A Genetic Algorithm Based Cell Switch-off Scheme for Energy Saving in Dense Cell Deployments

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***Abstract*—The energy consumption of mobile networks is rapidly growing. Operators have both economic and environmental incentives to increase the energy efficiency of their networks. One way of saving energy is to switch off cells during periods of light traffic. However, cell switch-off is a difficult problem to solve through conventional optimization; existing research makes various assumptions to simplify the problem and offers some heuristics to solve it. The problem can be constructed in different ways depending on the system model that is chosen. We examine the cell switch-off problem with the assumption that each user terminal (UT) has a minimum rate requirement, and show that it can be formulated and solved as a binary integer linear programming (BILP) problem when interference is considered to be constant. This formulation is equivalent to the bin-packing problem, which is NP-hard, if the spectral efficiency of each UT to all cells is fixed to a constant. Allowing the interference to be a function of the UT assignment, which allows for a more realistic construction of the problem, increases the complexity even further and thereby necessitates a heuristic method. For this case, we present a genetic algorithm based cell switch-off scheme which offers good results with linear complexity.**

I. Introduction

The mobile industry has experienced massive growth over the past decade. The introduction of smartphones and tablets, which combine cellular connectivity with powerful processing capabilities, has allowed the mobile application space to grow into areas such as social networking, online gaming, music and video streaming, online file storage, and other cloud-based services. Due to the scarcity of wireless spectrum, the most practical way for mobile operators to boost network capacity to serve this massive demand has been in aggressive frequency re-use through the deployment of more base stations (BSs). However, the rapidly growing number of BSs has contributed heavily to the growing energy consumption of cellular networks. In addition to the environmental concerns associated with the sharp rise in global energy consumption, energy consumption has also become a major component of operating expenditures (OPEX) for mobile network operators. In fact, energy consumption accounts for 13.5% of OPEX in mature markets and 26.3% in maturing markets, and 65-75% of the total power is consumed by BSs [1], [2]. There is great interest in the research community towards reducing the overall energy consumption of cellular networks [3].

As operators deploy greater numbers of BSs, cell sizes are reduced and therefore less power is required to satisfy cell edge UTs. This increases energy efficiency, since power amplifiers account for upwards of 40% of a BS's total energy consumption [2]. The energy consumption break-down at a typical 3G BS is as follows: 42% from the power amplifiers, 11% from the DC power supply, 25% from cooling, and 22% from baseband processing [4]. Moreover, an overwhelming ratio of the energy consumption of a BS is independent of traffic load, which is why for the schemes presented in this paper we assume that the energy saved in the network is proportional to the number of cells switched off [5].

Modern cellular networks are interference-limited (as opposed to noise-limited), and therefore in off-peak periods it can be possible to serve the same number of UTs with fewer BSs without increasing the transmit power. Current BSs are typically sectorized into three cells, and each cell can independently be switched off to save power [6]. Energy could be saved by adaptively reconfiguring cell parameters and switching them on or off based on spatial and temporal fluctuations in network traffic. For example, business areas experience higher traffic load than residential areas in the daytime, whereas the reverse would likely be true in evening hours. Since cellular networks are designed to meet peak demand, there will always be areas in the network which are underutilized at different times of the day.

There has been discussion among industry members at 3GPP meetings on the various use case scenarios for switching on and off cells in the network; three sample scenarios are described in [7] and [8] as follows:

- When there are two cells operating on different radio bands covering the same geographical area, one of the cells could be deactivated during times of light traffic.
- In a hierarchical cell structure where a macro-cell is deployed to provide continuous coverage to a large area and femto-cells are deployed to increase the capacity of specific sub-areas, the femto cells can be switched off when light traffic is detected.
- In areas where an LTE cell is totally covered by a legacy cell (e.g., UMTS or GSM), the LTE cell could be deactivated when there is no demand for high-speed data.

