The Effect of Channel Spatial Correlation on Capacity and Energy Efficiency of Massive MIMO Systems

Ahmed Alshammari,*Student Member, IEEE*, Saleh Albdran, *Student Member, IEEE*, and Mohammad Matin, *Senior Member, IEEE*
Department of Electrical Engineering, Daniel Felix Ritchie School of Engineering & Computer Science
University of Denver
Ahmad0046@yahoo.com

***Abstract*— Massive MIMO is an emerging technology that has the potential of bringing huge improvements to wireless communications in the future. This paper investigates the effects of spatial correlation on the capacity and energy efficiency of massive MIMO. We use a channel covariance matrix that is generated according to the one ring model. We consider linear minimum mean square error (LMMSE) for estimating channel properties with pilot signals. The impact of channels spatial correlation on the capacity and energy efficiency of the massive MIMO model used in this paper are demonstrated using computer simulation. We show that the capacity and energy efficacy improve as the correlation between the channels is reduced.**

Index Terms— Massive MIMO, Channel Estimation, Capacity, Energy efficiency Angular Spread, LMMSE

I. INTRODUCTION

The amount of data delivered over wireless networks has increased considerably during the recent years [1]. This growth in data exchange is going to continue in the future driven by new technologies such as augmented reality and device to device communications [2], [3]. This will represent a major challenge because the amount of available spectrum is limited and it will never increase [4]. Future wireless communications systems must be efficient in exploiting these resources. Hence, new technologies should substantially increase the transmission capacity without requiring additional bandwidth or consuming more energy.

Massive MIMO is a promising new technology that can help overcome the future challenges and meet the expected demand for higher data rates [5]. The idea of scaling up MIMO is relatively new [6]. This technology will play an important role of increasing the spectral efficiency of wireless communications. It is going to be an order of magnitude scale up of multi user MIMO technology. The concept of massive MIMO is illustrated in Fig. 1 where the base station (BS) that has a large number of antennas communicate with terminals equipped with single antenna each [2]. With the help of the huge antenna array, transmit beamforming focus the downlink signal at a certain terminal. As the number of antennas is increased, the accuracy of this focus improves [2]. Hence, the main feature of massive MIMO is that every user should only get the signal that is intended for him with the least interference possible from other terminals [7].

Exploiting time division duplex (TDD) scheme, Uplink and downlink transmission of Massive MIMO happen on same frequency but at different times [8]. Massive MIMO takes advantage of channel reciprocity which means channel state information (CSI) is the same for the uplink and the downlink. Therefore, the CSI estimated on the uplink is used to combine the received single on the uplink and also to beamform downlink data [9].

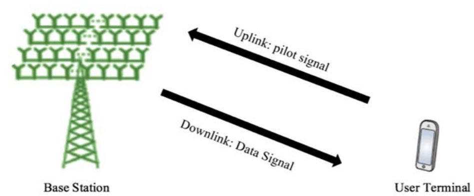

Fig.1. Massive MIMO base station (BS) equipped with hundreds of antennas while only one antenna is used in the user terminal.

Massive MIMO will send information only on the direction of the intended user. Therefore, transmit beamforming requires a good knowledge of the channel at the base station. Also, accurate CSI leads to reducing the bit error rate (BER) that result in enhanced spectral efficiency [10]. There are various channel estimation methods that can be used to obtain a good CSI. The most popular methods used for channel estimation use pilot signal. The quality of the estimated channel are affected by the environment and the channels spatial correlation (SC) [10]. The SC depends on the scattering objects that are present in the propagation environment and the antennas configuration.

Notations: $\mathbf{x}$, $\mathbf{X}$ denote column vectors and matrices respectively. $\mathbf{X}^{\boldsymbol{T}}$ denote transpose, $\mathbf{X}^{\boldsymbol{H}}$ denote conjugate transpose and $\mathbf{X}^{*}$ indicate. Trace of matrix $\mathbf{X}$ is indicated as $\mathrm{tr}(\mathbf{X})$. $\mathbf{x}\sim\mathcal{CN}(\bar{\mathbf{x}},\mathbf{R})$ is circular symmetric complex Gaussian vector where the mean and covariance matrix are $\bar{\mathbf{x}}$ and $\mathbf{R}$ respectively.

