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Energy-Efficiency (EE) Performance for 5G Wireless Systems Under The Presence Of Hardware Impairments

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Abstract

Fulfilling mobile data demands such as high-resolution (lower delay) applications, videos, IoT, videogames, virtual and augmented reality is expected to increase the amount of energy consumed by mobile networks. Massive MIMO is expected to play a key role in meeting this demand by significantly increasing the number of antennas at the base stations (BS). The growing amount of demand for mobile applications and the corresponding Radiofrequency (RF) architecture will have an impact on the energy consumed at the base station. It is known that within the mobile operators, base stations (BS) are the most energy-consuming entities and account for more than 50% of the total power consumption. To manage this energy challenge, a new metric has been introduced called "Energy-Efficiency (EE)", measured in bits/Joule. Itis often encountered in the literature that hardware circuitry's impact is best utterly simplified; however, at expected operating frequencies in 5G wireless systems (i.e., massive MIMO to play a key role), these effects cannot be neglected and need to be modeled properly. We further enhance this model and delivered performance simulations to analyze the EE performance under different channel gains and these hardware imperfections.

Keywords—*Massive MIMO, 5G, Energy Efficiency (EE).*

I. INTRODUCTION

The International Telecommunication Union (ITU) guides the standardization of every new emerging technology, which provides the performance requirements for operation. For the new 5G standard, [1]-[2] guide the minimum requirements of being an IMT-2020 radio interface.

But what is motivating this new emerging technology? For example, developments in the domain of the Internet of Things (IoT) and digitalization has increased and will continue to increase the use of Information and communication technology (ICT) applications (and therefore also the usage of connectivity) almost everywhere. The number of mobile devices in use, such as smartphones are growing globally, leading to increasing demand for mobile data [3].

Fulfilling the demand for mobile data and new services, such as high-resolution applications, videos, IoT, and virtual and augmented reality, is expected to increase the amount of energy consumed by mobile networks [4], as the bit rate is expected to increase to an estimate of 300 Mbps (downlink) in a dense urban area [5]. Hence the challenge: seeking for much greater throughput, much lower latency, ultra-high reliability, much higher connectivity density, and higher mobility range while at the same time taking care of the environment and thereby becoming an energy-efficient technology. Achieving this enhanced performance is expected to be provided along with the capability to control a highly heterogeneous environment and the capability to, among others, ensure security, reliability, trust, identity, and privacy [5]. To give an idea of the growth in all areas, For example, the Next Generation Mobile Networks (NGMN) Alliance has proposed that 5G should support 200 − 2500 connections within a square-kilometer with 750Gbps/km2 area throughput and also up to 2000 connected vehicles with 50Mbps per car downlink (DL) connection [5].

However, this growth in all connected devices brings a growing challenge: managing and optimizing the energy utilized by these devices. For example, a typical mobile phone network in the United Kingdom may consume approximately 40-50 megawatts (MW), even excluding the power consumed by the users' handsets [6]. In developing countries, direct electricity connections are not readily available, so Vodafone, for example, use over 1 million gallons of diesel per day to power their network [6]. Mobile communications thus contribute a significant proportion of the total energy consumed by the information technology industry [6]. The impact on the environment is even not yet truly quantified.

The typical power consumption of different elements of a current wireless network is shown in Figure 1, as presented in [6]. These results clearly show that reducing the base station's power consumption or access point must be an important element.

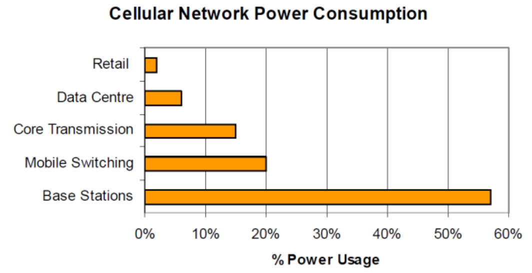


Fig. 1.Power consumption of a typical wireless cellular network - Source: Vodafone and [6]

It becomes noticeable with the evolution of communication technology that optimization in energy consumption is also growing and should become compulsory in deploying these new technologies. Across different surveys [5],[6], the mobile operators are amongst the top energy consumers, and their consumption is growing at a very fast rate. As mentioned in [6] and reproduced here in Figure 1, the base station consumes a large part of the energy generating a large electricity bill. Thus, not only from the operator's but also from the consumer's point of view, obtaining energy efficiency has significant economic benefits and therefore, becoming energy efficient becomes compulsory for new emerging technologies, like 5G.