There are a number of recently published works which study from various angles the issue of selectively switching off BSs. One study uses analytical methods to characterize the energy savings that can be achieved by reducing the number of active BSs during periods of low traffic [9]. Another study proposes a scheme where mobile operators offering service in the same area can save energy by switching off BSs and allowing customers to roam on each other's networks [10]. A centralized and distributed version of a scheme, called "cell zooming", iterates at a pre-defined interval to switch off BSs in areas with light traffic if the traffic demand can be satisfied by neighbouring BSs [11], [12].

We are interested in developing an energy-saving scheme which adapts the network to fluctuations in traffic demand by switching on and off cells. Selecting the set of cells to switch off can be a difficult problem to solve analytically due to the difficulty of taking all aspects of the problem into account such as the reduction in interference when switching off a cell. Real-world conditions complicate the problem even more due to issues such as irregular cell layouts and differing transmit powers, antenna heights, and energy consumption levels between cells. We believe that in these kinds of complex scenarios, approaches from artificial intelligence and biologically-inspired computing can be explored [13]. Examples of biologically-inspired algorithms include artificial neural networks, genetic algorithms, particle swarm optimization, and ant-colony optimization. In the sections that follow, we give a brief overview of genetic algorithms (GA) and then present our GA-based scheme which provides significant improvements over the scheme proposed in [12].

II. Overview of Genetic Algorithms

GAs belong to a larger class of evolutionary algorithms which are inspired by aspects of genetic evolution such as mutation, chromosomal crossover, and natural selection. Although there are some variations, GAs all share the approach of performing a heuristic search of a solution space with the goal of finding the optimal solution using the aforementioned evolutionary techniques. In order to apply a GA to a problem, the following two requirements must be met:

i. It must be possible to encode any solution from the solution domain as a string of "alleles", called a "chromosome".
ii. The quality of any solution, based on the objective of the optimization problem, should be quantifiable by using a "fitness function".

There are a number of key principles which should be followed when designing the fitness function and the chromosome representation for a problem. For example, the chromosome representation should be as concise as possible and should lend well to mixing and matching alleles for generating new, higher quality solutions. Also, a fitness function should be computationally efficient, since it will be used many times throughout the optimization process and will therefore have a high influence on computation time. The steps of a basic steady-state genetic algorithm are as follows [14]:

1) Generate initial population of chromosomes either randomly or through a heuristic which can find some sub-optimal solutions.
2) Assign each chromosome a fitness value.
3) Probabilistically select two chromosomes based on their fitness values – these will be the parent chromosomes.
4) Perform a genetic crossover to generate two child chromosomes.
5) Assign a fitness value to the two child chromosomes and insert them into the population by displacing two of the existing chromosomes.
6) Return to Step 3, unless a stopping condition has been met (e.g., maximum number of crossovers).
7) Select the chromosome with the highest fitness value as the optimal solution.

A crossover is a mechanism which takes two parent chromosomes and combines them to produce two child chromosomes. For example, the simplest crossover technique, called the one-point crossover, selects a sub-string of alleles and swaps them between the parent chromosomes. Choosing an appropriate crossover technique can often have a dramatic impact on the quality of the final solution.

Finally, mutation is the genetic operator which is designed to maintain diversity in the population in order to help the GA to avoid local optima. This is done by randomly selecting some chromosomes, based on a small pre-defined probability, and performing slight alterations such as flipping a binary bit at a random position or swapping two alleles.

III. Problem Formulation

We propose a centralized scheme which configures all of the cells in the network by either switching them on or off. We introduce the following notation, which will be used in the formulation:

- $x_{i,j}$: binary variable such that $x_{i,j} = 1$ if UT i is connected to sector j.
- y_j: binary variable such that $y_j = 1$ if base station j is active.
- $\rho_{i,j}$: spectral efficiency between UT i and sector j.
- B_j: total bandwidth for sector j.
- R_i: minimum rate requirement for UT i.
- I: number of UTs.
- J: number of sectors.

