Energy Efficient Massive MIMO System Design for Smart Grid Communications

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***Abstract*—Communication technologies are critical in achieving potential advantages of smart gird (SG), as they enable electric utilities to interact with their devices and customers. This paper focuses on the integration of a massive multiple-input multiple-output (MIMO) technique into a SG communication architecture. Massive MIMO has the benefits of offering higher data rates, whereas operating a large number of antennas in practice could increase the system complexity and energy consumption. We propose to use antenna selection to preserve the gain provided by the large number of antennas, and investigate an energy efficient massive MIMO system design for SG communications. Specifically, we derive a closed-form asymptotic approximation to the system energy efficiency function in consideration of channel spatial correlation, which exhibits an excellent level of accuracy for a wide range of system dimensions in SG communication scenarios. Based on the accurate approximation, we propose a novel antenna selection scheme aiming at maximizing the system energy efficiency, using only the long-term channel statistics. Simulation results show that the proposed antenna selection scheme can always achieve an energy efficiency gain compared to other selection schemes or baseline systems without antenna selection, and thus is particularly valuable for enabling an energy efficient communication system of the SG.**

I. Introduction

Smart Grid (SG) is a modernized electrical grid that uses information and communications technology for improving the efficiency, reliability, and economics of the traditional electrical grid [1]. Communication technologies are the key to achieving the potential advantages of SG, as they enable electrical utilities to interact with their devices and customers on a near real-time basis [2]. In general, a SG communication architecture consists of a home area network (HAN), neighbor area network (NAN), and wide area network (WAN) [3]. Various advanced communication technologies have been considered for their applications in the SG [4]. In this paper, we focus on implementing a massive multiple-input and multiple-output (MIMO) technique that improves the transmission reliability and system throughput for SG communications.

The idea of massive MIMO is that a large number of low-power antennas located at a base station node or distributed geographically transmit concentrated beams to the receivers concurrently using the same frequency band [5] [6]. The massive MIMO technique can be employed in NAN and/or WAN, and has the benefits of eliminating many random effects (e.g. uncorrelated noise and small-scale fading) and thus leading to higher data rates. However, deploying such systems in practice could increase the complexity and energy consumption for operating extra hardware at the base station, e.g. for multiple radio-frequency (RF) chains, and channel estimation, which can trigger energy-efficiency concerns for SG. In addition, insufficient spacing between antennas can yield highly correlated spatial channels [6]. To combat these difficulties in implementing the massive MIMO technique for SG communications, we design the number of RF chains at the base station to be smaller than the number of antenna elements to reduce the hardware complexity and high cost, and use appropriate antenna selection to preserve the gain provided by the large number of antennas. Regarding the massive MIMO technique, antenna selection has been discussed in [7] and [8]: an antenna selection algorithm is designed in [7] for the specific 60 GHz channel with a strong line-of-sight property; and in [8], the antenna subset is selected to maximize the system capacity. Compared to aiming at maximizing the capacity, maximizing energy efficiency (EE) or equivalently minimizing the total energy consumption is more meaningful for the system design [9], especially when there is a common requirement for the future SG communications to become more energy efficient.

In this paper, we design an energy efficient massive MIMO system in a smart grid NAN scenario. It is worth mentioning that the proposed system design is not limited to the NAN, and can be readily extended to a WAN scenario. Our main contributions can be summarized as follows. Firstly, we derive a closed-form asymptotic approximation to the system EE function in consideration of channel correlation and a realistic power model. The EE approximation exhibits a high level of accuracy for the entire range of system dimensions in the NAN scenario. In addition, We propose a novel antenna selection scheme that maximizes the system EE, based on long-term channel statistics. The proposed scheme can achieve an EE gain compared to other selection schemes or baseline systems without antenna selection.

The rest of this paper is organized as follows. Section II specifies the system model. The system EE is analyzed in Section III, and an energy efficient antenna selection scheme is proposed in Section IV. Simulation results are shown in Section V, and Section VI concludes the paper.

