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Area Spectral and Energy Efficiency Analysis of Cellular Networks with Cell DTX

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Abstract—Cell discontinuous transmission (DTX) has been proposed as an effective solution to reduce energy consumption of cellular networks. In this paper, we investigate the impact of network traffic load on area spectral efficiency (ASE) and energy efficiency (EE) of cellular networks with cell DTX. Closed-form expressions of ASE and EE as functions of traffic load for cellular networks with cell DTX are derived. It is shown that ASE increases monotonically in traffic load, while EE depends on the power consumption of base stations in sleep mode. If this power consumption is larger than a percentage of the active-mode power consumption, EE increases monotonically with traffic load and is maximized when the network is fully loaded. Otherwise, EE first increases and then decreases in traffic load. In this case, ASE and EE are maximized with different loads. The percentage threshold only depends on the path loss exponent of radio propagation environment and is calculated to be 56.2% when the path loss exponent is 4.

I. INTRODUCTION

Driven by the increasing usage of smart devices and mobile applications, the traffic of cellular network has grown dramatically and this trend would continue in the future. It is forecasted that the global mobile traffic would increase nearly tenfold from 2014 to 2019 [1]. Network densification has been proposed to increase the network capacity by increasing the reuse of radio resources [2]. However, deploying more base stations would lead to soaring energy consumption, which not only incurs severe environmental problems but also increases the cost of network operators. It is therefore critical to increase the EE of cellular networks.

As indicated in [3], the energy consumption of base stations accounts for almost 60% of all the energy consumed by cellular networks. Different approaches are proposed to reduce the energy consumption of base stations. Motivated by the fact that existing base stations are deployed to cater for the maximum traffic demand while network traffic may vary in time [4], one approach is to operate the base station with adaptation to the traffic demand, such as cell DTX. Cell DTX has been proposed as one of solutions for energy-efficient cellular communications [5]. It enables base stations to turn off power-consuming components and switch into the sleep mode during the idle transmission time intervals (TTIs) to save energy. Compared to long-period switching-on/off operations [4], cell DTX can adapt to both long-period load variation [4] and bursty traffic demand [6]. Furthermore, unlike the long-period switching-on/off operations which require inter-cell cooperation to assure the quality of service (QoS), cell DTX enables base stations to operate independently.

Many efforts have been devoted to studying the performance of cellular networks with cell DTX [7]–[9]. In [7], the feasibility of cell DTX in LTE networks was examined and it is shown that significant energy saving can be achieved with cell DTX. In [8], the authors studied the design aspects of cell DTX to mitigate inter-cell interference, such as the time scale of DTX operations and whether the DTX operations should be restricted to small cells only. The energy saving by jointly considering network deployment and cell DTX was studied in [9]. These works mainly focus on the power saving with cell DTX rather than the network EE (number of bits successfully sent per Joule of energy). Most of these works obtained study results through numerical simulations for certain specific scenarios and there is no general analytical expressions for the obtained results. In this paper, we endeavour to derive explicit expressions for the area spectral and energy efficiency of cellular networks using cell DTX.

Tools of statistical geometry [10] are utilized to analyse the performance of cellular networks and the cellular network is modelled as a homogeneous Poisson Point Process (PPP). This model could provide both accurate and tractable results on the network performance [11]. This approach has been extensively applied to analyse the performance of cellular networks [11]–[13]. Using stochastic geometry, the authors developed general models for multi-cell signal-to-interference-plus-noise ratio (SINR) in [11]. It was shown that modelling cellular networks with PPP results in a pessimistic performance evaluation of real cellular networks. In [12], the authors extended this work to the heterogeneous networks and derived the coverage probability in K-tier heterogeneous cellular networks. The impact of base station density and antenna numbers on the throughput and EE of small networks with multi-antenna base stations is investigated in [13]. All these works mainly focused on the network deployment aspects and studied the impact of base station densities.

In this paper, we consider the operation of cellular networks that have been deployed and investigate the impact of traffic load on the network performance. The contribution of this paper can be summarized as follows: 1) By modelling the cellular network as random spatial process and considering network traffic load, an SINR distribution model is derived to describe the impact of traffic load on the SINR distribution. 2) The impact of network traffic load on the area spectral and energy efficiency is analysed. The results show that the ASE is always maximized when the network is fully loaded

while the optimal load for the maximum EE depends on the power consumption in different modes of the base station. 3) Numerical simulations are conducted to further confirm the analytical results.