We begin with the assumption that the spectral efficiencies $\rho_{i,j}$ are independent from the binary variables y_j and $x_{i,j}$. As a result, the interference power must be fixed to a constant for all UTs by assuming either (a) the best-case scenario, which occurs when interference power is zero (i.e., $SINR = SNR$ for all UTs); or (b) the worst-case scenario, which occurs when all frequency blocks are being used by all of the cells. We observe that assumption (a) yields the upper-bound and (b) yields the lower-bound for the number of cells which can be switched off, since (a) over-estimates and (b) under-estimates the spectral efficiencies of the UTs. The authors of [12] followed assumption (a). However, it should be noted that (a) is an unachievable bound, since it is physically impossible for there to be no interference in the network; even if inter-cell interference coordination is used, it is at the expense of bandwidth and it still does not completely eliminate interference. On the other hand, (b) yields an achievable bound since it is the worst-case scenario. Following either assumption, the problem can be formulated as a BILP problem as follows:

$$\underset{x_{i,j},y_j,\forall i,j}{\text{minimize}} \quad \sum_{j=1}^{J} y_j \tag{1a}$$

$$\text{subject to} \quad \sum_{i=1}^{I} x_{i,j}\frac{R_i}{\rho_{i,j}} \leq B_j, \quad \forall j, \tag{1b}$$

$$x_{i,j} \leq y_j, \quad \forall i,j, \tag{1c}$$

$$\sum_{j=1}^{J} x_{i,j} = 1, \quad \forall i, \tag{1d}$$

$$x_{i,j}, y_j \in \{0,1\}, \quad \forall i,j. \tag{1e}$$

It should be noted that in general, integer programming problems are NP-hard. In fact, when

$$\frac{R_i}{\rho_{i,j}} = C, \quad \forall i,j,$$

where C is a constant (in other words, when the bandwidth requirement of each UT to all cells is equal) the problem is equivalent to the well-known bin packing problem which is NP-hard. Nevertheless, the problem can be solved efficiently for a relatively small number of UTs and can therefore serve as a benchmark for other heuristics. However, defining the spectral efficiencies $\rho_{i,j}$ as a function of the cell configuration y_j or UT assignment $x_{i,j}$ makes the problem non-linear and hence much more difficult to solve, thereby necessitating a good heuristic.

We build our heuristic based on Algorithm 1, which is the centralized "cell zooming" heuristic proposed in [12]. The variables are defined (based on the notation above) as follows:

- $\mathbf{X} = [x_{ij}]$ (UT to cell assignment).
- $\mathbf{W} = [\omega_{ij}]$, where ω_{ij} is the spectral efficiency of a UT i served by cell j.
- $\mathbf{B} = [b_{ij}]$, where b_{ij} is the bandwidth required for a cell j to satisfy the minimum rate requirement of UT i.
- $\mathcal{M}_j$ is the set of UTs being served by cell j.
- $\mathbf{L} = [L_j]$, where $L_j = \sum_{i\epsilon\mathcal{M}_j} \frac{b_{ij}}{B_j}$ gives the traffic load of cell j.

Algorithm 1 switches off cells only in increasing order based on traffic load. Although it intuitively makes sense to first attempt to switch off cells with low traffic load, following this strict ordering does not yield optimal results since the traffic load of neighbouring cells is also relevant to finding the optimal configuration.

Algorithm 1 does not put any UTs into outage at the instant that it is executed. However, as time passes, the UT distribution may change before the next time that the algorithm is scheduled to be executed. This is why the authors proposed that a protection margin α_j be introduced, which restricts the available bandwidth of the cells to $\tilde{B}_j = (1-\alpha_j)B_j$ in the execution phase of the algorithm. This leaves some spare bandwidth at each cell to decrease the blocking probability of subsequent UTs entering the network, and therefore results in less cells being switched off. As opposed to executing the algorithm at fixed intervals as suggested in [12], we believe that a better approach is to monitor the average traffic load and outage levels of all the cells in the network. A high (or low) average utilization would indicate that it is an appropriate time to re-execute the algorithm.