II. System Model

We consider a SG NAN consisting of a concentrator and a number of data aggregate points (DAPs) [3], as shown in Fig. 1. The NAN connects smart meters in a HAN, and interacts with a utility's head-end system in a WAN. In the NAN, the concentrator is equipped with N-antenna and the value of N is large. The concentrator communicates with K single-antenna DAPs, and the communication is operated on a time-division duplexing (TDD) mode with channel reciprocity.[1] The received signal y_m at the mth DAP can be expressed as

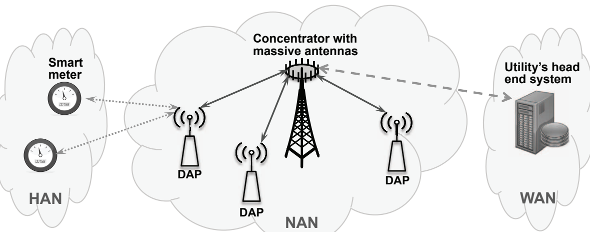

Fig. 1. Illustration of a SG communication architecture, where massive antennas are equipped at a concentrator in a NAN.

$$y_m = \sqrt{P_t}\,\boldsymbol{g}_m^H \boldsymbol{s} + n_m. \tag{1}$$

The N-by-1 vector $\boldsymbol{g}_m$ represents the uplink channel from the mth DAP to the concentrator, which can be obtained by using pilot-based channel estimation, and the scalar P_t denotes the average transmit power per antenna at the concentrator. We model the channel vector as $\boldsymbol{g}_m = \boldsymbol{\Phi}_m^{1/2}\boldsymbol{h}_m$ where $\boldsymbol{h}_m$ denotes the independent fast fading vector in which components are i.i.d. and have circularly-symmetric complex Gaussian random distribution with unit variance and zero mean. The N-by-N matrix $\boldsymbol{\Phi}_m$ denotes the long-term channel statistics (LTCS).[2] For a common channel model, i.e. a centralized massive MIMO system with all antennas colocated at one concentrator, we have $\boldsymbol{\Phi}_m = (K_t d_m^{\zeta})^{-1}\boldsymbol{\Theta}_m$, where $\boldsymbol{\Theta}_m$ represents the spatial correlation matrix at the concentrator side, d_m is the distance from the concentrator to the mth DAP, ζ is the path loss exponent, and K_t is a constant indicating the physical characteristics of the channel and the power amplifier [10]. In addition, the N-by-1 vector $\boldsymbol{s}$ in (1) represents the transmit vector at the concentrator, which can be given as $\boldsymbol{s} = \sqrt{\beta}\boldsymbol{W}\boldsymbol{x}$, where $\boldsymbol{W} = [\boldsymbol{w}_1 \cdots \boldsymbol{w}_K]$ is a N-by-K precoding matrix and the K-by-1 vector $\boldsymbol{x} = [x_1 \cdots x_K]^{\mathrm{T}} \sim \mathcal{CN}(0, \boldsymbol{I}_K)$ contains the data symbols intended for the K DAPs. The parameter β normalizes the average power per antenna to P_t, i.e. $\mathbb{E}[\frac{P_t}{N}\boldsymbol{s}^{\mathrm{H}}\boldsymbol{s}] = P_t$, where $\mathbb{E}[\cdot]$ denotes the expectation operation. We thus have $\beta = 1/\mathbb{E}[\frac{1}{N}\mathrm{tr}\boldsymbol{W}\boldsymbol{W}^{\mathrm{H}}]$. The scalar $n_m \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN) at the receiver, and σ^2 denotes the noise variance.

From a communications perspective, the total power supply of a concentrator (for supporting communications) includes various power elements such as the power for RF circuitry, baseband unit, and power amplifier. To quantify the total power consumption, we classify the power consumption P_{tot} into three categories: load dependent power, scaling circuit power, and static circuit power, i.e.,

$$P_{\text{tot}} = N\xi P_t + NP_0 + P_s, \tag{2}$$

where P_t is the transmit power, ξ is the scaling factor of the load-dependent power, P_0 is the circuit power scalable with N, and P_s is the static circuit power that describes most of the baseband processing power not scaling with N. Parameters of the power model for different concentrator types can be abstracted from the practical measurements as used in the EARTH project [11]. When N_t antennas are selected from N antennas for transmission, the total power consumption will be changed to $P_{\text{tot}}^{(s)} = N_t\xi P_t + N_t P_0 + P_s$.

[1] That is, the downlink channel vector is the Hermitian transpose of the associated uplink channel vector [6].

[2] The matrix $\boldsymbol{\Phi}_m$ is related to the concentrator antenna properties, the single-scattering angles for user m, and the path loss of user m.