The rest of the paper is organised as follows. The system model is described in section II. Section III presents the performance analysis of cellular networks with cell DTX. Then the numerical results is introduced in Section IV. Finally Section V concludes this paper.

II. SYSTEM MODEL AND PERFORMANCE METRICS

In this section, we first describe the system model and the necessary assumptions for the performance analysis. Then the definitions of the performance metrics are described.

A. Network Model

We consider the downlink transmission in a network where both the base stations (BS) and the users are randomly distributed. The network is assumed to be homogeneous in terms of both traffic demand and base stations. The distribution of base stations is modelled with an ergodic Poisson Point Process (PPP) Φ_B with density λ_B and that of users is modelled with a PPP Φ_u with density λ_u . Note that these two PPPs are independent. Compared to the planned real cellular the random PPP model exaggerates the impact of inter-cell interference and leads to pessimistic performance evaluation. The accuracy of this model has been validated in [11]. Furthermore, with the emergence of heterogeneous cellular networks where more and more low-power nodes are deployed, the networks are becoming more and more random. It is assumed that each user associates to the base station which can provide the strongest average received power, which means the user chooses its closest base station as the serving base station. Thus the coverage area of each BS can be modelled using the Poisson Voronoi Tessellation (PVT) method [10]. Fig. 1 illustrates an example of such a network. The universal frequency reuse is applied and the available bandwidth is W . The users within each cell share the resources in an orthogonal manner, for example, time or frequency division. Regarding the channel model, only path loss and fading are considered. The link between a base station and a user is modelled as follows:

$$P_{rx} = P_{tx} r^{-\alpha} h, \quad (1)$$

where P_{rx} , P_{tx} , r , and α denote the receive power, the transmit power, the distance between the base station and the user and the path loss exponent respectively. The random variable h follows a exponential distribution with mean 1 and is denoted by $h \sim \exp(1)$. It models the Rayleigh fading. Here we assume that the fast fading of signals from both the serving BS and the interfering BSs follow Rayleigh distribution with mean 1. The network is assumed to be interference limited. In fact, it can be proved that when the base stations are deployed densely enough, the impact of thermal noise is negligible. Due to the limit of space, detailed discussion on the impact of thermal noise is omitted here. Furthermore, all the base stations are assumed to transmit with a uniform power P_t .

With above assumptions, the SINR of a random downlink transmission of an user located at a distance of r from its associated base station b_0 can be expressed as

$$\begin{aligned} \text{SINR} &= \frac{P_t r^{-\alpha} h_0}{\sum_{i \in \tilde{\Phi}_a \setminus b_0} P_t r_i^{-\alpha} h_i + \sigma_0^2} \\ &= \frac{P_t r^{-\alpha} h_0}{I_r + \sigma_0^2}, \end{aligned} \quad (2)$$

where

$$I_r = \sum_{i \in \tilde{\Phi}_a \setminus b_0} P_t r_i^{-\alpha} h_i \quad (3)$$

represents the interference from the sets of active base stations $\tilde{\Phi}_a$ in the network, σ_0^2 denotes the thermal noise of the user and r_i , h_i represent the distance from the user to the interfering base station i and the fast fading of the signals from base station i respectively.

The base stations are assumed to support cell DTX. They stay in sleep mode during idle periods and switch into active mode when any traffic request is detected. The mode transition takes short time (several TTIs) [7]. In order to simplify the analysis, it is assumed that no time is needed for base stations to switch mode.

The base stations are assumed to experience homogeneous and independent traffic load and the base station activity factors are independently and identically distributed (i.i.d). Therefore, for a given instant, the network traffic load ρ is modelled as percentage of active base stations. The networks after base station sleeping can be modelled as a thinned PPP $\tilde{\Phi}_a$ with a new base station density λ_a . The relationship between the density of active base stations λ_a , the density of deployed base stations λ_B and the network traffic load ρ can be expressed as

$$\lambda_a = \rho \lambda_B. \quad (4)$$

Note that the base station is active not necessarily due to the data requests from users. It could be active to transmit control signals [7], such as cell reference and synchronization signals. In the following analysis, the impact of transiting control signals on the base station activity is ignored and we assume that there is only data transmission. In fact, the results derived with this idealization in the following sections can be easily extended to the case of actual downlink signal transmissions. This can be achieved by multiplying the derived results with certain factors which are determined by the transmission scheme of control signals.