Another issue is that in order for the algorithm to be executed, all of the UTs must have SINR measurements from all of the nearby cells in order to identify those with which their spectral efficiency is high enough to meet their minimum rate requirement. The authors of [12] suggest that every time when the algorithm is to be executed, all of the cells should be switched on for a short period to allow the UTs to collect the required SINR measurements. This implementation may be undesirable in real-world deployments. As an alternative solution, wireless network equipment could be equipped with efficient, low-power components dedicated for signaling purposes. This would allow cells to switch off data capabilities and go into a low-power sleep mode which allows signalling activity to continue. Based on the mobile industry's growing emphasis on energy efficiency, this idea is very conceivable for the future. In fact, the idea of separating data from signalling in green wireless networks is already being proposed by some researchers in academia and industry [15].

We present our improved heuristic in Algorithm 2, which attempts to switch off every cell in the network before terminating (as opposed to terminating when it encounters a cell which can not be switched off). Algorithms 1 and 2 are both linear in complexity with respect to the number of cells and UTs.

Finally, we propose a GA-based scheme in which interference is a function of which cells are switched on. We continue to use the iterative approach of switching off cells, which raises the problem of ordering since each decision to switch off a cell will impact the subsequent decisions. Therefore, we use a GA to search for the ordering which results in the most cells being switched off. We show that the GA succeeds in finding an ordering which results in more cells being switched off when compared to switching them off in the order of least load. The GA is designed as follows:

- The genetic encoding (denoted by $\mathcal{B}$ in Algorithm 3) is an array of numbers where each number represents a cell. The order of the numbers represents the order in which the algorithm will attempt to switch off the cells.
- The fitness value of each chromosome is the number of cells that are successfully switched off using this ordering, less the average cell load. Consequently, if there are two distinct solutions which both succeed in switching off the same number of cells, the solution which results in a lower average load will be favoured. The fitness function uses Algorithm 3 to determine how many cells can be switched off with a given ordering $\mathcal{B}$.

Given the genetic encoding described above, where each allele must appear exactly once in the chromosome, the previously mentioned one-point crossover technique can not be used. However, we may use ordered crossover methods which

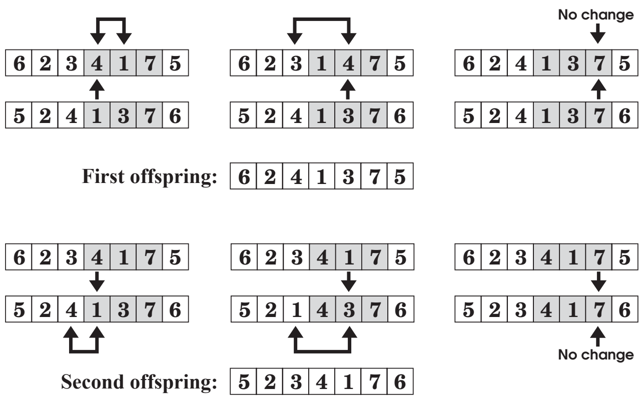

Fig. 1. Partially matched crossover (figure taken from [17]).

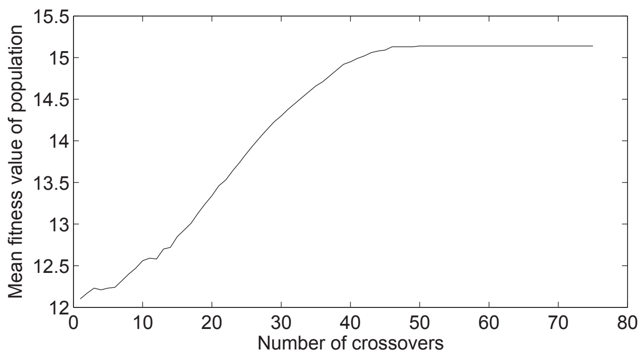

Fig. 2. Convergence time of IAGA (result from a single UT drop).

were designed for ordering problems such as the travelling salesman problem. The technique we used is called the Partially Matched Crossover (PMX) and is demonstrated in Figure 1 [16]. In this method, two crossover points are randomly selected to form a "matching" section. A child is then created by copying the alleles from the matching section of one parent chromosome to the other, while moving the displaced alleles from the second parent in a way which preserves the validity of the chromosome.