II. System And Channel Model

In this paper, we study the impact of spatial correlation on the capacity and energy efficacy of a single link under the effect of a random interference conditions. The base station (BS) in this link contain N-antennas whereas the terminals only have a single antenna each. The key principle in this study is that we can increase the quantity of antennas N in the base station to a very large number. We consider a TDD scheme that uses the same flat fading subcarrier when switching the transmission between the uplink and the downlink. This makes the process of channel estimation more efficient [11]. This is because the estimation accuracy and the amount of the overhead required in the uplink are independent of the number of antennas [12], [9]. Channel reciprocity of the TDD protocol is illustrated in Fig.2 where the estimated channel is used for detecting the uplink data and then to transmit data on the downlink.

We assume that the channel is fixed during a coherence period T_{coher} with channel realizations that are random and independent between fading blocks. We are considering the TDD mode in Fig. 2 that was used in many sources such as [13], [14]. Every block starts with uplink pilots, followed by uplink data. After that, the system switches to the downlink which begins with downlink pilot that enable the terminals of estimating their channels and the existing interference conditions. The downlink signaling does not scale with the number of antenna N because their numbers are scalar regardless of N. The downlink data transmission concludes the coherence period for T_{Data}^{DL} uses of the channel. The following equation is valid for the TDD protocol $T_{\text{pilot}}^{\text{UL}} + T_{data}^{UL} + T_{pilot}^{DL} + T_{Data}^{DL} = T_{coher}$.

We model the random channel $\mathbf{h} \in \mathbb{C}^{N\times 1}$ between the base station and the terminal as an ergodic random process that has a constant independent realization for every coherence time $\mathbf{h} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R})$. The covariance matrix is denoted as $\mathbf{R} = \mathbb{E}\{\mathbf{h}\mathbf{h}^{\boldsymbol{H}}\} \in \mathbb{C}^{N\times N}$. We assume that the spectral norm of the covariance matrix $\mathbf{R}$ is uniformly bounded.

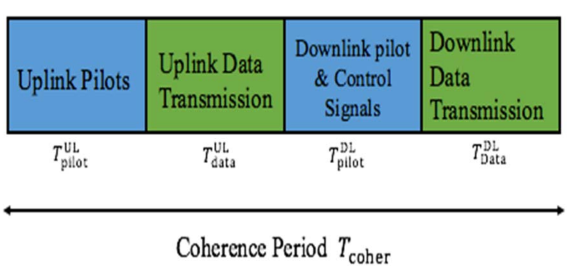

Fig. 2. Illustration of TDD protocol where the coherence time is divided between uplink/downlink pilot and data transmissions.

A. Downlink/Uplink channel model

The task of the downlink channel is transmitting data and estimating channels based on pilots. The received downlink signal $z \in \mathbb{C}$ for multiple input single outputs flat fading channel is modeled as

$$z = \mathbf{h}^{\boldsymbol{T}}\mathbf{d} + v \tag{1}$$

where $\mathbf{d} \in \mathbb{C}^{N\times 1}$ can be a training sequence to estimate the channel or a random data signal with zero mean. The covariance matric is indicated as $\mathbf{X} = \mathbb{E}\{\mathbf{d}\mathbf{d}^{\boldsymbol{H}}\}$ and $p^{\text{BS}} = \text{tr}(\mathbf{X})$ is the average power. $\mathbf{X}$ is a parameter that depends on the realization of the channel $\mathbf{h}$. Hence, $\mathbf{X}$ remains constant for every coherence time but changes after that because the channel realization changes. The v term in (2) is a random process that contains the noise of the receiver $v_{noise} \sim \mathcal{CN}(0, \sigma_{\text{UE}}{}^2)$ and interference from other terminals $v_{\boldsymbol{interf}}$ which is independent of the data signal and has zero mean.

$$v = v_{\boldsymbol{noise}} + v_{\boldsymbol{interf}} \tag{2}$$

The uplink channel is used to send training sequences for channel estimation and to transmit data; see Fig. 1. The system model that we consider in the uplink with a received signal $\mathbf{y} \in \mathbb{C}^N$ at the base station is

$$\mathbf{y} = \mathbf{h}s + \mathbf{n} \tag{3}$$

where $s \in \mathbb{C}$ can be a random data signal or a training signal to estimate the channel. The average power of that signal is $p^{UE} = \mathbb{E}\{|s|^2\}$. The term $\mathbf{n} \in \mathbb{C}^{N\times 1}$ in (4) consists of the receiver noise $\mathbf{n}_{\boldsymbol{noise}}$ and interference of the transmission from other terminals. The interference depends on the channel realization but does not depend on s.