Analysis within [6] shows that the greatest potential for increasing the overall base station efficiency comes from improving the efficiency of the PA and antenna, as well as optimizing the power transfer between them.

Figure 2 shows the different elements of a MIMO transmit chain [6] to clearly understand the elements that contribute to more power consumption in the RF transmitter chain. Sometimes, for simplifications in the mathematic analysis, these impairments are neglected, leading to unrealistic results or its generalization without setting clear conditions where they can become neglected.

Generally, MIMO systems are divided into two categories: single-user MIMO (SU-MIMO) and multiuser MIMO (MU-MIMO). In SU-MIMO, the transmitter and receiver are outfitted with more than one antenna. The performance is enhanced in terms of coverage, link reliability, and sum-rate can be executed, for instance, via strategies such as beamforming, diversity-oriented space-time coding, and spatial multiplexing of numerous data streams. These methods cannot be thoroughly used simultaneously;therefore, we commonly add a tradeoff between them. The situation with MU-MIMO is different: the wireless channel is now spatially shared byway of different User Terminals (UTs), and the users transmit and obtain barring joint encoding and detection amongst them. By exploiting differences in spatial signatures at the BS antenna array caused by spatially dispersed users, the BS communicates concurrently to the users. Thus, overall performance beneficial properties regarding sum rates of all users can be significantly improved. Signal processing techniques in MU-MIMO regularly targets at suppressing inter-user interference; thus spatial channel knowledge turns into another indispensable in contrast to SU-MIMO

Scaling up MIMO provides many extra degrees of freedom in the spatial domain than any other trendy systems. This issue rescues us from the state of affairs that wireless spectrum has to turn out to be congested and expensive, mainly in frequency bands beneath 6 GHz [16]. In contrast to traditional MU-MIMO with up to eight antennas, we name MIMO with a large variety of antennas“massive MIMO”, “very-large MIMO,” or “large-scale MIMO”.

In massive MIMO operation, we consider an MU-MIMO scenario, where a base station geared up with a large number of antennas serves many terminals in the same time-frequency resource. Processing efforts can be done at the base station side, and terminals have simple and inexpensive hardware.

Massive MIMO is, therefore, a new notion that makes use of hundreds of antennas at the BS to serve tens of UTs simultaneously in the same time-frequency resource (a.k.a. coherence interval). Massive MIMO mostly approves us to reap all the benefits of conventional MIMO on a large scale. In Massive MIMO systems, a huge number of BSantennas enhance spectral efficiency and radiated energy efficiency compared to the present wireless technologies.

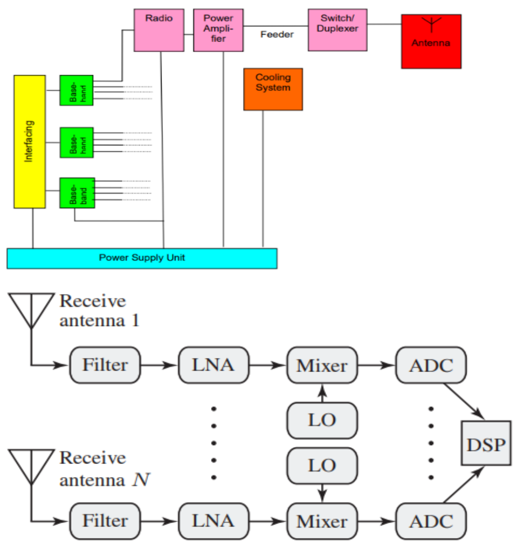


Fig.2.One transmitter chain of a MIMO system is shown [6]. The right side shows the main circuits, but these can complement additional intermediate filters and amplifiers, depending on the implementation. Most of the circuits affect only one antenna, while the LO can be common for all antennas or different, as described in [11].