The inclusion of an interference model in the fitness function adds some computation time to the algorithm, since all SINRs are recalculated each time a cell is switched off. Also, the GA performs many iterations before converging to a final solution. However, the complexity of the algorithm is still linear and it can be executed within a few minutes in MATLAB using a modern personal computer. This is a reasonable amount of time considering that the algorithm would be executed in intervals on the scale of hours, in contrast to other procedures such as scheduling algorithms which are executed on the scale of milliseconds.

IV. Simulation Setup and Results

The simulation setup is based on parameters and assumptions taken from the ITU-R guidelines for evaluating IMT-Advanced systems [18]. The urban micro-cell (UMi) downlink scenario was chosen, with the associated parameters listed in Table I. The UTs are distributed uniformly over the entire area, with each UT requiring a constant bit rate of 500 kbps. The GA was set up with an initial population of 57 random orderings and a mutation probability of 0.1. Reproduction was done by randomly selecting 7 solutions from the population and

Algorithm 1 Cell zooming algorithm [12] (worst-case interference assumed).

Input: $\mathbf{W}, \mathbf{B}$
Output: $\mathbf{X}$
$\mathbf{L} \Leftarrow \mathbf{0}$
$\mathbf{X} \Leftarrow 0_{i \times j}$
for each UT i **do**
  Assign UT to cell j with highest ω_{ij} with condition $L_j B_j + b_{ij} \leq B_j$. Otherwise, UT i is blocked.
  Update $\mathbf{L}$ and $\mathbf{X}$.
end for
Switch off all cells with $\mathcal{M}_j = \emptyset$.
loop
  Select cell j with smallest L_j
  Re-associate, if possible, all UTs from $\mathcal{M}_j$ to other cells in the network.
  if $\mathcal{M}_j = \emptyset$ **then**
    Switch off cell j
    Update $\mathbf{X}$ and $\mathbf{L}$
  else
    Terminate loop
  end if
end loop

Algorithm 2 Improved cell zooming algorithm (worst-case interference assumed).

Input: $\mathbf{W}, \mathbf{B}$
Output: $\mathbf{X}$
$\mathbf{L} \Leftarrow \mathbf{0}$
$\mathbf{X} \Leftarrow 0_{i \times j}$
for each UT i **do**
  Assign UT to cell j with highest ω_{ij} with condition $L_j B_j + b_{ij} \leq B_j$. Otherwise, UT i is blocked.
  Update $\mathbf{L}$ and $\mathbf{X}$.
end for
Switch off all cells with $\mathcal{M}_j = \emptyset$.
$\mathcal{A} \Leftarrow$ Set of all currently active cells
while $\mathcal{A} \neq \emptyset$ **do**
  Select cell j with smallest L_j
  Re-associate, if possible, all UTs from $\mathcal{M}_j$ to other cells in the network.
  if $\mathcal{M}_j = \emptyset$ **then**
    Switch off cell j
    Update $\mathbf{X}$ and $\mathbf{L}$
  end if
  $\mathcal{A} = \mathcal{A} - \{cell\ j\}$
end while

Algorithm 3 Fitness function for interference-aware GA (IAGA), used for fitness assignment in steps 2 and 5 for GA described in Section II.