B. Power Consumption Model

The base stations operate in two different modes: the active mode and the sleep mode. In the active mode, the base station power consumption is modelled as below:

$$P_a = \xi P_t + P_c, \quad (5)$$

where P_t and P_c are the transmit power and the circuit power respectively, and ξ accounts for the power consumption that is proportional to the transmit power, such as the power

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

consumed by the amplifier. The base station is assumed to schedule all the bandwidth to serve its users in active mode to increase the available time for sleep mode. Therefore the active-mode power consumption is assumed to be constant. In sleep mode, the base station consumes a smaller power P_s . Define θ as the ratio between the sleep-mode power consumption and the active-mode power consumption and we have

$$P_s = \theta P_a. \quad (6)$$

For a traffic load ρ , the average power consumption in unit area is

$$\mathbb{E}[P_u] = \lambda_a P_a + (\lambda_B - \lambda_a) P_s = \lambda_B P_a (\rho + (1 - \rho)\theta). \quad (7)$$

C. Performance Metrics

The focus of this paper is to analyse the network performance. The ergodic average ASE and EE are used as metrics to evaluate the network performance. Here the ergodic average is spatial average in an infinite plan and it accounts for both the random Rayleigh fading and the random distribution of base stations and users. The Shannon bound of the spectral efficiency η_{SE} of a given link with SINR γ is defined as

$$\eta_{SE} = \log_2(1 + \gamma). \quad (8)$$

Therefore the ergodic average link spectral efficiency is given as

$$\mathbb{E}[\eta_{SE}] = \mathbb{E}[\log_2(1 + \gamma)], \quad (9)$$

where $\mathbb{E}[x]$ is the expectation of a random variable x . For a given traffic load ρ , the ergodic average ASE $\mathbb{E}[\eta_{ASE}]$ can be defined as

$$\mathbb{E}[\eta_{ASE}] \stackrel{(a)}{=} \lambda_a \mathbb{E}[\eta_{SE}] \stackrel{(b)}{=} \rho \lambda_B \mathbb{E}[\eta_{SE}], \quad (10)$$

where (a) follows from the fact that the average number of active base stations in unit area is λ_a and (b) is derived with (4). The unit of ASE is $\text{bps}/\text{Hz}/\text{m}^2$.

The ergodic average EE $\mathbb{E}[\eta_{EE}]$ is defined as the average number of bits that can be successfully transmitted with unit energy. For a given traffic load ρ , the average network throughput in unit area is $\mathbb{E}[T_u] = W \mathbb{E}[\eta_{ASE}]$. Considering

the power consumption model described in II-B, the average EE $\mathbb{E}[\eta_{EE}]$ is given as

$$\mathbb{E}[\eta_{EE}] = \frac{\mathbb{E}[T_u]}{\mathbb{E}[P_u]} = \frac{\rho W \mathbb{E}[\eta_{SE}]}{P_a (\rho + (1 - \rho)\theta)}. \quad (11)$$

The unit of the average EE is *bits/Joule*.

III. PERFORMANCE ANALYSIS

In this section, we investigate the impact of traffic load on the area spectral and energy efficiency. Firstly, the distribution of the downlink SINR as a function of traffic load is derived. Then, the impact of traffic load on the area spectral and energy efficiency are separately analysed.

A. SINR Distribution

In [11], the SINR distribution of cellular networks has been studied by modelling the locations of base stations with homogeneous PPP. In the work of [11], the base stations are assumed to be always transmitting regardless of network traffic load. For real networks, base stations do not transmit when there is no traffic request. This would undoubtedly reduce the interference suffered by the active users. Following the same approach of [11], the distribution of SINR as a function of traffic load can be derived as follows.