However, the energy efficiency challenge remains, and to properly manage it, a new metric has been introduced in [1], which is called "Energy-Efficiency (EE)" whose definition is given by [7],[8] as:

$$\mathrm{EE}\ \left[{}^{bits}/_{joule}\right] = \frac{\text{Data rate}\ \left[{}^{bits}/_{s}\right]}{\text{Energy consumption}\ \left[{}^{joule}/_{s}\right]} \quad (1)$$

As said in [9], this equation is a benefit-cost ratio, and the energy consumption term should include transmitting power and dissipation power in the transceiver hardware and baseband processing. A general view is that higher data rates can only be achieved by consuming more energy; if the EE is constant, then 100× higher data rate in 5G is associated with a 100× higher energy consumption [9]. This remains an environmental concern since wireless networks are generally not powered from renewable green sources, and therefore, it is highly desirable to increase the EE in 5G [9] vastly.

There is a clear shift towards becoming more "efficient", and this is only further reinforced with the constant evolution of the Internet of Things (IoT), which is expected to grow exponentially in the bandwidth consumption, and therefore the need to become more efficient, as shown in [12].

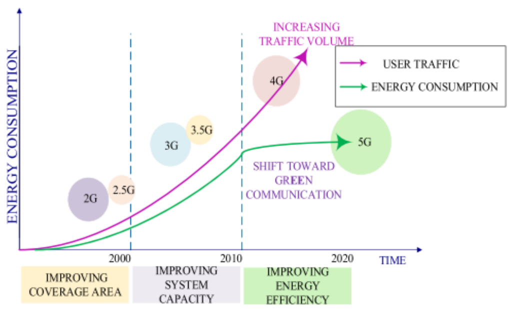


Fig.3.A shift on reducing energy consumption in 5G implementations, as shown in [12].

In summary, we could argue that there are at least three key challenges to consider when deploying new 5G technologies:

- ***Infrastructure/Technical Requirements:*** The expected growth in connected devices request for low latency, higher bandwidth (despite some applications may need less; however, the number of applications/devices connected are expected to continue growing), higher reliability, among others.

- ***Economic Requirements:*** Current networks are designed to maximize the capacity by scaling up the transmit powers or proving certain "fair" capacity at certain power constraints or any combination in between. However, given the expected growth of the number of connected devices, such an approach is not sustainable. Using more and more energy to increase the (physical) capacity will result in unacceptable operating costs that current operators may not afford. Present wireless communication techniques are thus simply not able to provide the desired capacity increase by merely scaling up the transmit powers.

- ***Environmental Requirements:*** Current wireless communication systems are mainly powered by traditional carbon-based energy sources as not yet renewable green sources are available. At present, information and communication technology (ICT) systems are responsible for 5% of the world's CO_2 emissions [13], [14], but this percentage is increasing as rapidly as the number of connected devices. Following this trend, it is foreseen that 75% of the ICT sector will be wireless by 2020 [15], thus implying that wireless communications will become the critical sector to address as far as reducing ICT-related CO_2 emissions is concerned.

Figure 4 shows the critical requirements in bandwidth and delay for the applications expected to be used extensively over the new 5G networks. From that analysis, we can conclude that the quality of service applied to each application may play a key role.