III. System Energy Efficiency Evaluations

In this section, we evaluate the system spectral efficiency and EE for the NAN using the massive MIMO technique, and derive a tight and explicit approximation to the EE function. The EE approximation will provide analytical insight into the design of the antenna selection scheme in Section IV.

A. Achievable Rates and Asymptotic Analysis

It is shown in [6] that when the antenna arrays grow large, linear precoding methods with perfect channel state information can have a good level of performance, which is comparable to the capacity-achievable nonlinear precoding strategies (e.g. dirty paper coding). We thus consider a linear precoder, matched filter (MF) pre-coder, at the concentrator, and have $\boldsymbol{W} = \boldsymbol{G} = [\boldsymbol{g}_1 \cdots \boldsymbol{g}_K]$. The ergodic achievable rate of the mth DAP is $R_m = B_m\mathbb{E}[\log_2(1+\gamma_m)]$ where B_m is the communication bandwidth allocated to the mth DAP, and γ_m is the signal-to-interference-plus-noise ratio (SINR) which is given by [12]

$$\gamma_m = \frac{\mathbb{E}\left[|\boldsymbol{g}_m^{\mathrm{H}}\boldsymbol{w}_m|^2\right]}{\mathbb{E}\left[\frac{\sigma^2}{\beta P_t} + \sum_{i=1, i\neq m}^{K} |\boldsymbol{g}_i^{\mathrm{H}}\boldsymbol{w}_m|^2\right]}. \tag{3}$$

As the massive MIMO technique is used, we consider the system where N grows infinitely large, i.e., $N \to \infty$, and $\limsup_{N\to\infty} \frac{K}{N} < \infty$. In realistic systems, one would expect that more than one hundred antennas at the concentrator serve tens of single-antenna DAPs simultaneously [6]. We use the asymptotic analysis to provide approximations for finite N and K. Now we derive deterministic approximations $\bar{\gamma}_m$ of the SINR γ_m, such that $\gamma_m - \bar{\gamma}_m \xrightarrow[N\to\infty]{a.s.} 0$ where $\xrightarrow{a.s.}$ denotes almost sure convergence.

Proposition 1: Consider a NAN where an N-antenna concentrator communicates with K DAPs; The massive MIMO technique is deployed, i.e., $N \to \infty$ and $\limsup_{N\to\infty} \frac{K}{N} < \infty$; Suppose that the long-term channel matrices are uniformly bounded with respect to N, i.e., $\limsup\limits_{N\to\infty} \sup\limits_{1\le m\le K} \|\boldsymbol{\Phi}_m\| < \infty$. Then the approximation $\bar{\gamma}_m$ of the SINR γ_m can be given by

$$\bar{\gamma}_m = \frac{\left(\operatorname{tr}\boldsymbol{\Phi}_m\right)^2}{\frac{\sigma^2}{P_t N}\sum_{i=1}^{K}\operatorname{tr}\boldsymbol{\Phi}_i + \sum_{i=1}^{K}\operatorname{tr}\boldsymbol{\Phi}_m\boldsymbol{\Phi}_i}. \tag{4}$$

Proof: See Appendix A.

The approximations of γ_m and R_m become more accurate as N grows. According to the continuous mapping theorem of convergent sequences [13], we have

$$R_m - B_m\log_2(1+\bar{\gamma}_m) \xrightarrow[N\to\infty]{a.s.} 0. \tag{5}$$

B. Energy Efficiency Analysis

We use the well-known definition of the achievable EE as the number of bits transmitted per Joule of energy, i.e. E_s= KR_m/P_{tot} in bits/Joule/aggregator [10].