Input: $\mathcal{B}$, $\mathbf{W}, \mathbf{B}$
Output: $\mathbf{X}$

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L ⇐ 0
X ⇐ 0_{i×j}
for each UT i do
    Assign UT to cell j with highest ω_ij with condition
    L_j B_j + b_ij ≤ B_j. Otherwise, UT i is blocked.
    Update L and X.
end for
Switch off all cells with M_j = ∅ and remove from B
for each cell j in B do
    Recalculate cell load vector L and all spectral efficien-
    cies ω_ij assuming that cell j is switched off
    Re-associate, if possible, all UTs from M_j to other
    cells in the network.
    if M_j = ∅ then
        Switch off cell j
        Update W, X and L
    end if
end for
```

TABLE I
SIMULATION PARAMETERS [18].

Parameter	Assumption or Value
Cellular layout	Hexagonal grid with wrap-around
Number of cells	57 (19 sites with 3 cells each)
Inter-site distance	200 m
Min. dist. b/w UT and BS	10 m
UT distribution	Randomly & uniformly distributed, 50% UTs indoor & 50% UTs outdoor
Outdoor-to-indoor Pathloss	20 dB
Bandwidth (downlink)	10 MHz
Carrier frequency (f_c)	2.5 GHz
Thermal noise level	-174 dBm/Hz
BS antenna height	10 m
BS antenna gain	17 dBi
UT height	1.5 m
UT antenna gain	0 dBi
BS transmit power	41 dBm
Antenna tilt (ϕ_{tilt})	12° [19]
Feeder loss	2 dB
Horizontal BS antenna pattern	$A(\theta) = -\min\left[12\left(\frac{\theta}{70^\circ}\right)^2,\ 20\,\mathrm{dB}\right]$
Elevation BS antenna pattern	$A_e(\phi) = -\min\left[12\left(\frac{\phi-\phi_{tilt}}{15^\circ}\right)^2,\ 20\,\mathrm{dB}\right]$
Combined BS antenna pattern	$-\min\left[-\left(A(\theta)+A_e(\phi)\right),\ 20\,\mathrm{dB}\right]$
Path loss	$36.7\log_{10}(d) + 22.7 + 26\log_{10}(2.5)$
Shadowing standard dev.	4 dB

replacing the two lowest-fitness solutions with the offspring of the two highest-fitness solutions after doing a PMX crossover. Using these parameters, which were chosen experimentally, the population converges after performing about 70 crossover operations as can be seen in Figure 2.

Figure 3 compares the results of Algorithm 1, Algorithm 2, and the optimal solution found with the BILP formulation when worst-case interference is assumed. It can be seen that there is a substantial improvement going from Algorithms 1 to 2, and a further improvement with the BILP solution.

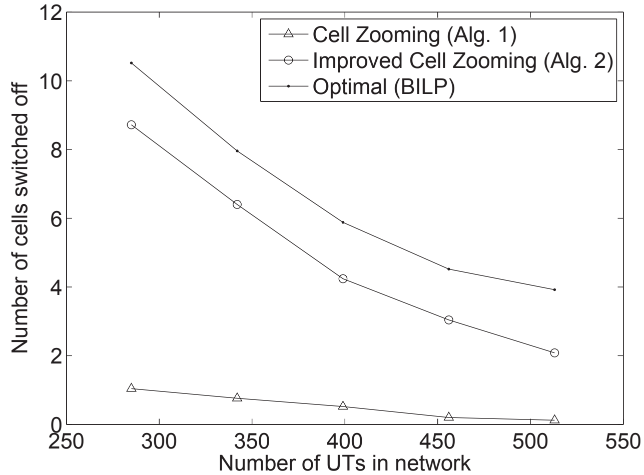

Fig. 3. Comparison of non-interference-aware algorithms.

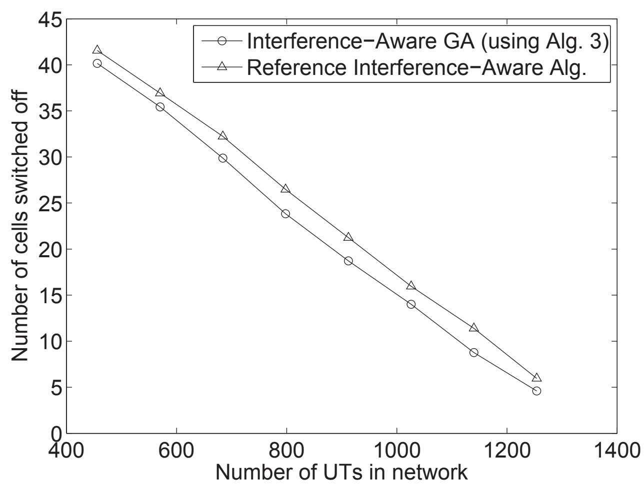

Fig. 4. Energy savings comparison of interference-aware algorithms.

Figure 4 presents the results from our GA-based scheme in the case where interference is made to be a function of which cells are switched on. We compare the energy savings with a reference interference-aware heuristic based on the fitness function that we use for the GA (see Algorithm 3), where the cells are switched off in order of least utilization the same way that it is done in Algorithm 2. This allows us to observe the improvement gained by using the GA to search through different orderings to find the best solution.