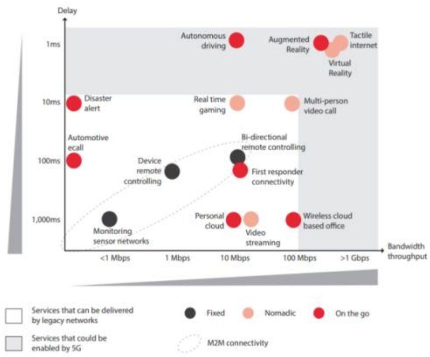


Fig.4.Bandwidth and latency requirements for typical applications over 5G networks, Source: GSMA Intelligence

II. SYSTEM MODEL

We will start by showing the single antenna model and then extend it to the multi-antenna.

A. *Single Antenna Systems*

For the case of a single antenna, the EE would be given by:

$$EE = \frac{Capacity}{Total\ Power} = \frac{B\ \log_2(1+\frac{P\,|h|^2}{B\,N_0+P\,\alpha})}{P_T} \quad (2)$$

Where $|h|^2 = \beta$ will denote the channel gain, P is the transmit power, B is the bandwidth, N_0 is the noise power spectral density, and α ($\alpha > 0$)corresponds to the sum of the channel gains from all the interfering transmitters. P_T will denote the total consumed power, including the transmit power $P_t$plus any other power considered as, the power to fuel the circuit systems.

B. Multiple Antenna Systems

We assume the transmitter has $\boldsymbol{M}$ antennas, and the receiver is equipped with $\boldsymbol{N}$ antennas, forming a MIMO system. The channel matrix describes the channel $\boldsymbol{H} \in \mathbb{C}^{\boldsymbol{NxM}}$, If we initially assume there is no interference, as in [9], the received signal $\boldsymbol{y} \in \mathbb{C}^{\boldsymbol{N}}$ is:

$$\boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{n} \quad (3)$$

Where $\boldsymbol{x} \in \mathbb{C}^{\boldsymbol{M}}$ is the transmit signal and $\boldsymbol{n} \sim \boldsymbol{\mathcal{N}}_{\mathbb{C}}(\boldsymbol{0}, \boldsymbol{BN_0I_N})$ is **AWGN**

The channel capacity of this MIMO system is given by [10] and is reproduced here as:

$$C = \max_{K \succcurlyeq 0: tr(K) \leq P} B \log_2 \det(I_N \frac{1}{BN_0} HKH^H) \quad (4)$$

And is achieved by $x \sim \boldsymbol{\mathcal{N}}_{\mathbb{C}}(\boldsymbol{0}, \boldsymbol{K})$ where the positive semidefinite correlation matrix $\boldsymbol{K}$is selected based on the water-filling algorithm.

C. Analyzing Power contributors (Hardware impairments)

Let's start with the simple definition of the EE as in (1), and let's now consider not only the transmit power but also the power of circuit systems, letting it $\boldsymbol{P_{cs}}$ be the power of circuit systems.

$$\mathrm{EE} = \frac{\mathcal{F}_r \text{ x B x } \mathcal{N}_{sp} \text{ x} \log_2\left(1+SINR(d)\right)}{P_t+P_{cs}} \quad (5)$$

Where $\mathcal{F}_r$ is the frequency re-use factor (within a cellular network; for a backhaul, we can assume a single frequency factor $\mathcal{F}_r = 1$), B is the signal bandwidth, $\mathcal{N}_{sp}$ is the number of spatial beams - spatial multiplexing factor-, d corresponds to a single link distance, SINR is the signal-to-interference-plus-noise ratio at the receiver that increases with decreasing d (from basic propagation analysis and it likely becomes more complex when considering all interference) and P_t is the transmit power.

When decreasing the coverage of area per cell (a.k.a. "small cells"), it is no longer possible to make the simplification often used as $P_t + P_{cs} \approx P_t$ so then we need to find another way to model the dependence on B and other variables (i.e., sampling rate is proportional to B and at the same time the energy consumed by the Analog-Digital (A/D), Digital-to-Analog (D/A) converters is proportional to the sampling rate).