Proposition 2: Consider the NAN where the N-antenna concentrator communicates with K DAPs; Suppose $N\to\infty$, $\limsup\limits_{N\to\infty}\frac{K}{N} < \infty$, and $\limsup\limits_{N\to\infty} \sup\limits_{1\le m\le K} \|\boldsymbol{\Phi}_m\| < \infty$. Then the deterministic EE approximation $\bar{E}_m$ is given by

$$\bar{E}_m = KR_m\times \left\{\xi\sigma^2\left[\frac{(\operatorname{tr}\boldsymbol{\Phi}_m)^2}{(2^{R_m}-1)\sum_{i=1}^{K}\operatorname{tr}\boldsymbol{\Phi}_i} - \frac{\sum_{i=1}^{K}\operatorname{tr}\boldsymbol{\Phi}_m\boldsymbol{\Phi}_i}{\sum_{i=1}^{K}\operatorname{tr}\boldsymbol{\Phi}_i}\right]^{-1} + NP_0 + P_s\right\}^{-1}. \tag{6}$$

Proof: Both P_{tot} and R_m are related to the transmit power P_t; we thus reshape E_m as

$$E_m = KR_m[N\xi f^{-1}(R_m) + NP_0 + P_s]^{-1}, \tag{7}$$

where f^{-1}: $R_m\in[0,+\infty)\mapsto P_t\in[0,+\infty)$ is the inverse function of R_m. Due to the random channel realizations, $f^{-1}(R_m)$ does not have a straightforward formulation. A feasible approach would be to use the deterministic approximations $\bar{\gamma}_m$ for finding an explicit solution. We use (5) and (4) to solve $f^{-1}(R_m)$ and then insert it into (7), leading to (6). This completes the proof.

The above approximations of EE will become increasingly accurate as N grows. Our simulations will show that the approximations are also tight for a practical set of N and K in realistic system dimensions. The antenna selection is performed by maximizing EE using the approximation in (6).

IV. Energy Efficient Antenna Selection Scheme

We aim to use antenna selection to reduce the cost of too many RF chains and to improve the system EE for SG communications. Suppose that at the concentrator, the number of RF chains N_t is smaller than N. We propose to select N_t out of N transmit antennas based on the EE maximization criterion, as shown in Fig. 2, using only LTCS. The channel statistics normally vary with the antenna spacing, the single-scattering angles and the path loss, and thus may change very slowly. As a result, the proposed selection process does not change at each channel instance, but is updated when the channel statistics vary or new DAPs enter.

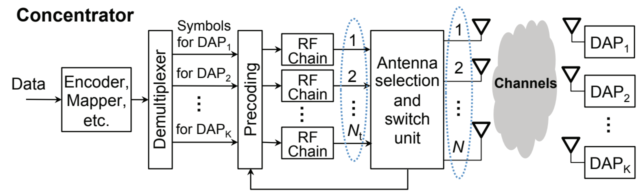

Fig. 2. A block diagram of a massive MIMO system with antenna selection for the SG NAN scenario.

Fig. 2 shows a block diagram of antenna selection for the NAN implemented with the massive MIMO technique. From a communications perspective, the concentrator comprises a baseband unit (including a forward error correction encoder, a symbol mapper, a demultiplexer, and a precoder [14]), N_t RF chains, an antenna selection and switch unit, and N antennas. In the antenna selection and switch unit, LCS is obtained and then used to select the best N_t antennas out of N antennas. The selection criterion will be shown in the following. The selected N_t antennas are connected to the RF chains and then used for transmission; and the selected antenna index is fed back to the precoder such that the updated N_t-by-K channel matrix is used for precoding.

From the approximation $\bar{E}_m$ shown in (6), we clearly distinguish the long-term channel effect on EE from the instantaneous channel effect. We can now proceed with antenna selection based on LTCS. Since $\operatorname{tr}\boldsymbol{\Phi}_m$ is only related to the number of selected antennas N_t but not affected by how the antennas are selected, the selection criterion that maximizes EE is equivalent to minimizing the term $\sum_{i=1,i\neq m}^{K}\operatorname{tr}\boldsymbol{\Phi}_m\boldsymbol{\Phi}_i$. This selection criterion is asymptotically optimal.

The work flow of the proposed LTCS-based antenna selection scheme (LASS) in shown in Table I. We begin by considering all N antennas and perform antenna selection in stages. In the jth stage, we consider all possible antenna subsets $\boldsymbol{\Lambda}^l(j), 1\le l\le(N-j+1)$, update the channel statistics $\boldsymbol{\Phi}_1 ... \boldsymbol{\Phi}_K$, compute the corresponding term $\boldsymbol{\Omega}_{\boldsymbol{\Lambda}^l(j)} = \sum_{i=1,i\neq m}^{K}\operatorname{tr}\boldsymbol{\Phi}_m\boldsymbol{\Phi}_i$, and then select the optimal subset $\boldsymbol{\Lambda}^*(j)$ with the minimum $\boldsymbol{\Omega}_{\boldsymbol{\Lambda}^l(j)}$. As described in Table I, the process will repeat and continue until N_t antennas are left.