$$\mathbf{n} = \mathbf{n}_{\boldsymbol{noise}} + \mathbf{n}_{\boldsymbol{interf}} \tag{4}$$

B. One ring model

We consider the one ring model from [15] to investigate the impact of spatial correlation on the capacity and energy efficacy of massive MIMO. The model assumes that the terminal is surrounded by a ring of scattering objects with radius r as shown in Fig. 3. However, no scattering objects is around the base station according to the one ring model. It also assumes that the terminal is located at distance d and has an azimuth angle θ with the base station. The angular spread of the multipath components is denoted as Δ. The channel covariance matrix $\mathbf{R}$ for the antennas $1 \leq n, p \leq N$ is given in (5) [16].

$$[\mathbf{R}]_{n,p} = \frac{\mathbf{1}}{\mathbf{2}\Delta}\int_{-\Delta}^{\Delta} e^{jk^T(\alpha+\theta)(u_n-u_p)}\, d\alpha \tag{5}$$

where

$$k(\alpha) = -\frac{2\pi}{\lambda}(\cos(\alpha), \sin(\alpha))^{\text{T}}$$

$u_n,\ u_p$ denote the position vectors of the BS

The antenna spacing is assumed to be half the wavelength with a uniform linear array (ULA). The channel covariance matrix is given in its Toeplitz form in (6).

$$[\mathbf{R}]_{n,p} = \frac{\mathbf{1}}{\mathbf{2}\Delta}\int_{-\Delta+\theta}^{\Delta+\theta} e^{-j2\pi D(n-p)sin(\alpha)}\, d\alpha \tag{6}$$

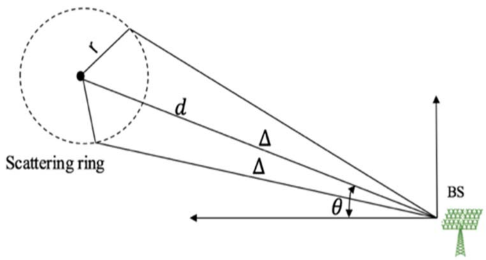

Fig. 3. A terminal at distance d from the base station that is surrounded by a ring of a scattering objects.

III. UPLINK CHANNEL ESTIMATION

The channel state information $\mathbf{h}$ is estimated on the uplink by comparing an already known uplink training sequence s with the received uplink signal $\mathbf{y}$ in (3). We are considering Rayleigh fading channel which is affected by independent complex Gaussian noise [17]. The channel $\mathbf{h}$ is estimated at the base station using linear minimum mean square error estimator (LMMSE) from the received uplink signal in (3).

$$\hat{\mathbf{h}} = s^{*}\mathbf{R}\overline{\mathbf{Y}}^{-\mathbf{1}}\mathbf{y} \tag{7}$$

where $\mathbf{R}$ indicates the covariance matrix and $\bar{\mathbf{y}}$ is given in (8)

$$\overline{\mathbf{Y}} = \mathbb{E}\{\mathbf{y}\mathbf{y}^{\boldsymbol{H}}\} = p^{\boldsymbol{UE}}\boldsymbol{R} + \boldsymbol{S} + \sigma_{BS}{}^{2}\mathbf{I} \tag{8}$$

The MSE is

$$\mathrm{MSE} = \mathrm{tr}(\mathbf{G}) = \mathbb{E}\left\|\hat{\mathbf{h}} - \mathbf{h}\right\|_{\mathbf{2}}^{\mathbf{2}} \tag{9}$$

$$\mathbf{G} = \mathbb{E}\{(\hat{\mathbf{h}} - \mathbf{h})\left(\hat{\mathbf{h}} - \mathbf{h}\right)^{\boldsymbol{H}}\} = \mathbf{R} - p^{\boldsymbol{UE}}\mathbf{R}\overline{\mathbf{Y}}^{-1}\mathbf{R} \tag{10}$$

where $\mathbf{G}$ indicate the error covariance matrix. The channels consists of the LMMSE estimate in (7) pulse an unknown estimation error.

$$\mathbf{h} = \hat{\mathbf{h}} + \boldsymbol{\epsilon} \tag{11}$$

where $\boldsymbol{\epsilon} \in \mathbb{C}^{\boldsymbol{N}\times\mathbf{1}}$ indicate the estimation error.