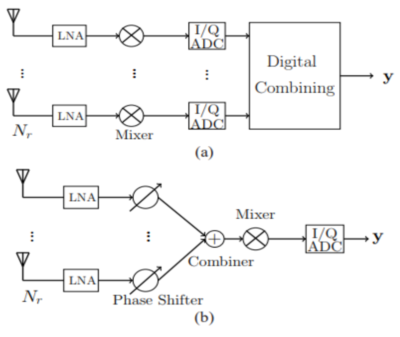
Let's now evaluate the different components of the P_{cs} and how to model it properly to capture the essence of their contributions to this analysis.

1) ADC Analysis

We will consider only the digital combining, despite the analysis can be easily extended to the analog combining too, as described in [18]. For digital combining, ADCs are employed to quantize the signal before the baseband combiner; each block labeled "I/Q ADC" represents two ADCs, one for the in-phase and another for the corresponding quadrature one., both with a sampling rate equal to the Nyquist rate. For the digital combining architecture, we have N LNAs and N mixers but also N ADCs[1]. Figure 7 reproduces the digital combining as analyzed in [18], and for the sake of completeness, it also includes the analog combining.

We assume each ADC consists of a b-bin scalar quantizer. We will use the same approach as in [18], considering an Additive Quantization Noise Model (AQNM) for the quantizer assuming Gaussian quantization noise and Gaussian inputs. Denoting the output of the ADC corresponding to input z by $Q(z)$ and considering the quantizer output $z_q = E[(z|z_q)]$, the quantizer $Q(.)$ can be represented by the following AQNM [19]:

$$z_q = \alpha z + n_q \quad (6)$$



[1]For the analog combining, there would be N LNAs, N phase shifters, one combiner, one mixer and one I/Q ADC

Fig 7: Receiver Architectures in MIMO systems a) Digital Combining b) Analog Combining, as [18].

Where n_q is the additive quantization noise such that z and n_q are uncorrelated. As noted in [18], the following equations hold true:

$$E[n_q] = (1-\alpha)\,\mathrm{E[z]} \tag{7}$$

$$\sigma_{n_q}^2 = (1-\alpha)\alpha\sigma_z^2 \tag{8}$$

Where $\sigma_{n_q}^2$ is the variance of the additive quantization noise and α can be computed as $\alpha = 1-\beta$ where $\beta = \frac{\sigma_{e_q}^2}{\sigma_z^2}$, $\sigma_{e_q}^2$ corresponds to the variance of quantization error, $e_q = z - z_q$ and σ_z^2 is the variance of the quantization input.

2) LNA Analysis

The low noise amplifier (LNA) is an analog circuit that amplifies the received signal. It is shown in [20] that the behavior of an LNA is characterized by the figure of merit (FoM) expression, given by:

$$F_oM_{LNA} = \frac{G}{(F-1)P_{LNA}} \tag{9}$$

Where $F \geq 1$ is the noise amplification factor, G is the amplifier gain, and P_{LNA} is the power dissipation in the LNA. Hence, LNA contributes to the receiver noise variance ξ with $F\sigma^2$. For optimized LNAs, F_oM_{LNA} is a constant determined by the circuit architecture [20].

3) Local Oscillator (LO) Analysis

Phase noise in the LOs is the main source of multiplicative phase drifts and changes the phases gradually at each channel use. We will model here the phase noise by a Wiener process (random walk) as in [9], yielding to the phase noise variance given by:

$$\delta = 4\,\pi^2 f_c^2 T_s\,\varsigma \tag{10}$$

where f_c is the carrier frequency, T_s is the symbol time, and ς is a constant that characterizes the LO's quality, as demonstrated in [21].

The power consumed by P_{LO} is coupled to (the constant) ς such that $P_{LO}\varsigma \approx F_oM_{LO}$ where the figure-of-merit value F_oM_{LO} depends on the circuit architecture and hardware quality (cost), [9], [21].

As it is well known, imperfections in the LOs also cause intercarrier interference in OFDM systems (as the orthogonality of the subcarriers is lost).