TABLE I
Work Flow of the Proposed LASS

Inputs: The long-term channel statistics $\boldsymbol{\Phi}_1\cdots\boldsymbol{\Phi}_K$.
1. **Initialize** $j=0$, $\boldsymbol{\Lambda}^*(0)=\{1,2,\cdots,N\}$.
2. **Repeat**
a). $j=j+1$;
b). obtain all possible antenna subsets $\boldsymbol{\Lambda}^l(j)$, $1\le l\le(N-j+1)$, by removing only one antenna each time from the original set $\boldsymbol{\Lambda}^*(j-1)$;
c). for each subset, update $\boldsymbol{\Phi}_1\cdots\boldsymbol{\Phi}_K$, and calculate $\boldsymbol{\Omega}_{\boldsymbol{\Lambda}^l(j)} = \sum\limits_{i=1,i\neq m}^{K}\operatorname{tr}\boldsymbol{\Phi}_m\boldsymbol{\Phi}_i$;
d). select the optimal antenna subset by $\boldsymbol{\Lambda}^*(j) = \arg\min\limits_{\boldsymbol{\Lambda}^l(j)}\boldsymbol{\Omega}_{\boldsymbol{\Lambda}^l(j)}$.
3. **Until** $j\ge N-N_t$, stop antenna selection.
4. **Outputs:** The optimal antenna subset $\boldsymbol{\Lambda}^*(j)$.

V. Simulation Results and Discussions

In this section, we present the EE performance gain obtained by using the proposed massive MIMO system with antenna selection for the SG NAN senario. The physical channel propagation parameters are adopted from the 3GPP LTE standard models. The channels are modeled as Rayleigh fading channel. The average distance from the concentrator to the DAPs is set to 1500 meters, the path loss exponent is set to 4, and the constant indicating the physical characteristics of the channel and the power amplifier is set to 10^{-3} [10]. We consider the noise power density as -174 dBm/Hz, and data channel is 10 MHz. The values of the power model parameters for the concentrator are calculated from practical measurements as used in the EARTH project [11]: We select the Micro type of transmitter and thus $\xi = 2.6$, $P_0 = 23.6$ W, and $P_s = 64.8$ W. The target spectral efficiency (SE) is set to 2 bits/s/Hz/aggregator. A uniform linear antenna array under rich scattering conditions is considered, and an exponential model is used to quantify the spatial correlation. More specifically, the antenna correlation matrix is constructed using a single coefficient $\phi(|\phi| \leq 1)$: The entries $[\boldsymbol{\Theta}(\phi)]_{ij}$ equals $\phi^{|j-i|}$ if $i \leq j$, and the complex conjugate of $\phi^{|i-j|}$ if $i > j$.

We firstly exam the accuracy of our closed-form approximations to the ergodic achievable rate given in (4) and (5). Fig. 3 shows both simulation and analytical results of R_m as a function of N for K = 20 DAPs. We consider that the averaged received SNR equals 10 dB, and use different values of ϕ to represent different levels of correlation. The figure shows that the proposed closed-form approximations are quite closed to the simulation results for the entire range of N (even when N is not large, i.e. for realistic system dimensions), regardless of the values of ϕ, and thus used for analytically addressing the antenna selection problem.

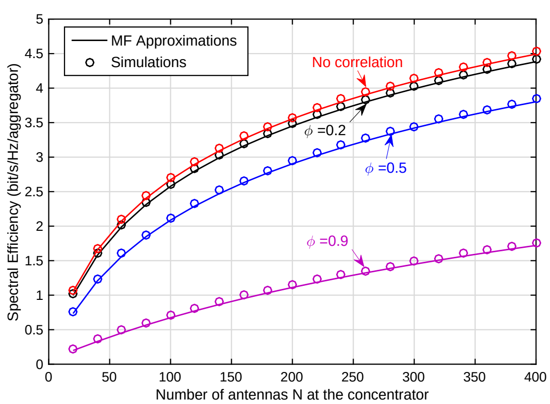

Fig. 3. Simulations and approximations of the system spectral efficiency versus the number of antennas N, where K = 20 and the averaged SNR equals 10 dB.

