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On the Spectral Efficiency of Energy Constrained Short-Range Communicating Systems

Randa Jaouadi¹ · Guillaume Andrieux¹ · Jean-Yves Baudais² · Jean-François Diouris¹

¹ UMR6164: Institut d'Electronique et de Télécommunications de Rennes (IETR), Polytech Nantes, Université Bretagne Loire, Université de Nantes, Rue C. Pauc, BP 50609, 44306 Nantes Cedex 3, France

² CNRS, IETR UMR 6164, 35708 Rennes, France

Abstract Recently the energy efficiency (EE) in wireless communication is becoming one of the key performance metric for wireless communicating systems. For battery driven system like wireless sensor networks and ad-hoc networks, the energy conservation is a critical factor for node life. In addition, the spectral efficiency (SE) has been traditionally used as a performance index for wireless transmission. This paper investigates the optimum spectral to energy efficiency tradeoff especially for short range communications. The analysis starts with the Shannon case in additive white gaussian noise channel where some theoretic results are developed when considering both transmit and circuit energy. Then, point to point communication system with uncoded M -ary quadrature amplitude modulation (MQAM) is considered. At the device layer, a system level power consumption model is proposed. At the physical layer, a novel and accurate approximation of the bit error rate (BER) function of the signal to noise ratio is made. The total energy per bit is formulated and the link between the Shannon limit capacity and MQAM based communication is established. The impact of distance, bandwidth, power consumption and BER as a quality-of-service parameter on EE–SE tradeoff is analyzed. It is shown that, varying distance, bandwidth and circuit power consumption induce more impact in the low SE regime whereas, the BER has more impact on the high SE regime. Moreover, the energy optimal spectral efficiency for MQAM is obtained in closed-form and confirmed by numerical results.

Keywords Energy efficiency · Spectral efficiency · Tradeoff · MQAM · Power model

1 Introduction

Owing to the rapid growth of wireless communicating devices with the prevalent concept of all connected world and zero distance communication, attaining a high energy efficiency has become a key condition for wireless communication technologies [1]. Moore's [2] Law states that computing power doubles every 18 months. Moreover, as computing devices become smaller, dense and mobile, energy conservation is a critical factor for battery driven technologies such as distributed wireless sensors networks and machine-to-machine communications. These technologies are susceptible to many different applications in diverse fields such as monitoring and control, health care (i.e., medical body sensors, diagnostics), home automation and intelligent buildings (i.e., security, lighting), military, traffic coordination [3]. Despite the large range of applications, there are stringent energy consumption constraints in these devices due to their limited power source. Therefore energy-efficient communication schemes have become a main challenge in the design of these systems [4, 5] in order to prosper into large-scale autonomous networks. Furthermore, the spectral efficiency (SE) is another important metric which has been the main performance indicator for designing and optimizing networks. However improving SE with the excessive demand in high data rate application could lead to an increased energy consumption [6]. Therefore, in order to design practical energy saving strategies, future networks should be designed by considering energy efficiency (EE) and SE jointly [7].

One of the most important requirement for an EE–SE evaluation is to consider an appropriate power consumption model. Under practical formulation, this relationship has been influenced by several hardware such as power amplifier efficiency and circuit power. For instance, the authors in [1, 7–9] have studied the EE–SE tradeoff and they showed the impact of using a realistic power consumption model for comparing and analyzing the power efficiency of various networks. In [10], the authors have explored the mechanism towards energy and spectral efficiency tradeoff of various wireless communication systems. They have shown the strong impact of circuit power in wireless sensors network scenarios. As the distance between nodes is small (typically ≤ 10 m), the circuit power for transmitting and receiving may prevails over the transmission power [11].

At the physical layer, there are two main components that contribute to the total energy budget in wireless transmission. The circuit energy needed to run transmitter and receiver circuits [12] and the transmitted energy. The latter is needed to compensate the channel loss in order to obtain the signal to noise ratio (SNR) necessary to demodulate and decode the transmitted information under a given BER. Thus, the communication energy budget depends on choices such as the modulation scheme, packet structure and transmission power [13]. It is commonly assumed that for low-power-low-rate architecture, the most energy efficient modulation are M-FSK, BPSK and QPSK. For instance, in [14], the authors shows that noncoherent M-FSK is more energy efficient than MQAM for microsensors networks. However, when the transmission distance shortens, the optimal choice shifts to higher modulation order like 16-QAM and even 64-QAM resulting in 600% increase in the transceiver lifetime [15]. Moreover, a low modulation order decreases the SE and thus the throughput of the system. By scaling MQAM modulation, authors in [16–18] showed that an optimal modulation exists which can save energy. Recently, authors in [19] have studied the optimal choice for so-called *green modulation* in wireless sensors networks. A similar analysis can be found in [20, 21] in the case of one hop and multi-hop scenarios. Nevertheless, the EE–SE tradeoff is not considered in these studies, the closed-form expression of the optimal constellation size is still not determined and it is usually obtained via a numerical algorithm.