Theorem 1. *For cellular networks with cell DTX, the cumulative density function (CDF) of the downlink transmission SINR under the traffic load ρ is*

$$P[\text{SINR} \leq \gamma] = 1 - \pi \lambda_B \int_0^\infty e^{-\pi \lambda_B x (1 + \rho \beta(\gamma, \alpha)) - \frac{1}{P_t} \gamma \sigma_0^2 x^{\alpha/2}} dx, \quad (12)$$

where

$$\beta(\gamma, \alpha) = \gamma^{2/\alpha} \int_{\gamma^{-2/\alpha}}^\infty \frac{1}{1 + y^{\alpha/2}} dy. \quad (13)$$

Proof. The proof of this theorem is developed with the same approach as [11]. The difference is to take the impact of network traffic load into consideration. Consider a homogeneous cellular network with load ρ and the density of deployed base stations is λ_B . With cell DTX, the sleeping base stations can immediately switch into active mode when there is a traffic request. Therefore the density of serving base stations for the users is λ_B , regardless the traffic load ρ . However, for a given downlink transmission, the density of interfering base stations is that of active base stations λ_a and it is tightly related to the traffic load by (4). As a result, the serving base stations is a PPP Φ_B with density λ_B while the interfering base stations is a thinned PPP $\tilde{\Phi}_a$ with density λ_a . Then the theorem can be proved by following the same approach as [11]. $\square$

By neglecting the impact of thermal noise, a simplified form of the SINR distribution can be obtained as follows,

$$P[\text{SINR} \leq \gamma] = 1 - \frac{1}{1 + \rho \beta(\gamma, \alpha)}, \quad (14)$$

where $\beta(\gamma, \alpha)$ is defined as (13).

Taking the derivative of the simplified CDF over ρ gives

$$\frac{\partial P[\text{SINR} \leq \gamma]}{\partial \rho} = \frac{\beta(\gamma, \alpha)}{(1 + \rho\beta(\gamma, \alpha))^2}.$$

As $\beta(\gamma, \alpha) > 0$, $\frac{\partial P[\text{SINR} \leq \gamma]}{\partial \rho}$ is positive. Therefore the CDF of the downlink SINR is increasing in traffic load. This indicates that the higher the traffic load is the worse the average link quality is.

B. Area Spectral Efficiency

In this subsection we investigate the impact of network traffic load on ergodic average ASE.

The ergodic average spectral efficiency for a single link and the ergodic average ASE for the network are given in the following theorem.

Lemma 1. *For interference-limited cellular networks with cell DTX, the ergodic average spectral efficiency for a single link is*

$$\mathbb{E}[\eta_{SE}] = \int_0^\infty \frac{1}{1 + \rho\beta(e^{\tau \ln 2} - 1, \alpha)} d\tau, \quad (15)$$

and the ergodic average area spectral efficiency for the network is

$$\mathbb{E}[\eta_{ASE}] = \lambda_B \rho \int_0^\infty \frac{1}{1 + \rho\beta(e^{\tau \ln 2} - 1, \alpha)} d\tau. \quad (16)$$

As $\frac{\partial \mathbb{E}[\eta_{SE}]}{\partial \rho} = \int_0^\infty \frac{-\beta(e^{\tau \ln 2} - 1, \alpha)}{(1 + \rho\beta(e^{\tau \ln 2} - 1, \alpha))^2} d\tau < 0$, the average link spectral efficiency η_{SE} decreases as the traffic load ρ increases. This is consistent with the relationship between the SINR distribution and the traffic load. Regarding the average ASE, the impact of the traffic load is contrary. As

$$\frac{\partial \mathbb{E}[\eta_{ASE}]}{\partial \rho} = \int_0^\infty \frac{\lambda_B}{(1 + \rho\beta(e^{\tau \ln 2} - 1, \alpha))^2} d\tau > 0, \quad (17)$$

the average ASE η_{ASE} is monotonically increasing with the traffic load ρ . These can be explained by fact that as the traffic load increases, the interference suffered by each link becomes stronger while the resource reuse factor in unit area becomes higher. The increase of the resource reuse overcomes the deterioration of link quality and leads to higher ASE.

C. Energy Efficiency

In this section we study the impact of traffic load on the average EE of cellular networks with cell DTX.

By plugging (15) into (11), the ergodic average EE can be easily derived as follows,

$$\mathbb{E}[\eta_{EE}] = \int_0^\infty \frac{W\rho}{P_a(1 + \rho\beta(e^{\tau \ln 2} - 1, \alpha))(\rho + (1 - \rho)\theta)} d\tau. \quad (18)$$

The impact of traffic load on the average EE can be described with following theorem.