IV. DL/UL DATA TRANSMISSION

We now analyze the channel capacity of the downlink in (1) and the uplink in (3). The analysis is based on having an imperfect pilot estimated channel as we discussed in the previous section. Therefore, the capacity depends on the CSI acquired using the LMMSE estimator. We are considering the channel capacities (in bit/channel use) of the downlink in (1) and the uplink in (3) for a random knowledge of CSI at the base station (BS) and the user equipment (UE). In every coherence period، the base station is assumed to have a random knowledge $\mathcal{H}^{\mathrm{BS}}$ of the channel $\mathcal{H}$. The base station uses this knowledge to choose the conditional distribution of the transmitted signal $\mathbf{d}$ $f = (\mathbf{d}|\mathcal{H}^{\mathrm{BS}})$. Also, UE has a different random knowledge of the channel $\widetilde{\mathcal{H}}^{UE}$. Therefore, the downlink capacity is

$$\mathrm{C}^{\mathrm{DL}} = \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\mathbb{E}\left\{\max_{f = (\mathbf{d}|\mathcal{H}^{\mathrm{BS}})\,:\,\mathbb{E}\|\mathbf{d}\|_{\mathbf{2}}^{\mathbf{2}} \le p^{\mathrm{BS}}} \mathfrak{I}\left(\mathbf{d}; z|\mathcal{H}, \mathcal{H}^{\mathrm{BS}}, \widetilde{\mathcal{H}}^{\mathrm{UE}}\right)\right\} \tag{12}$$

where $\mathfrak{I}(\mathbf{d}; z|\mathcal{H}, \mathcal{H}^{\mathrm{BS}}, \widetilde{\mathcal{H}}^{\mathrm{UE}})$ indicates the mutual information between the received signal z and the transmitted signal $\mathbf{d}$. Also the capacity of the uplink system in (3) is

$$\mathrm{C}^{\mathrm{UL}} = \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\mathbb{E}\left\{\max_{f = (s|\mathcal{H}^{\mathrm{UE}})\,:\,\mathbb{E}\{\|s\|_{\mathbf{2}}^{\mathbf{2}}\} \le p^{\mathrm{BS}}} \mathfrak{I}\left(\mathbf{d}; \mathbf{y}|\mathcal{H}, \mathcal{H}^{\mathrm{BS}}, \widetilde{\mathcal{H}}^{\mathrm{UE}}\right)\right\} \tag{13}$$

where $\mathfrak{I}(\mathbf{d}; \mathbf{y}|\mathcal{H}, \mathcal{H}^{\mathrm{BS}}, \widetilde{\mathcal{H}}^{\mathrm{UE}})$ is also the mutual information between the received signal $\mathbf{y}$ and the transmitted signal s. The joint distribution of $\mathcal{H}, \mathcal{H}^{\mathrm{BS}}, \widetilde{\mathcal{H}}^{\mathrm{UE}}$ is used to find the expectation in (13). Note also that $\frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}$ and $\frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}$ denote the fraction of channel uses given for downlink and uplink data transmissions.

Assuming that $\widetilde{\mathcal{H}}^{UE}$ and $\widetilde{\mathcal{H}}^{BS}$ are the channel estimated at the receiver for the DL/UL respectively. These estimates are not identical to the actual $\mathcal{H}^{\mathrm{BS}}$ and $\mathcal{H}^{\mathrm{UE}}$. The capacities in (12) and (21) become

$$\mathrm{C}^{\mathrm{DL}} = \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\mathbb{E}\left\{\log_2(1 + \mathrm{SINR}^{\mathrm{DL}}(\mathbf{x}^{\mathrm{DL}}))\right\} \tag{14}$$

$$\mathrm{C}^{\mathrm{UL}} = \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\mathbb{E}\left\{\log_2(1 + \mathrm{SINR}^{\mathrm{UL}}(\mathbf{x}^{\mathrm{UL}}))\right\} \tag{15}$$

where $\mathbf{x}^{\mathrm{DL}} = [u_1^{\mathrm{DL}} \ldots u_k^{\mathrm{DL}}]^{\boldsymbol{T}}$ and $\mathbf{x}^{\mathrm{UL}} = [u_1^{\mathrm{UL}} \ldots u_k^{\mathrm{UL}}]^{\boldsymbol{T}}$ indicate the beamformig and receive combining vectors that are both a function of $\hat{\mathbf{h}}$ and have a unit norms respectively. The SINR for the downlink and the uplink are given in (16) and (17) respectively.

