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Energy and Spectral Efficiency of Cellular Networks with Discontinuous Transmission

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Abstract- **Cell discontinuous transmission (DTX) has been proposed as a solution to reduce energy consumption of cellular networks. This paper investigates the impact of network traffic load on spectral and energy efficiency of cellular networks with DTX. The SINR distribution as a function of traffic load is derived firstly. Then sufficient condition for ignoring thermal noise and simplifying the SINR distribution is investigated. Based on the simplified SINR distribution, the network spectral and energy efficiency as functions of network traffic load are derived. It is shown that the network spectral efficiency increases monotonically in traffic load, while the optimal network energy efficiency depends on the ratio of the sleep-mode power consumption to the active-mode power consumption of base stations. If the ratio is larger than a certain threshold, the network energy efficiency increases monotonically with network traffic load and is maximized when the network is fully loaded. Otherwise, the network energy efficiency firstly increases and then decreases in network traffic load. The optimal load can be identified with a binary search algorithm.**

1. INTRODUCTION

Driven by the increasing usage of smart devices and mobile applications, the traffic of cellular networks has grown dramatically and this trend would continue in the future. It is forecasted that the global mobile traffic would increase by nearly tenfold from 2014 to 2019 [1]. Therefore network densification has been proposed to increase the network capacity by increasing the reuse of radio resources [2]. However, deploying more base stations (BSs) would lead to soaring energy consumption, which not only incurs severe environmental problems but also increases operation cost. It is therefore critical to increase the energy efficiency of cellular networks. As indicated in [3], the energy consumption of BSs accounts for almost 60% of all the energy consumed by cellular networks. Different approaches have been proposed to reduce the energy consumption of BSs. One is to develop low-energyconsuming hardware and the other is to operate BSs to traffic demand. The latter is motivated by the fact that the existing BSs are deployed and operated to cater for the maximum traffic demand while the network traffic may vary in time [4]. BSs can be switched into lower energy consumption sleep mode when there is lower traffic demand to save energy.

OBJECTIVE:

The SINR distribution as a function of traffic load is derived firstly. Then sufficient condition for ignoring thermal noise and simplifying the SINR distribution is investigated. Based on the simplified SINR distribution, the network spectral and energy efficiency as functions of network traffic load are derived.

It is shown that the network spectral efficiency increases monotonically in traffic load, while the optimal network energy efficiency depends on the ratio of the sleep-mode power consumption to the active-mode power consumption of base stations. If the ratio is larger than a certain threshold, the network energy efficiency increases monotonically with network traffic load and is maximized when the network is fully loaded.

Otherwise, the network energy efficiency firstly increases and then decreases in network traffic load. The optimal load can be identified with a binary search algorithm.

2. LITERATURE SURVEY

Many research efforts have been devoted to studying BS sleeping operations. In [5], the authors studied the performance of a real network and proved the energy saving potential of dynamic BS on/off operation. The impact of BS on/off operation frequency on energy savings is investigated in [10] and it is shown that the daily traffic pattern plays a central role in the design of dynamic BS operation strategy. In [11], a theoretical framework for BS energy saving that encompasses dynamic BS operation and user association is proposed and the optimal user association and BS sleeping operation is investigated considering both energy saving and flow-level delay. In [12], the authors studied the design of energy efficient cellular networks through the employment of BS sleep mode strategies as well as small cells, and investigated the tradeoff issues associated with these techniques. A distributed switching-on/off based energy saving algorithm is proposed in [4].

DRAWBACKS:

- The long-term traffic variation, for which the time scale is at level of hours.
- The average traffic intensity varies from hour to hour.
- Incoming traffic request in certain slots and then switched into micro sleep mode during idle slots.

3. PROPOSED SYSTEM:

In this paper, we investigate the impact of traffic load on network performance and endeavor to discover the explicit relationship between traffic load and spectral and energy efficiency of cellular networks using cell DTX.

1. Derive the network SINR distribution while considering network traffic load. Then we further derive network spectral and energy efficiency.
2. Present a sufficient condition for a cellular network to be interference-limited.
3. Analyze the impact of network traffic load on network spectral and energy efficiency.
4. Run numerical simulations to further confirm the analytic results.

A. Network Model

In this section, we first describe the system model and the necessary assumptions for the performance analysis. Then the network traffic load and power consumption model are explained. In the end, the performance metrics are described.