Theorem 2. *For cellular networks with cell DTX, the average energy efficiency is a strictly quasi-concave function of network traffic load. If $\theta = \frac{P_s}{P_a} \geq 1 - \frac{1}{1 + \Omega(\alpha)}$, the average energy efficiency is increasing with traffic load ρ . Otherwise there exists a unique traffic load ρ^* that is less than 1 and maximizes the average energy efficiency. The average energy*

efficiency increases with traffic load on $[0, \rho^)$ and decreases with traffic load on $(\rho^*, 1]$. Here P_s and P_a are the base station power consumptions in sleep and active modes respectively. $\Omega(\alpha)$ is defined as*

$$\Omega(\alpha) = \frac{\int_0^\infty \frac{\beta(e^{\tau \ln 2} - 1, \alpha)}{(1 + \beta(e^{\tau \ln 2} - 1, \alpha))^2} d\tau}{\int_0^\infty \frac{1}{(1 + \beta(e^{\tau \ln 2} - 1, \alpha))^2} d\tau}. \quad (19)$$

Proof. In order to simplify the notations, we note $\beta(e^{\tau \ln 2} - 1, \alpha)$ as β in this proof.

Taking the derivative of $\mathbb{E}[\eta_{EE}]$ over ρ , we can get

$$\frac{\partial \mathbb{E}[\eta_{EE}]}{\partial \rho} = \int_0^\infty \frac{W(\theta - \rho^2\beta(1 - \theta))}{P_a(1 + \rho\beta)^2(\theta + \rho(1 - \theta))^2} d\tau.$$

This derivative is denoted as $f(\rho)$. Define a function $g(\rho)$ of ρ as

$$g(\rho) = \int_0^\infty \frac{\theta - \rho^2\beta(1 - \theta)}{(1 + \rho\beta)^2} d\tau.$$

We have

$$f(\rho) = g(\rho) \frac{W}{P_a(\theta + \rho(1 - \theta))^2}.$$

As $\frac{W}{P_a(\theta + \rho(1 - \theta))^2}$ is strictly positive, the function $f(\rho)$ and $g(\rho)$ have the same sign. The derivative of $g(\rho)$ over ρ is

$$\begin{aligned} \frac{\partial g}{\partial \rho} &= \int_0^\infty \frac{-2\rho\beta(1 - \theta)(1 + \rho\beta) - 2\beta(\theta - \rho^2\beta(1 - \theta))}{(1 + \rho\beta)^3} d\tau \\ &= \int_0^\infty \frac{-2(\rho\beta(1 - \theta) + \beta\theta)}{(1 + \rho\beta)^3} d\tau. \end{aligned}$$

As $\frac{-2(\rho\beta(1 - \theta) + \beta\theta)}{(1 + \rho\beta)^3}$ is strictly negative, $\frac{\partial g}{\partial \rho}$ is negative. Thus $g(\rho)$ is continuous and monotonically decreasing in ρ . Based on the fact that $\rho \in [0, 1]$, we have

$$g_{max} = g(0) = \int_0^\infty \theta d\tau,$$

and

$$g_{min} = g(1) = \int_0^\infty \frac{\theta}{(1 + \beta)^2} d\tau - \int_0^\infty \frac{\beta(1 - \theta)}{(1 + \beta)^2} d\tau.$$

It is clear that g_{max} is positive.

Now we study the sign of g_{min} . If g_{min} is positive, the following inequality must be true.

$$\theta > 1 - \frac{1}{1 + \Omega(\alpha)}, \quad (20)$$

where Ω is defined as (19). In this case $g(\rho)$ is positive on $[0, 1]$. So is $f(\rho)$. Thus the ergodic average EE is increasing in traffic load ρ . If the inequality (20) is false, which means $\theta \leq 1 - \frac{1}{1 + \Omega(\alpha)}$, we have $g_{min} \leq 0$. As $g(\rho)$ is continuous and decreasing in ρ , there exists one unique ρ^* that makes $g(\rho)$ to be zero. This ρ^* also makes $f(\rho)$ to be zero. For $\rho \in [0, \rho^*)$, $f(\rho) > 0$ and for $\rho \in (\rho^*, 1]$, $f(\rho) < 0$. As a result, the average EE is increasing on $[0, \rho^*)$ while decreasing on $[\rho^*, 1]$. According to the definition of quasi-concave function, it can be easily derived that the average EE is a quasi-concave function of the traffic load. This completes the proof. $\square$

The relationship between the traffic load and the average EE can be explained by analyzing the relationship between the increase of ASE and the increase of power consumption when traffic load increases. The power consumption increases linearly with traffic load and increase rate depends on the power ratio θ (see (7)). The smaller θ is, the larger the increase rate is. According to (17), the increase rate of ASE decreases in traffic load since the average link quality deteriorates when traffic load increases. As a result, for large θ , the increase of power consumption is always relatively slower than the increase of ASE and the EE consequently always increases in traffic load; for small θ , the increase of ASE is relatively faster than the increase of power consumption in low load zone ($[0, \rho^*)$) but slower in high traffic zone ($(\rho^*, 1]$) and the EE first increases and then decreases with traffic load. This can be further validated by simulation results in section IV.