$$\mathrm{SINR}^{\mathrm{DL}}(\mathbf{x}^{\mathrm{DL}}) = \frac{\left|\mathbb{E}\{\mathbf{h}^{H}\mathbf{x}^{\mathrm{DL}}|\widetilde{\mathcal{H}}^{\mathrm{UE}}\}\right|^{2}}{\mathbb{E}\left\{\left|\mathbf{h}^{H}\mathbf{x}^{\mathrm{DL}}\right|^{2}\left|\widetilde{\mathcal{H}}^{\mathrm{UE}}\right.\right\} - \left|\mathbb{E}\{\mathbf{h}^{H}\mathbf{x}^{\mathrm{DL}}|\widetilde{\mathcal{H}}^{UE}\}\right|^{2} + \frac{\mathbb{E}\left\{I_{\mathcal{H}}^{\mathrm{UE}}\middle|\widetilde{\mathcal{H}}^{UE}\right\}}{p^{\mathrm{BS}}} + \frac{\sigma^{2}{}_{\mathrm{UE}}}{p^{\mathrm{BS}}}} \tag{16}$$

$$\mathrm{SINR}^{\mathrm{UL}}(\mathbf{x}^{\mathrm{UL}}) = \frac{\left|\mathbb{E}\{\mathbf{h}^{H}\mathbf{x}^{\mathrm{UL}}|\widetilde{\mathcal{H}}^{\mathrm{BS}}\}\right|^{2}}{\mathbb{E}\left\{\left|\mathbf{h}^{H}\mathbf{x}^{\mathrm{UL}}\right|^{2}\left|\widetilde{\mathcal{H}}^{\mathrm{BS}}\right.\right\} - \left|\mathbb{E}\{\mathbf{h}^{H}\mathbf{x}^{\mathrm{UL}}|\widetilde{\mathcal{H}}^{BS}\}\right|^{2} + \frac{\mathbb{E}\left\{\left(\mathbf{x}^{\mathrm{UL}}\right)^{H}(\mathrm{Q}_{\mathcal{H}} + \sigma_{\mathrm{BS}}^{2}\mathrm{I})\mathbf{x}^{\mathrm{UL}}\middle|\widetilde{\mathcal{H}}^{\mathrm{BS}}\right\}}{p^{\mathrm{UE}}}} \tag{17}$$

Capacities on (14) and (15) can be calculated numerically for any downlink beamforming vector and any uplink receive combining vector for the estimated channel $\hat{\mathbf{h}}$.

A. Numerical Results

In this section we illustrate the effect of channel spatial correlation on the capacity of massive MIMO. The average SNRs we consider for the downlink and the uplink are defined as $p^{\mathrm{BS}}\frac{\mathrm{tr}(\mathbf{R})}{N\sigma^2{}_{\mathrm{UE}}}$ and $p^{\mathrm{UE}}\frac{\mathrm{tr}(\mathbf{R})}{N\sigma^2{}_{\mathrm{BS}}}$ respectively. We vary the angular spread and the number of antennas, while we fix the SNR values. In order to make the downlink and uplink capacities identical and we fix the ratio of the downlink and uplink data $\frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}} = \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}} = 0.45$.

Fig 4. considers spatially correlated scenario for three different numbers of antennas: 50,100 and 300 where SNR is fixed at 0 dB. Simulation results shows the capacity as a function of angular spread of the one ring model for the three cased. The capacity grows as the angular spread is increased. This means that the least correlated channels give the best performance while the lowest performance happens with the strongly correlated channels. The figure also shows that capacity grows as we add more antennas to the base station. Fig. 5. is similar to Fig. 4 but with different SNR value. The overall capacity is increased for all the antennas as a result of increasing the SNR to 25 dB. Also, the capacity is more sensitive to changes in the spatial correlation between the channels.

