{hyst} is the fixed hysteresis margin for all the base stations and is set to 6 dB in this study.

3. Proposed architecture

In the proposed scheme, we exploit the hidden dependencies present in the RRM parameters, and optimize them in order to improve the KPIs of the network. The RRM parameters optimized in this case are the α-parameters of individual eNBs. The KPIs optimized are called accept rate, file transfer time (FTT) and the average bit rate (ABR) of all the mobiles in the network. Owing to the mobility of mobiles, their changing distribution, fading phenomenon and interference etc.,
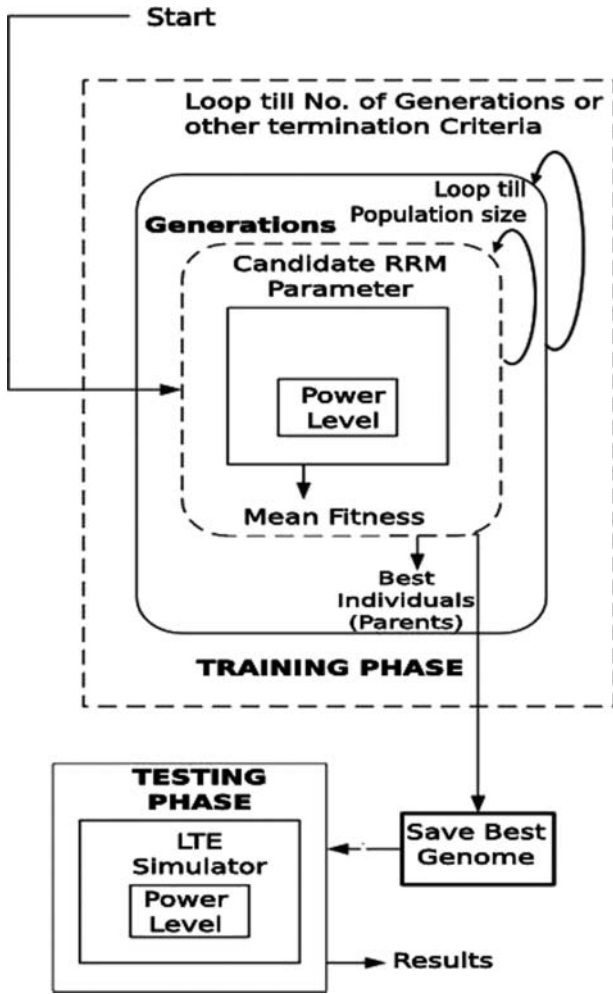
Figure 2. Proposed architecture.

the KPIs are a nonlinear function of α. Furthermore, this relationship is not available in a closed form. Hence, we have chosen GA to achieve our optimization objective. Figure 2 shows the the generalized diagram for the proposed approach. As shown, the proposed optimization method consists of two main steps: the training phase, followed by the testing phase. In the training phase, the α parameters are optimized using GA. The dimension of a chromosome depends upon the number of genes, where each gene uniquely represents the α parameter of an individual eNB. The total number of genes in a chromosome equals the number of base stations. The population size determines the number of chromosomes in a generation. These populations are scored and sorted based upon their individual fitness values. The next generation is evolved by employing genetic operators of cross-over, mutation and replication on the best performing individuals in the previous generation (see Table 1 for algorithm details). The process continues till the termination criterion is reached, which may be based on time limit, number of generations or a predefined acceptable fitness value. The termination criteria in this case are the number of generations. The optimum

Table 1. RRM parameter optimization using genetic algorithm.

Step 1: Create z randomly generated solutions to form first generation P_1.

FOR each P_s: $s = 1, \ldots, v$ and
   Step 1.1: Compute fitness value of all individuals in P_s using LTE simulator.
   Step 1.2: Evaluate fitness using the predefined fitness function.
   Step 1.3: Check the following conditions:
   IF Termination Criteria is reached, go to step 2.
   ELSE Create new generations using genetic operations
      Step 1.3.1 Crossover
      Step 1.3.2 Mutation
      Step 1.3.3 Replication
      Step 1.3.4 Select solutions based on their fitness using genetic operators and assign them to $P_s + 1$. Delete the low-ranked individuals.
   END IF
END
Step 2: Save the best evolved Solution and terminate the procedure.

values retained are then used in testing phase to validate the generalization for real-world applications.