We observe from the results of the interference-aware algorithms in Figure 4 that many more cells are switched off compared to the results of the non-interference-aware scenario in Figure 3. This is because when worst-case interference is considered, it is much more difficult to hand off UTs from

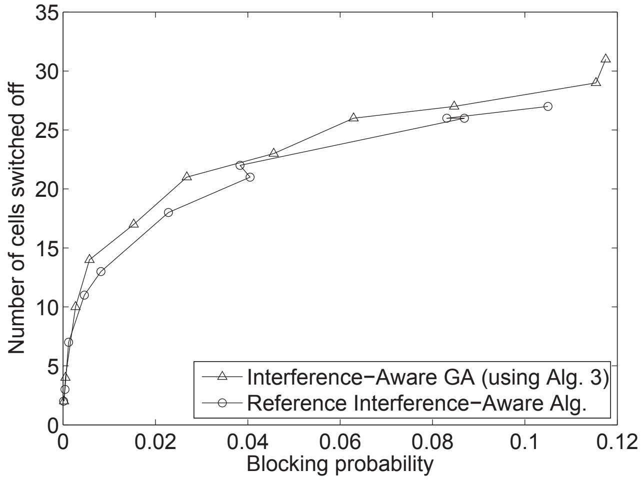

Fig. 5. Energy savings versus blocking probability trade-off comparison of interference-aware algorithms, with an average of 684 UTs in the network.

one cell to a neighbouring cell due to the high interference. However, if the spectral efficiency of a UT with a neighbouring cell is re-calculated by ignoring the received power from its current cell, it allows for more flexibility in handing off UTs. It is also seen in both Figures 4 and 3 that choosing which cells to switch off becomes harder as the number of UTs increases. The percentage gap between Algorithm 2 and the optimal solution in Figure 3 increases as the number of UTs increases, and the same happens between the GA-based algorithm and the reference algorithm in Figure 4. The easiness in light-load scenarios is due to the fact that the micro-cell environment is heavily interference-limited and also that the UTs only require a fixed minimum rate in order to be satisfied. In the extreme case of only a single UT in the network, it is likely that any of the 57 cells would satisfy its rate requirement, due to the high spectral efficiency which results from close proximity (due to the dense deployment) and the lack of interference.

Finally, Figure 5 compares the blocking probability of our interference-aware GA with the reference algorithm discussed above. A simple traffic model is chosen as was done in [12], where the average number of UTs is fixed and new UTs enter the network according to a Poisson process and remain for an exponentially distributed time with a mean of 1 minute. It can be seen that the curve for the interference-aware GA appears to the left of the reference curve, indicating that the GA is able to achieve lower blocking probability without negatively impacting energy savings.

V. Conclusion

We have shown that in the simplest scenario that we consider, the cell switch-off problem can be formulated as a binary linear integer programming problem. However, integer programming is NP-hard, and therefore in more sophisticated system models (e.g., when interference is made a function of cell configuration, or when advanced tools such as coordinated multipoint transmission/reception or inter-cell interference coordination are taken into account) it is necessary to develop suboptimal heuristics which are computationally efficient. For the non-interference-aware scenario, we improved upon a reference heuristic with linear complexity. We then extended the heuristic, while maintaining linear complexity, to be interference-aware and further improved its performance by using a genetic algorithm.

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