In Fig. 4, we compare the proposed antenna selection scheme to the random antenna selection scheme (RASS) in terms of the EE performance gain. With RASS, we randomly select N_t from N antennas. We consider the total number of antennas is fixed ($N = 256$), $K = 20$ DAPs, and the number of selected antennas N_t varies. The expected SE is set to 2 bits/s/Hz/aggregator. Two cases of the correlation with $\phi = 0.2$ and 0.6 are investigated. The proposed LASS can achieve an EE gain compared to RASS. The gain improves with increasing the value of the coefficient ϕ.

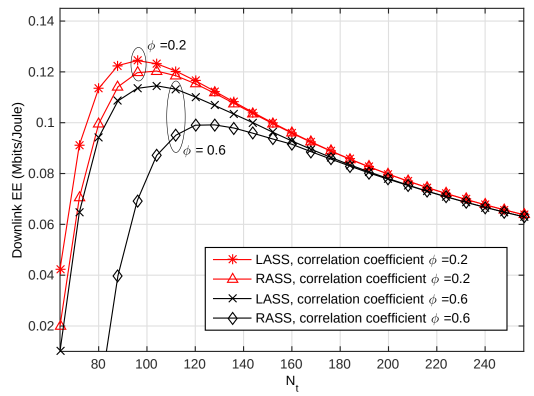

Fig. 4. System downlink EE versus the number of selected antennas N_t. (The total number of antennas N = 256; the number of DAPs K = 20; SE = 2 bits/s/Hz/aggregator.)

In Fig. 5, we compare the EE performance achieved by the LASS to conventional massive MIMO systems without selection (i.e. N or N_t antennas are used without selection) to highlight the importance of antenna selection in spatially correlated massive MIMO channels for SG communications. The correlation coefficient ϕ = 0.2 and 0.6, and the same fixed number of antennas $N = 256$, $K = 20$ DAPs and SE = 2 bits/s/Hz/aggregator as used in the above two figures. In contrast with the system using all the 256 antennas, LASS provides a huge performance gain in terms of EE for a wide range of N_t. Using LASS, there exists a certain region of N_t corresponding to a better level of EE performance, which provides insight into how many antennas should be selected to maximize the system EE. In addition, compared to the base-line case N_t antennas (without selection) used at the concentrator, deploying additional $(N - N_t)$ antennas and employing LASS can provide a superior level of performance, especially when the correlation level is high. Therefore, the proposed system design with the associated LASS is particularly valuable for enabling an energy efficient SG communication architecture.

VI. Conclusions

In this paper, we have investigated the integration of the massive MIMO technique into the SG communication architecture, and focused on improving the system EE. Considering spatially correlated fading channels and a realistic power model, we have derived the asymptotic approximation to the EE function in a simple and closed form; the approximation exhibits a very good accuracy for a wide range of N, even for realistic system dimensions. Based on the accurate approximation, we proposed an antenna selection scheme that maximizes the system EE. The selection criterion is based on

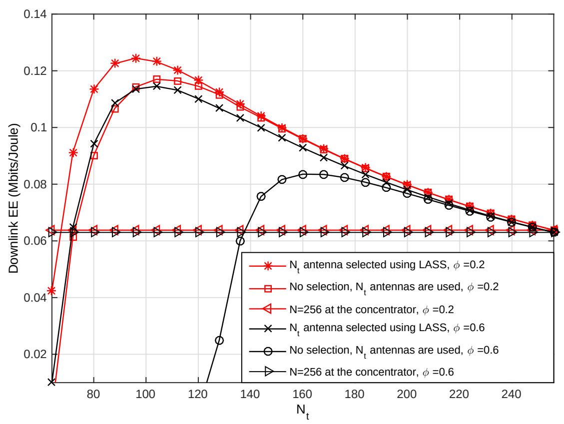

Fig. 5. EE performance comparisons between LASS and conventional systems ($N = 256$, $K = 20$, SE $= 2$ bits/s/Hz/aggregator).

long-term channel statistics, instead of instantaneous channel information, and thus the computational burden is low.

Our results have demonstrated that, the proposed antenna selection scheme for the SG massive MIMO systems can achieve an EE gain compared to other selection schemes. The obtained EE gain improves with an increase in the correlation level. Compared to the conventional systems without antenna selection, deploying additional antenna elements and employing LASS to perform antenna selection can help to improve the system EE, especially when the channel correlation level is high. The proposed massive MIMO system with the associated LASS is thus particularly valuable and attractive for future SG communication networks to become more energy efficient.