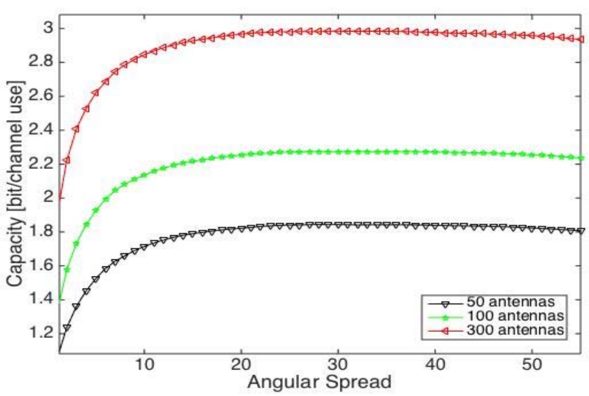

Fig. 4. Channel capacity as a function of the angular spread for different number of antennas SNR:0 dB.

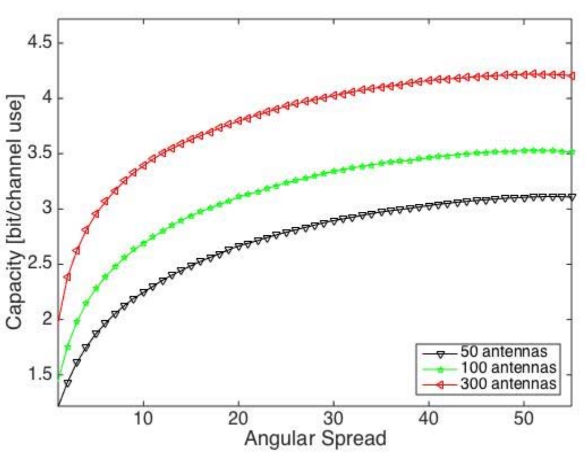

Fig. 5. Channel capacity as a function of the angular spread for different number of antennas SNR:25 dB.

V. Energy Efficiency

Energy efficiency (EE) of massive MIMO is considered in this section. The energy efficiency can be found by taking the ratio capacity (bit/channel use) and the transmitted power which is measured in (joule/channel use). Thus, the measurement unit of EE is bit/Joule. With the TDD mode, the energy used by the amplifiers in the transmitters in every coherence time is

$$E_{\mathrm{amp}} = \left(T_{\mathrm{pilot}}^{\mathrm{DL}} + T_{\mathrm{data}}^{\mathrm{DL}}\right)\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}} + \left(T_{\mathrm{pilot}}^{\mathrm{UL}} + T_{\mathrm{data}}^{\mathrm{UL}}\right)\frac{p^{UE}}{\omega^{\mathrm{UE}}} \quad (18)$$

where $\omega^{\mathrm{BS}}, \omega^{\mathrm{UE}}$ denote the efficiency of the amplifiers at the base station and the user equipment respectively. The average power (Joule/channel use) is given as

$$\frac{E_{\mathrm{amp}}}{T_{\mathrm{coher}}} = \underbrace{\alpha_{\mathrm{DL}}\left(\frac{T_{\mathrm{pilot}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}} + \frac{T_{\mathrm{pilot}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}}\right) + \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}}}_{\text{DL power}}$$

$$+ \underbrace{\alpha_{\mathrm{UL}}\left(\frac{T_{\mathrm{pilot}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}} + \frac{T_{\mathrm{pilot}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}}\right) + \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}}}_{\text{UL power}} \quad (19)$$

where α_{DL} and α_{UL} are the ratios of the downlink and the uplink transmission respectively

$$\alpha_{\mathrm{DL}} = \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{data}}^{\mathrm{DL}} + T_{\mathrm{data}}^{\mathrm{UL}}} \quad (20)$$

$$\alpha_{\mathrm{UL}} = \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{data}}^{\mathrm{DL}} + T_{\mathrm{data}}^{\mathrm{UL}}} \quad (21)$$

The EE (in bit/Joule) of massive MIMO system is defined as the following.

$$\mathrm{EE}^{\mathrm{DL}} = \frac{\mathrm{C}^{\mathrm{DL}}}{\alpha_{\mathrm{DL}}\left(\frac{T_{\mathrm{pilot}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}} + \frac{T_{\mathrm{pilot}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}} + N\rho + \zeta\right) + \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}}} \quad (22)$$

$$\mathrm{EE}^{\mathrm{DL}} = \frac{\mathrm{C}^{\mathrm{UL}}}{\alpha_{\mathrm{UL}}\left(\frac{T_{\mathrm{pilot}}^{\mathrm{DL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{BS}}}{\omega^{\mathrm{BS}}} + \frac{T_{\mathrm{pilot}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}} + N\rho + \zeta\right) + \frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}}\frac{p^{\mathrm{UE}}}{\omega^{\mathrm{UE}}}} \quad (23)$$

where $N\rho + \zeta$ denote the baseband circuit power consumption.