3.1. GA control parameters

The convergence of selective breeding is governed by an application-oriented predefined fitness function. Other factors contributing to the decreased time of convergence are different control parameters customized for a typical application. The control parameters in our GA simulations are population and generation sizes, selection method, cross-over and mutation probabilities, and termination criteria, etc. In addition, probabilities of genetic operators of replication, cross-over and mutation are repeatedly used to optimize a highly complex cost function.

3.1.1. Population initialization

Initially, the population is initialized by pseudo-random values drawn from the standard normal distribution assuring ramped half and half strategy. A random number is picked between the minimum and maximum possible values for each decision variable, where decision variables are the mean fitness values, obtained by simulating concerned chromosome using LTE simulator.

3.1.2. Termination criterion

In GA, termination criterion for simulations can be based upon the number of generations or on some threshold of fitness level or on some predefined time limit. In our case, we have limited the simulations by specifying maximum numbers of generations to be 30. The best evolved solution is saved.

3.1.3. Fitness function

The fitness function score of the chromosomes is used to select the best performing chromosomes in a population. We have used mean ABR of all mobiles in the

Table 2. Genetic algorithm simulation parameters.

Parameters	Settings
Fitness function	Given as Equation (3)
Selection	Generational
Population size	80
Survival mechanism	Keep best
Termination	30 generations
Selection method	Roulette wheel selection method

network as the fitness function, given as:

$$U = \sum_{i=0}^{n} \frac{ABR_i}{n} \qquad (3)$$

where ABR_i denotes the average bit rate of all mobiles in communication with the ith base station at that instant. The improvement of mean ABR is directly correlated with the improvement/reduction of overall FTTs in the network. Consequently, the accept rate of network improves. ABR_i is a function of α_i:

$$ABR_i = f(\alpha_i) \qquad (4)$$

Hence our optimization objective can be given as

$$\alpha_i = \underset{\alpha_{i'}}{argmax} \ U\left(\alpha_{i'}\right) \qquad (5)$$

The settings for the control parameters of GA given in Table 2. In Figure 2, it can be seen that the LTE simulations run at two times: first, when calculating mean fitness values for each genome in GA during the training phase; second, when the KPIs are averaged for the optimized and non-optimized cases during the testing phase. The simulations for calculating each chromosome's mean fitness value run for 30 sec. Hence, the total time required to obtain optimized α distribution is $30 \times 80 \times 30$ sec = 72,000 sec or 20 hr). While for averaging KPIs during testing phase, the simulations run for 2000 sec for both self-optimized and non-optimized cases.

4. Numerical results

4.1. Simulation environment

The simulations have been performed using the downlink LTE MATLAB simulator as described in [11]. The network diagram of the simulated system is shown in Figure 3.

The simulator performs correlated Monte Carlo snapshots with the resolution of 1 sec to account for the time evolution of the network. At the end of each time-step mobile positions are updated, HO events are processed, new mobiles are admitted according to the access conditions and some other users leave the network (end their communications or are dropped). Traffic model used to simulate the arrival of new
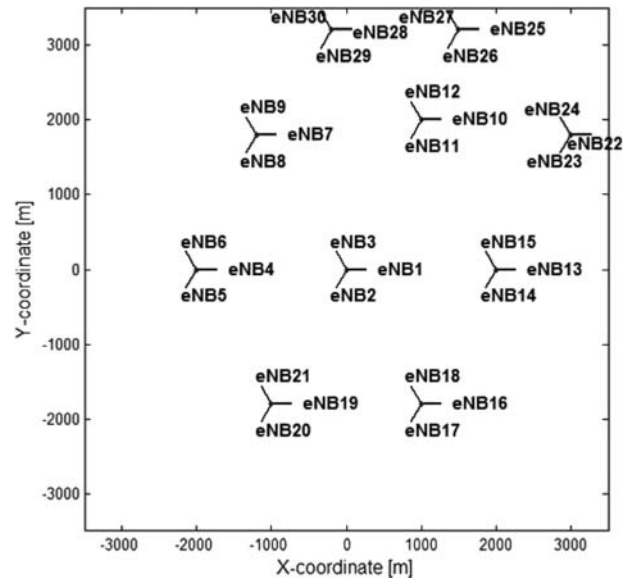
Figure 3. The network diagram of the simulated system.