4) Encoding/Decoding Analysis

In the transmitter, the information symbols need to be encoded and modulated to counteract the effects of the noise and interference. The users then use demodulation and decoding to recover the desired signal. Higher data rates will require larger codebooks, and the largest number of bits will incur more power for encoding and decoding on baseband circuit boards.

The BS applies channel coding, and modulation to K sequences of information symbols, and each User Equipment (UE) applies some suboptimal fixed-complexity algorithm to decode it. Power consumption is $K(P_{cod} + P_{dec})$ Joule/channel use, where P_{cod} and P_{dec} are the coding and decoding powers, respectively.

The power consumption could be assumed to be a function of the number of bits, as:

$$P_{CD} = (P_{code} + P_{dec})\delta(r_b) \tag{11}$$

Where $(P_{code} + P_{dec}) \geq 0$ [W/bits/s] equals a constant and $\delta(r_b)$ is a differentiable, strictly increasing, and convex function of a specific data rate r_b satisfying $\delta(0) = 0$.

5) Putting all impairments together

Now we can include all the hardware impairments contributors, leading to:

$$P_{cs}(1-\alpha)\alpha\sigma_z^2 + \frac{G}{(F-1)P_{LNA}} + 4\,\pi^2 f_c^2 T_s\,\varsigma\,(P_{code} + P_{dec})\delta(C) + P_{BT}\delta(C) \tag{12}$$

Where the term $P_B\delta(r_b)$ Stands for the power consumed by the backhaul, defining the backhaul where it is used to communicate data signals between the core network and the base stations.

Here, the power consumption largely depends on the employed backhaul technology but can be modeled by this term, where P_{BT} [W/bit/s] gives the power consumption due to backhaul and network switches for a rate unit. This also scales with the data rate.

Therefore, inserting (12) into (2) and replacing r_b for the capacity$C$ will lead to:

$$EE = \frac{C}{P_T} = \frac{C}{P_t + (1-\alpha)\alpha\sigma_z^2 + \frac{G}{(F-1)P_{LNA}} + 4\,\pi^2 f_c^2 T_s\, \varsigma + (P_{code} + P_{dec})\delta(C) + P_{BT}\delta(C)} \qquad (13)$$

Reorganizing (13), and simplifying based on dependencies, will lead to:

$$EE = \frac{C}{P_t + u\sigma_u^2 + v\sigma_v^2 + w\sigma_w^2 + \varphi C} \qquad (14)$$

Where u, v, and w are hardware characterizing constants given by the circuit architecture, representing the ADC, LNA and LO terms, respectively and σ_u^2 , σ_v^2 and σ_w^2 are their corresponding variances (power) and φ corresponds to the hardware characterization dependent on the overall capacity (encoding/decoding and backhaul power).

6) Analyzing and simplifying the EE expression

Using the Lambert W function as in [9],[22], and doing the substitution of $z = {}^{P_t}/_{B}$, and noticing that u and w terms are dependent on the bandwidth (i.e., the sampling rate is proportional to B and the energy consumption -power consumed- of the AD/DA converters is proportional to the sampling rate and also proportional to the quantization bits), we can rewrite (14) in the following way:

$$EE = \frac{{}^{C}/_{B}}{{}^{P_t}/_{B} + u' + v' + w' + \varphi\, {}^{C}/_{B}} \qquad (15)$$

Which can be further simplified by knowing that $C = B\log_2(1 + \frac{P_t|h|^2}{BN_0'})$, $z = {}^{P_t}/_{B}$, and therefore, leading to:

$$\frac{\log_2(1 + \frac{|h|^2}{N_0'}z)}{z + (u' + w') + v' + \varphi \log_2(1 + \frac{|h|^2}{N_0'}z)} \qquad (16)$$

Where u' , v' , w' account for the same variables u,v, and w but now independent on the bandwidth by the given variable change (using the Lambert W function).