Acknowledgment

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Appendix A
Proof of Proposition 1

To prove this proposition, we first recall several preliminary results on large random matrices [13, Thm. 3.4, Thm. 3.8]: Let $\boldsymbol{A} \in \mathbb{C}^{N\times N}$ be deterministic and $\boldsymbol{z} \in \mathbb{C}^N$ be a random vector of independent entries. Suppose that $\boldsymbol{z} \sim \mathcal{CN}(\mathbf{0}, \frac{\mathbf{1}}{\mathbf{N}}\boldsymbol{I}_{\mathbf{N}})$ and $\boldsymbol{A}$ is uniformly bounded with respect to N. For $p \geq 1$, we have

$$\boldsymbol{z}^{\mathrm{H}}\boldsymbol{A}\boldsymbol{z} - \frac{1}{N}\mathrm{tr}\boldsymbol{A} \xrightarrow[N\to\infty]{a.s.} 0; \tag{8}$$

$$\mathbb{E}\left[\left|\boldsymbol{z}^{\mathrm{H}}\boldsymbol{A}\boldsymbol{z} - \frac{1}{N}\mathrm{tr}\boldsymbol{A}\right|^p\right] = \mathcal{O}\left(\frac{1}{N^{p/2}}\right). \tag{9}$$

Since the MF detector is considered, from (3), we have

$$\gamma_m = \frac{\mathbb{E}\left[|\boldsymbol{g}_m^{\mathrm{H}}\boldsymbol{g}_m|^2\right]}{\mathbb{E}\left[\frac{\sigma^2}{\beta P_t} + \sum_{i=1,i\neq m}^{K}|\boldsymbol{g}_i^{\mathrm{H}}\boldsymbol{g}_m|^2\right]}. \tag{10}$$

Dividing the denominator and numerator of γ_m by $\frac{1}{N^2}$, and using (8) and (9), the computation of signal power yields

$$\frac{1}{N^2}\mathbb{E}\left[|\boldsymbol{g}_m^{\mathrm{H}}\boldsymbol{g}_m|^2\right] = \mathbb{E}\left[\left|\frac{1}{N}\boldsymbol{h}_m^{\mathrm{H}}\boldsymbol{\Phi}_m\boldsymbol{h}_m\right|^2\right] \xrightarrow[N\to\infty]{a.s.} \left(\frac{1}{N}\mathrm{tr}\,\boldsymbol{\Phi}_m\right)^2. \tag{11}$$

Then for the noise and interference power, considering $\beta = \frac{1}{\mathbb{E}[\frac{1}{N}\mathrm{tr}\boldsymbol{W}\boldsymbol{W}^{\mathrm{H}}]}$, we have

$$\begin{aligned}\frac{1}{N^2}\mathbb{E}\left[\frac{\sigma^2}{\beta P_t}\right] &= \frac{\sigma^2}{P_t N^2}\mathbb{E}\left[\frac{1}{N}\sum_{l=1}^{K}\boldsymbol{g}_l^{\mathrm{H}}\boldsymbol{g}_l\right] \\ &\xrightarrow[N\to\infty]{a.s.} \frac{\sigma^2}{P_t N^2}\left(\sum_{l=1}^{K}\frac{1}{N}\mathrm{tr}\,\boldsymbol{\Phi}_l\right),\end{aligned} \tag{12}$$

$$\frac{1}{N^2}\mathbb{E}\left[\sum_{i=1,i\neq m}^{K}\boldsymbol{g}_i^{\mathrm{H}}\boldsymbol{g}_m\boldsymbol{g}_m^{\mathrm{H}}\boldsymbol{g}_i\right] \xrightarrow[N\to\infty]{a.s.} \frac{1}{N^2}\sum_{i=1}^{K}\mathrm{tr}\,\boldsymbol{\Phi}_m\,\boldsymbol{\Phi}_i. \tag{13}$$

We add one term $(\mathrm{tr}\,\boldsymbol{\Phi}_m^2)/N^2$ in (13) which can be neglected for large N. Inserting (11), (12), and (13) into (10), we thus have (4). This completes the proof. □

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