The threshold of power ratio θ is determined by the minimum increase rate of ASE. The increase rate of ASE is minimized at full load ($\rho = 1$). According to (17), the increase rate of ASE at full load is only determined by the path loss exponent. This explains why the threshold of power ratio θ is only determined by the path loss exponent α in Theorem 2. As larger α leads to increase rate of ASE, the threshold of θ for larger α is smaller than that of smaller α . By numerically calculating (19), the threshold is found to be 56.2% for $\alpha = 4$ and 59.3% for $\alpha = 3$.

IV. NUMERICAL RESULTS

In this section, the above analysis on the performance of cellular networks with cell DTX are demonstrated with Monte Carlo simulations. For the simulations, the base stations and the users are randomly placed as two independent PPPs. The size of the simulated area is $100Km^2$ and the number of base stations is 1000. The number of users is varied from 100 to 4000 to simulate different traffic loads. The system bandwidth is $10MHz$. Regarding the base station power consumption, there exists various simulation settings in different works [9], [13], [14]. In our simulations, the power consumption in active mode is normalized to be 1 and that in sleep mode is normalized by the active-mode power, ranging from 0.05 to 1. In order to investigate the impact of the radio propagation environment, two path loss exponents ($\alpha = 3$ and $\alpha = 4$) are simulated. Besides the results with simulations, the performances metrics are also calculated according to their expressions in section III.

Fig.2 shows how the average SINR changes as the traffic load increases. Firstly, it is 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 base stations 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. The is due the fact that the relative

Figure 2. Distribution of average SINR with traffic load

Figure 3. Distribution of average link spectral efficiency with traffic load

Figure 4. Distribution of average area spectral efficiency with traffic load

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 ASE. The vertical axis is normalized with the base station density λ_B . Unlike SINR and the link spectral efficiency, ASE increases as the load increases. The maximum ASE can be achieved when the network is fully loaded. This is resulted by the fact that as the

Figure 5. Distribution of average energy efficiency with traffic load (Simulation result), $\alpha = 4$

traffic load increases, in spite of the deterioration of single link quality, the frequency reuse factor increases. Thus, the network bandwidth is more reused. According to Shannon Theory, the bandwidth linearly contributes to the increase of ASE and overcomes the loss resulted by the link quality deterioration.

Fig.5 illustrates the change of the average EE as the traffic load increases. The vertical axis is normalized with the system bandwidth W and the power consumption P_a of active base stations. The relationship between the average EE and the traffic load is highly influenced by the ratio θ . For small ratio, the EE would first increase and then decrease as the traffic load increases. There exists a load ρ^* that can maximize the EE. The higher the ratio is, the higher the optimal load ρ^* is. While for large ratios the EE would increase as the traffic load increases. The EE is maximized when the network is fully loaded. This is consistent with our analytical result in section III-C.

Comparing Fig. 4 and Fig. 5 we can find that when the power ratio θ is large, both the average ASE and EE increase in traffic load and they are maximized when the network is fully loaded. However, when θ is small, the trends of the average ASE and EE are different. The ASE is always increasing in traffic load and is maximized with a full load while the EE first increases and then decreases in traffic load is maximized with a load smaller than 1. The smaller θ is, the larger the discrepancy between the two metrics is.

V. CONCLUSION

In this paper we have investigated the relationship between network performance and traffic load for networks with cell DTX. The network is analysed with theories of stochastic geometry. Analytical expressions are obtained to describe the impact of the traffic load on the performances, such as the average link spectral efficiency, ASE and EE. It is shown that as traffic load increases, the average link spectral efficiency decreases while the average ASE increases. The average EE is strictly quasi-concave on traffic load and the relative power

consumption in sleep mode plays a key role. For small sleep-mode power consumption, the EE would firstly increase and then decrease as traffic load increases. If the sleep-mode power consumption is large than a threshold, the EE would monotonically increase as traffic load increases. The maximum EE is achieved when the network is fully loaded.

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