mobile users is Poisson process with a certain arrival rate λ (arrivals/sec). The time difference between two simulation time steps is 1 sec. Hence, the probability Pr of generation of k mobiles during each simulation time step is given as

$$Pr(k) = \frac{\lambda^k e^{-\lambda}}{k!} \qquad (6)$$

Poisson distribution approximation of binomial distribution is used to calculate k for each simulation time step [21]. The network simulation parameters are listed in Table 3.

Reference solution

Reference solution is the default optimal α value for all eNBs. Its value has been chosen as 0.5 as determined in [22].

4.2. Simulation results

Performance obtained using adaption of α-parameters using GAs is compared with the reference solution.

Table 3. The system-level simulation parameters.

Parameters	Settings
System bandwidth	5 MHz
Cell layout	30 eNBs, single sector
Maximum eNB transmit power	32 dBm
Inter-site distance	1.5–2 km
Subcarrier spacing	15 kHz
PRBs per eNB	24 (8 in each sub-band) + 1 for pilot channel
Path loss	L=128.1+37.6 $\log_{10}(R)$, R in kilometers
Thermal noise density	−173 dBm/Hz
Shadowing standard deviation	6 dB
Traffic model	FTP
File size	6300 Kbits
PRBs assigned per mobile	1–4 (first-come, first-serve basis)
Mobility of mobiles	10%
Mobile speed	8.33 m/sec

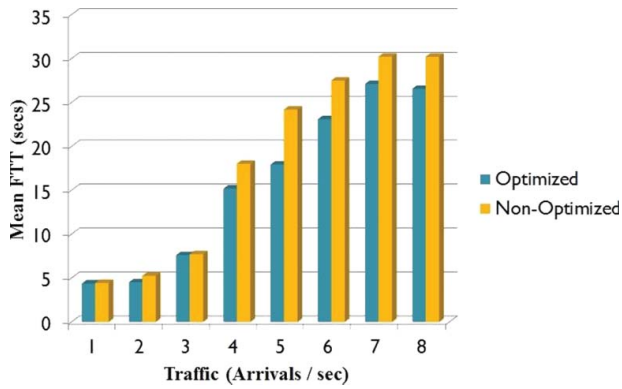**Figure 4.** The mean FTT as a function of traffic intensity for the optimized and non-optimized case.

Figure 5. The mean ABR as a function of traffic intensity for the optimized and non-optimized cases.

As mentioned earlier, the network performance is evaluated in terms of three KPIs: call accept rate, FTT and ABR of mobile stations. Figure 4 presents a comparison between the FTT of the two systems relative to traffic arrival rate. It can be observed that for the traffic value of 1 arrivals/sec, the improvement is only marginal. This is due to the fact that the number of mobiles entering the network is not large enough. Consequently, due to low interference and allocation of PRBs in the edge band, the mobiles quickly download the file and leave the network. Therefore, the employment of self-optimization mechanism does not significantly improve the mean FTT value. The same holds true for the case of the traffic values of 2 and 3 arrivals/sec. However, for traffic value of 4 arrivals/sec, and onwards, we can see a clear improvement in the FTT. As the number of mobiles present in the network increases, they stay longer in the network due to congestion and are also allocated PRBs in the centre band. Hence, adaptation of α leads to greater improvement. Overall, the FTT increases, but when comparing the two systems, it can be concluded that the proposed model is better to be used for high traffic rate situations.