Similarly, we can extend this analysis to cover MU-MIMO systems by starting from (4) and assuming all singular values of H are equal to the maximum value $\sigma_{max}(H)$ of the matrix (equivalent to the upper bound), yielding to (17):

$$\mathrm{C} = \min(\mathrm{M},\mathrm{N})\,\mathrm{B}\log_2(1 + \frac{P}{MBN_0'}\sigma_{max}^2(\mathrm{H})) \qquad (17)$$

here we can intuitively notice that $\sigma_{max}^2(\mathrm{H}) \le 1$ as the receiver could never receive more signal power than P as per the law of energy conservation. Using the equality in $\sigma_{max}^2(\mathrm{H}) = 1$ would take us to calculate the EE limit in this MU-MIMO system by further working from (15) and using the change of variable $z = \frac{P_t}{B\min(\mathrm{M},\mathrm{N})}$ will lead to:

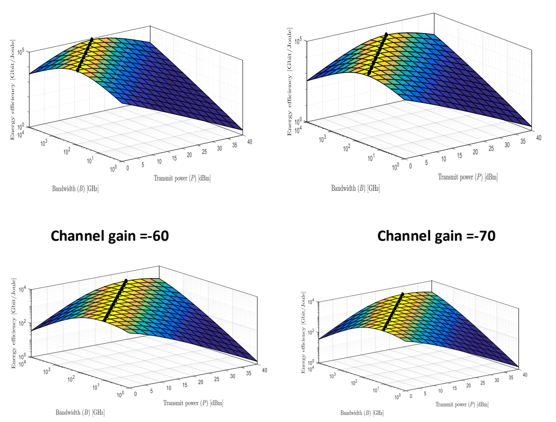
$$EE = \frac{\log_2(1 + \frac{z}{N_0'}\sigma_{max}^2(\mathrm{H}))}{z + (u' + v' + w') + \varphi\log_2(1 + \frac{z}{N_0'}\sigma_{max}^2(\mathrm{H}))} \qquad (18)$$

Having something very similar in structure to the single-antenna case. We will use here also the Lambert function.

I. NUMERICAL RESULTS AND PERFORMANCE ANALYSIS

The analysis considers a $N_0' = -174$ dBm/Hz as in [9] and a channel gain $|h|^2$ to vary from -60 to -110 dB.

Results from this simulation are depicted in Fig. 8. A thick line across the plot illustrates the maximum EE for certain combinations of P_t and B. Certainly, a constraint in the data rate could be added to reduce the set of possible feasible (maximum) points, but it is left for future work. For each equivalent hardware impairments variables, we can optimize the EE based on a given P_t and B (similar approach in [9]; however, we have extended the circuit hardware analysis, to our opinion). The current values account for current hardware circuitry imperfections, using the same parameters as in [9], for comparison purposes..



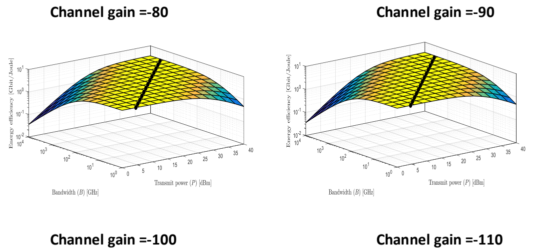


Fig 8: EE variation with P_t and B for different channel gains

CONCLUSIONS

It has been motivated and conceptually proven that hardware impairments at the RF chain cannot be neglected in the deployment of 5G wireless systems as they vary with the (growing) number of antennas, the bandwidth (due to the sampling rate), and the overall capacity of the system (base station). This new technology will likely make use of a higher frequency range, and therefore, these impairments cannot be neglected nor simplified as in previous developments.

We have derived a mode where the total power now encompasses different power contributors' terms that affect the performance on energy-efficient wireless systems and therefore need to and must be included for any further problem formulation to be optimized in MU-MIMO systems.

We have shown the EE performance for different channel gains using the model derived here, where all these hardware impairments are considered separate and aggregated to a close form expression. As circuitry technology evolves, this model can be easily adjusted in every part.

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