We consider the downlink transmission in a network where both BSs and users are randomly distributed. The network is assumed to be homogeneous in terms of both traffic demand and BS distribution. The distribution of BSs is modelled with an ergodic PPP Φ_B with density λ_B. Note that we consider homogeneous networks and the case of heterogeneous networks is beyond the scope of this paper. Each user is associated to its closest BS. Thus the coverage area of each BS can be modelled using the Poisson Voronoi Tessellation (PVT) method. Fig. 1 illustrates an example of such a network. All the BSs are assumed to support DTX. The BS stays in active mode and transmits when there is any traffic request. Otherwise, it switches into sleep mode and does not transmit. The universal frequency reuse is applied and the system bandwidth is W. The users within each cell equally share the resources in an orthogonal manner. Only path loss and fast fading are considered. The link between a BS and a user is modelled as follows:

$P_r = P_t C K r^{-\alpha} h = P_e r^{-\alpha} h$, (1)

where P_r, P_t, C, K, r, and α denote the receive power, the transmit power, the antenna gain, the path loss constant at unit distance, the distance between the BS and the user and the path loss exponent respectively. In order to simplify notations, the product $P_t CK$ is noted as P_e. The random variable h models Rayleigh fading, i.e. $h \sim \exp(1)$. Here we assume that the signals from both the serving BS and the interfering BSs experience Rayleigh fading. The power control is out of the scope of this paper and all the active BSs are assumed to transmit with the same power P_t.

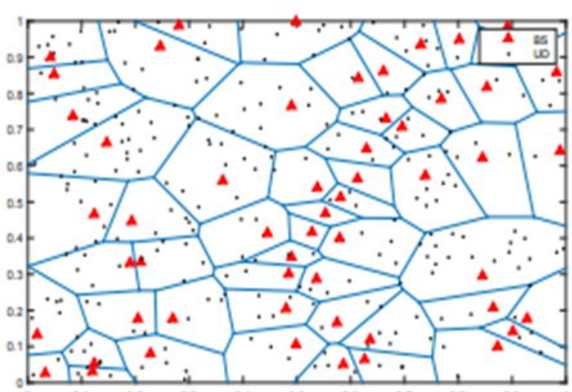

Figure 1. Distribution of base stations (BS) and user devices (UD) in a cellular network

B. Traffic Load Model We consider packet based traffic request. The arrival of traffic request is modeled as a homogeneous temperal-spatial Poisson arrival process with intensity λu(t) packets per second per square meter. Note that traffic density λu(t) is constant during a short period, like one hour, but it may vary during a longer period, like from day time to deep in the night, [5], [6]. In this paper, we consider network performance during the period that λu(t) keeps constant and network performance is stationary. For a given BS, its load is defined as the percentage of utilized resources to satisfy its traffic requests. In order to maximize the available time for the sleep mode of cell DTX, it is assumed that the BS schedules all the bandwidth to serve its traffic requests to minimize its time in data transmission mode. Thus the BS load is modeled as the percentage of time that the BS is active. It is equivalent to the likelihood that the BS is active at any given instant. It should be noted that the more users that a BS serves, the more time it takes for the BS. Consequently, the BS is more likely to be active at any given instant. In general, due to the load-coupling among BSs caused by mutual interference, it is rather complex to identify an explicit relationship between the number of users served by a BS and its active probabilities [24].

In this paper, the coverage area sizes of all BSs follow the same distribution and they are on average the same [25].Furthermore, the traffic intensity is homogeneously distributed across different areas. Therefore, we assume that all BSs experience i.i.d traffic demands and the active probabilities of all BSs at an instant are the same. This active probability is used to model network traffic load ρ and also serves as an input to evaluate network performance. It is equivalent to the percentage of active BSs at a given instant, which can be easily measured by the network. As each BS independently decides its operation mode, the distribution of BSs after BS sleeping can be modelled as a thinned PPP Φ˜ a with a new BS density λa. The relationship between the density of active BSs λa, the density of deployed BSs λB and the network load ρ can be expressed as λa = ρλB. (4) Remark.