For a traffic value of 5 arrivals/sec we see a maximum comparative decrease/improvement of 25% in FTT. Overall, the greater FTT value shows that the network has taken more time for these transfers.

Figure 5 compares mean ABR of mobile stations of two systems. It is evident that the proposed algorithm performs better than the non-optimized one at all traffic values considered. Same as other KPI values, it shows greater improvement at traffic values of 4 and 5 arrivals/sec. For a traffic value of 5, we see a 25% increase in the ABR. After that, it tends to decrease but even then the results are better than the non-optimized case.

From Figure 6, it is seen that the call accept rate for both the cases is approximately same for traffic values of 1 and 2 arrivals/sec. This is due to the fact that initially there are less number of mobiles in network. So, the mobiles are served quickly. While as the traffic
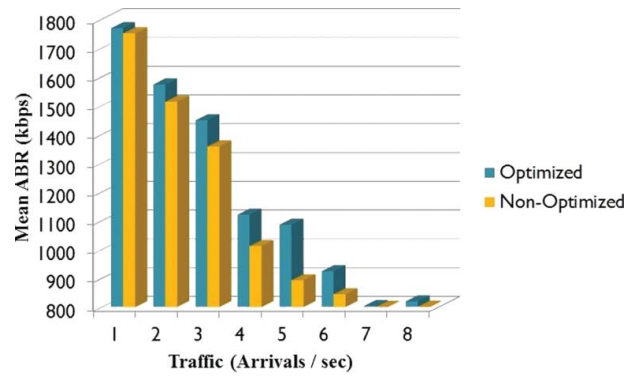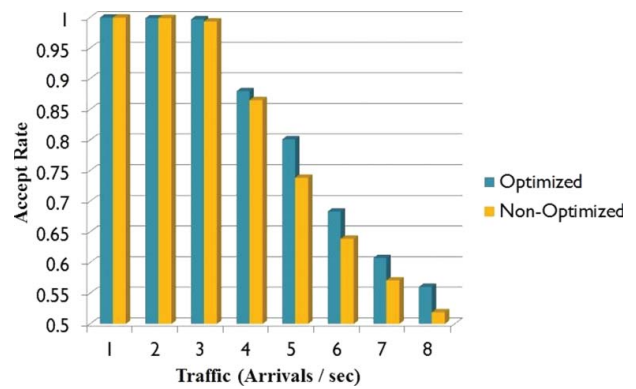

Figure 6. The accept rate as a function of traffic intensity for the optimized and non-optimized cases.

increases accept rate decreases, but at the same time, the self-optimization algorithm becomes more effective due to congestion. Hence, for a traffic value of 5 arrivals/sec, we see an 8% increase in the call accept rate.

Figures 7–12 compare the CDF plots of the ABR of mobiles of two systems for traffic values of 3–8 arrivals/sec, respectively.
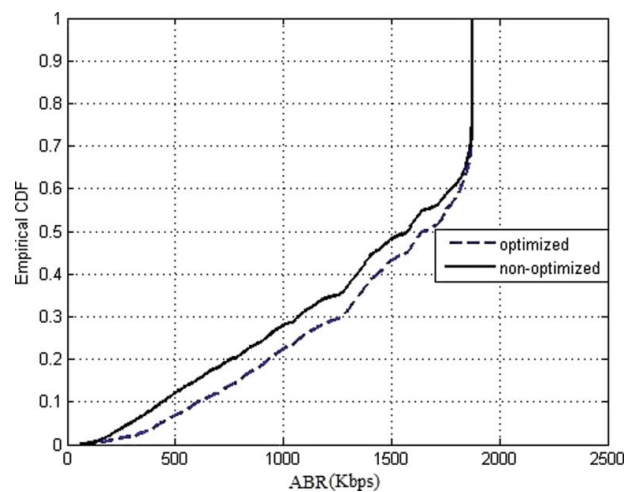