A. *Numerical Results*

Now, we illustrate how EE behave depending on the number of antenna, spatial correlation, transmit power. We setup: $\rho + \zeta = 0.02\frac{\mu\mathrm{J}}{\text{Channel use}}$ which represent the power consumed by the circuit if only one antenna is used. However, the circuit power for any number of antennas N is $N\rho + \zeta$. Therefore, we use splitting between ρ and ζ: $\frac{\rho}{\rho+\zeta} = 0$. We also set the amplifiers efficiencies to $\omega^{\mathrm{BS}} = \omega^{\mathrm{UE}} = 0.3$. The covariance matrix of the channel is generated using the one ring model in (6) with angel spread that varies between 10 to 50. In order to make the EE of the downlink and the uplink equal, we let $\alpha_{\mathrm{DL}} = \alpha_{\mathrm{UL}} = 0.5$ and $\frac{T_{\mathrm{data}}^{\mathrm{UL}}}{T_{\mathrm{coher}}} = \frac{T_{\mathrm{data}}^{\mathrm{DL}}}{T_{\mathrm{coher}}} = 0.05$.

Fig. 6 shows EE of the downlink and the uplink for three different number of antennas using the capacities in (12) and (13). EE increase as the number of antennas goes up. Hence, EE is very important feature of massive MIMO. The figure also shows that the performance improves as the angular spread is increased. Thus, EE improves as the correlation between the channels is decreased.

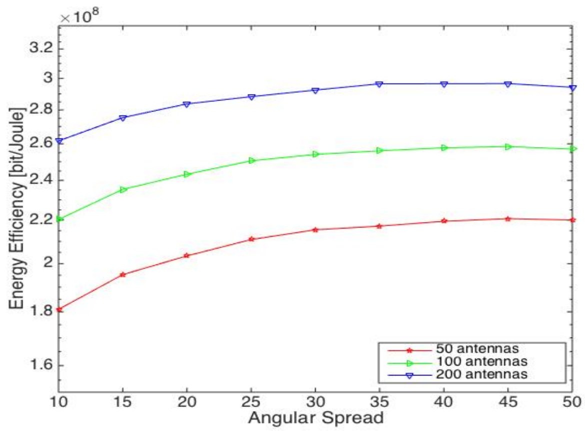

Fig. 6. Achievable energy efficiency as function of the angular spread for three different scenarios N (50, 100, 200) and a fixed SNR: 20 dB.

Fig. 7 shows the power allocations that corresponded to the curves in Figure. 6. Although higher number of antennas N is more energy efficient, more transmit power is required as the number of antennas is increased. The transmit power grows as the correlation between the channels is decreased.

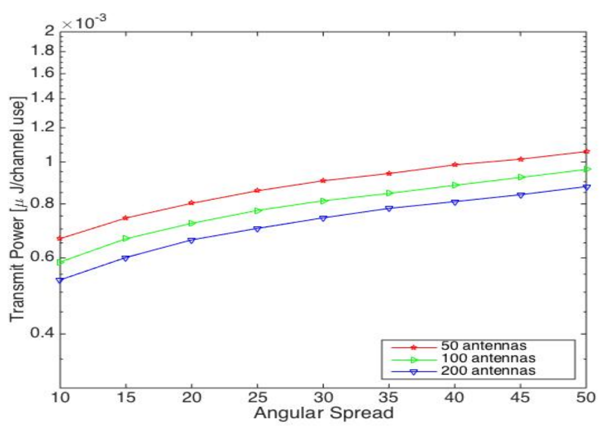

Fig. 7. The corresponding transmit power of the curves in Fig. 6.

VI. Conclusion

This paper studied the impact of channel spatial correlation on the capacity and energy efficacy of massive MIMO. The study was founded on a system model which considers spatial correlation between the channels. We showed that the performance of the enormous antenna array gain of massive MIMO systems might vary depending on the degree of channel correlation. Simulation results show that the capacity and energy efficiency can be limited by the channel correlation matrix that was generated using the one ring model. We showed that higher levels of channel spatial correlation results in a degradation in capacity and energy efficiency of massive MIMO systems.

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