For a given network topology, which is a realization of the PPP, the coverage area sizes of different BSs could be different, which leads to asymmetric traffic demands in each BS if users select their closest BSs as serving BS. Here, the active probability of each given BS is approximated with its expectation. As we focus on the macroscopic performance of network rather than each BS, this approximation is valid. This approach has been used and validated with real traffic data in [26]. Furthermore, in our numerical simulations, each user selects its closest BS as its serving BS and different BSs may have asymmetric traffic demands. The simulation results are very close to the results based on the proposed approximation of active probability.

4. SIMULATION RESULTS

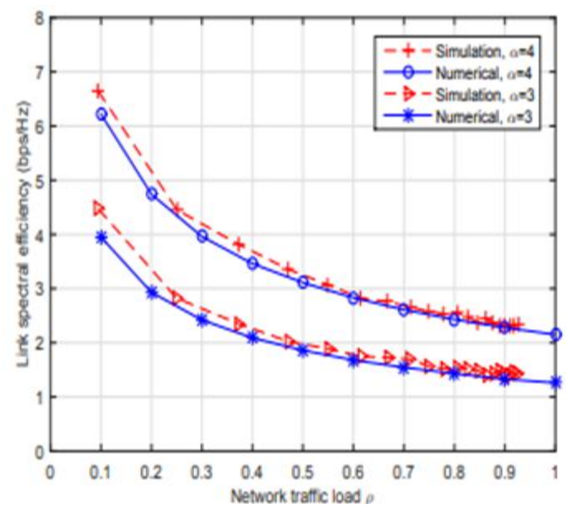

Figure 2. Distribution of average link spectral efficiency under different network load

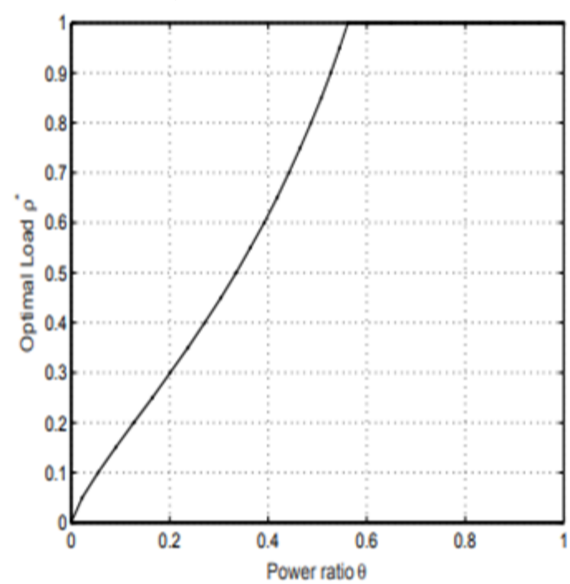

Figure 3. Distribution of optimal traffic load with power ratio, α = 4

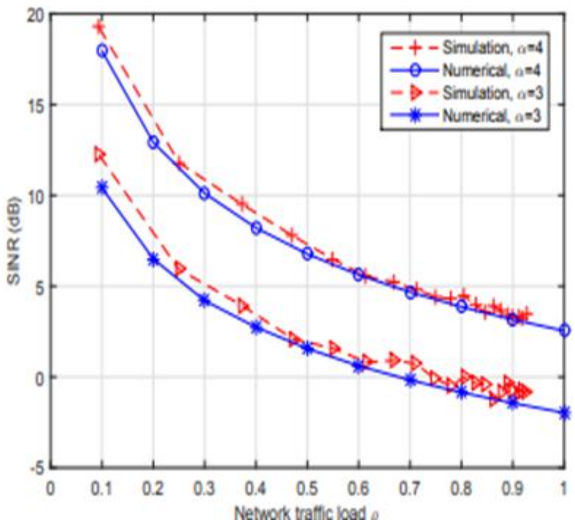

Figure 4. Distribution of average SINR under different network load

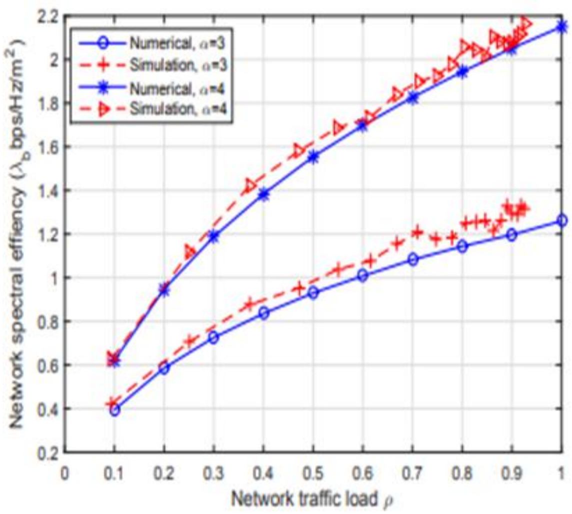

Figure 5. Distribution of average network spectral efficiency under different network load