Figure 7. CDF of individual ABR values for all mobiles in the network for traffic intensity of 3 arrivals/sec, with and without optimization.
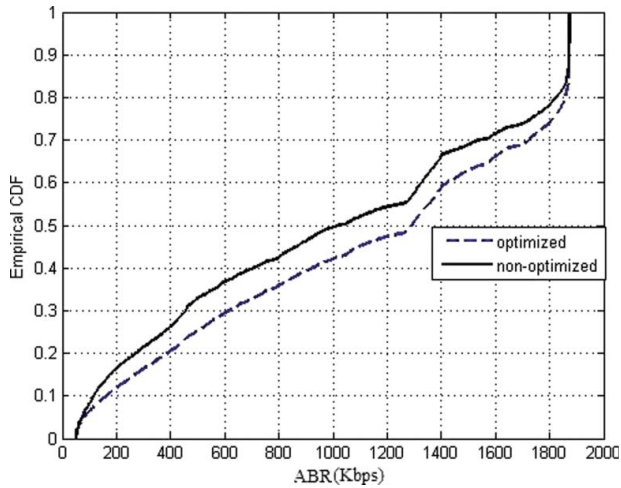
Figure 8. CDF of individual ABR values for all mobiles in the network for traffic intensity of 4 arrivals/sec, with and without optimization.

Figure 10. CDF of individual ABR values for all mobiles in the network for traffic intensity of 6 arrivals/sec, with and without optimization.

Figure 7 shows that for traffic value of 3 arrivals/sec the optimized system performs better. As shown, more than 60% mobiles have ABR values greater than 1500 Kbits/sec in the optimized case. While in the non-optimized case, 60% mobiles have ABR values greater than 1300 Kbits/sec. We see a greater improvement for traffic value of 4 arrivals/sec, as shown in Figure 8. Here 70% mobiles have ABR less than 1750 Kbits/sec for optimized case, while for non-optimized, 70% are with ABR values less than 1500 Kbits/sec. So, for both traffic values, 3 and 4 arrivals/sec, optimized case shows greater improvement in mobile ABR. The same is true for traffic value of 5 as shown in Figure 9. The results for the traffic values of 6–8 arrivals/sec are shown in Figures 10–12, respectively. However, the improvements tend to decrease. This is due to the fact that now the increasing congestion has increased interference to such a point that optimizing α has very little effect. For example, for the

Figure 11. CDF of individual ABR values for all mobiles in the network for traffic intensity of 7 arrivals/sec, with and without optimization.
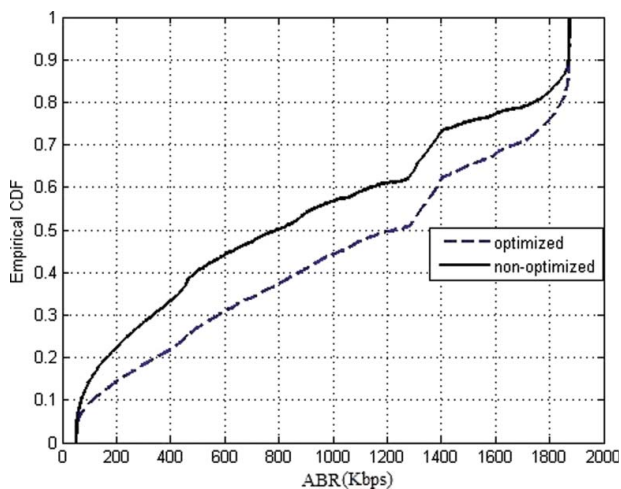

Figure 9. CDF of individual ABR values for all mobiles in the network for traffic intensity of 5 arrivals/sec, with and without optimization.
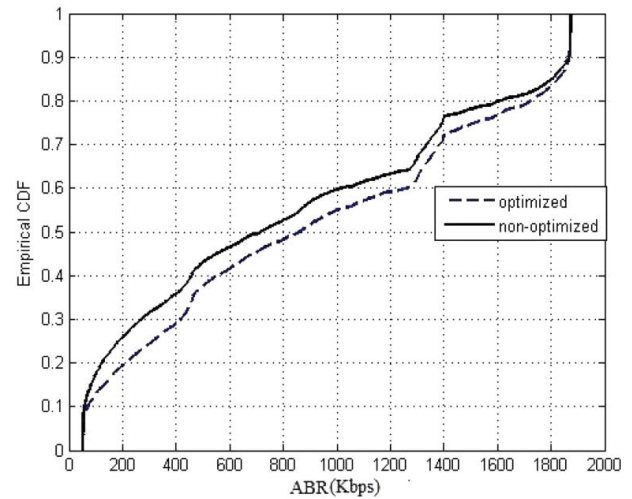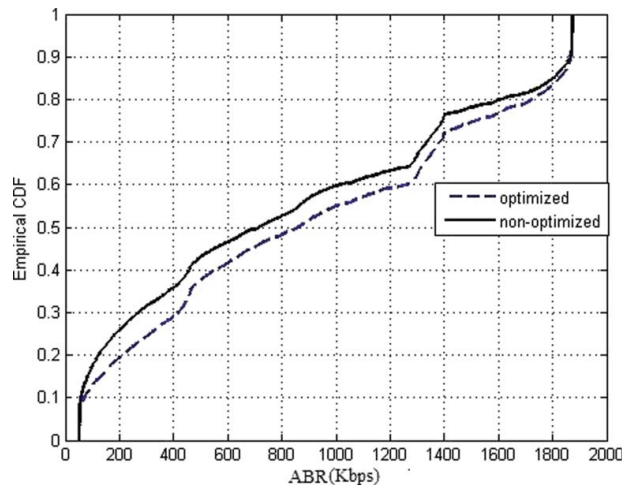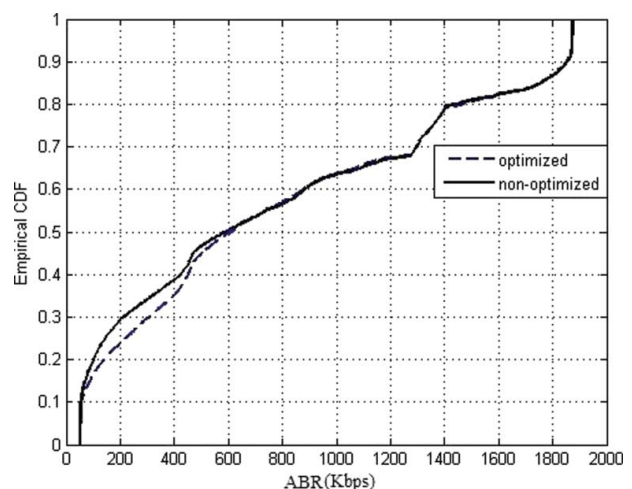

Figure 12. CDF of individual ABR values for all mobiles in the Network for traffic intensity of 8 arrivals/sec, with and without optimization.

traffic of 7 arrivals/sec, 30% of mobiles have ABR values less than 350 Kbits/sec for the self-optimized case. While for non-optimized case, 38% of mobiles have ABR values less than 350 Kbits/sec. Similarly, for traffic value of 8 arrivals/sec, 60% of mobiles have ABR values greater than 400 Kbits/sec. While for the non-optimized case, 35% of mobiles have an ABR value greater than 400 Kbits/sec.

5. Conclusion

Interference mitigation is a challenging issue in modern wireless communication systems. Our main focus in this proposed work is on the self-optimization part of SONs. The objective was to reduce interference in LTE networks and simultaneously improve network performance by self-optimization of related RRM parameters. In turn, this automated management will reduce OPEX of the network. By comparing all the results for optimized and non-optimized cases, a quite significant improvement in network KPIs is observed. The proposed self-optimization model can easily be extended to other RRM parameters like mobility load balancing and packet scheduling.

Disclosure statement

No potential conflict of interest was reported by the authors.

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