Fig. 2 shows how the average SINR changes as the traffic load increases. Firstly, it is also shown that the simulation results and the numerical calculation results follow the same trend, although there is a minor gap between them. The results tell that the higher the traffic load is, the lower the average SINR is. This is due to the fact as the traffic load increases, there will be more active BSs in the network, which brings in stronger interference. Therefore the average SINR deteriorates. Comparing the results with different path loss exponents, we can find that the higher the exponent is, the better the SINR distribution is. This is due the fact that the relative fading between the interference signals and the serving signals is more significant in an environment with larger path loss exponent. As the link spectral efficiency is a monotonically increasing function of SINR, the similar results can be found for the link spectral efficiency (see Fig. 3). Fig. 4 shows the impact of traffic load on network spectral efficiency. The vertical axis is normalized with the BS density λB. Unlike SINR and link spectral efficiency, the network spectral efficiency increases as the network traffic load increases. The maximum network spectral efficiency can be achieved when the network is fully loaded. This is resulted from the fact that as the traffic load increases, in spite of the deterioration of single link quality, the frequency reuse factor increases. The later linearly contributes to the increase of network spectral efficiency and overcomes the loss resulted from the link quality deterioration.

Fig. 5 illustrates the change of average energy efficiency as the traffic load increases. The vertical axis is normalized with the system bandwidth W and the power consumption Pa of active BSs. The relationship between the average energy efficiency and the network traffic load is highly influenced by the ratio θ of the sleep-mode power to the active-mode power. For small ratios, the energy efficiency would first increase and then decrease as the traffic load increases. There exist a load ρ ∗ that can maximize the energy efficiency. The higher the ratio is, the higher the optimal load ρ ∗ is. While for large ratios the energy efficiency would increases as the traffic load increases. The energy efficiency is maximized when the network is fully loaded.

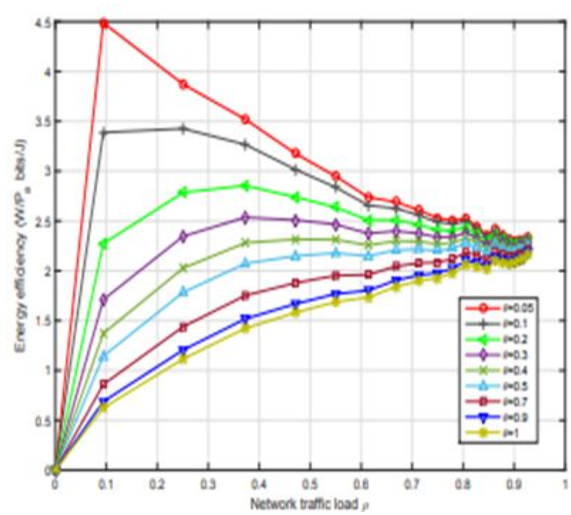

Figure 6. Distribution of average energy efficiency with traffic load (Simulation result), α = 4

5. CONCLUSION

In this paper we have investigated the relationship between network performance and network traffic load for networks with cell DTX. The network is analyzed with theories of stochastic geometry. The SINR distribution as a function of traffic load is derived firstly and a sufficient condition for the networks to be interference-limited is presented. Based on the simplified SINR distribution, analytical expressions are obtained to describe the impact of the network load on the performances, including link spectral efficiency, network spectral and energy efficiency. It is shown that as the network load increases, the average link spectral efficiency decreases while the network spectral efficiency increases. The network energy efficiency is strictly quasi-concave on the network load and the relative power consumption in the sleep mode plays a key role. For small sleep-mode power consumption, the energy efficiency would first increase and then decrease as the network load increases. If the sleep-mode power consumption is larger than a threshold, the energy efficiency would monotonically increase as the network load increases, and the maximum energy efficiency is achieved when the network is fully loaded.

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