In this paper we provide a holistic approach by studying the EE–SE relation with and without energy gap introduced by feasible modulation. We analyze first the Shannon limit case where we provide some theoretical properties. Then, we investigate the EE–SE for uncoded square MQAM for point to point system in AWGN channel, which turns out to study the energy efficiency and the constellation size tradeoff. We use a precise power model for the device layer. The power model includes the transmission power which depends on the modulation order and the required error probability level. Besides, the RF front-end power dissipation, digital signal processing including modulation scheme is also considered for both transmitter and receiver side. Most previous works uses a power consumption model that considers only the transmit power with a constant RF power [16, 22] neglecting the digital part. Recently many works [23, 24] have demonstrated that the accuracy of this model is not enough and the digital part must be taken into account. Thus by considering a channel attenuation model and an accurate expression for the SNR as a function of the BER, the overall expression of the energy consumption as a function of spectral efficiency is evaluated for variable duty cycle system. The challenge in this analysis is then to find a closed form expression of the optimal constellation size that minimizes the energy.

The remainder of this paper is organized as follows. In Sect. 2, the EE–SE tradeoff in Shannon limit case including circuit power consumption is characterized. In Sect. 3, we introduce an accurate energy consumption model and we present the communication system scenario. Section 4 gives an accurate approximation for the BER and formulates the EE–SE relation when considering uncoded square MQAM for a given BER constraint. Next, numerical results are discussed in Sect. 5. Finally, Sect. 6 concludes the paper.

2 Theoretical Investigation and Motivation

The fundamental relation between the channel capacity and the received energy per bit E_b is given by Shannon’s formula over AWGN channel [25]. For a maximum achievable information rate R this relation gives

$$R = B \log_2 \left(1 + \frac{RE_b}{BN_0} \right) \quad (1)$$

where B is the signal bandwidth and N_0 represents the power spectral density of white Gaussian noise.

2.1 Energy Efficiency-Spectral Efficiency Tradeoff Analysis

2.1.1 Fundamental Tradeoff

By denoting $\theta = \frac{R}{B}$ the spectral efficiency of the system expressed in bit/s/Hz, (1) gives E_b as function of θ

$$E_b = N_0 \cdot \frac{2^\theta - 1}{\theta} \quad (2)$$

This equation illustrates the fundamental relation between energy and spectral efficiency which deserves careful study [1, 26]. The result shows only the limit case without considering practical modulation and coding and it considers also only the amount of energy

per bit E_b in the signal itself without counting for the energy expended by the communication system to run its circuits, such as powering non-signal paths components like oscillators, baseband processors. Hence, as the circuit energy will be included, the penalty in terms of circuit processing cost can be large compared with signal energy.

2.1.2 Practical Tradeoff

Now let consider, in addition to transmission power over AWGN channel, an extra power consumed in the total communication system including the transmitter and the receiver. We assume a k th-power path-loss model at distance d (in m) between the transmitter and the receiver. The power gain factor is $G = G_1 d^k$, where d represents the distance, G_1 is the gain factor (including path loss and antenna gain) measured at a reference distance equal to 1 m and k the path loss coefficient of the environment. Therefore the transmit power P_t is related to the rate by $R = B \log_2 \left(1 + \frac{P_t}{GBN_0} \right)$. The overall consumed power of the link can be modeled in general [5] by

$$P_{\text{tot}} = \alpha P_t + P_{\text{pr}} \quad (3)$$

where $1/\alpha$ refers to the amplifier efficiency, P_{pr} refers to all circuit power consumption in the signal path (source and channel coding, modulation and other analog block consumption). we assume that this power depends linearly on the bandwidth. It can be modeled as $P_{\text{pr}} = \varepsilon B + P_c$, where ε models the bandwidth-dependent power and P_c the non-dependent part. Hence, the energy efficiency defined as the consumed energy per bit can be obtained as

$$E_{\text{bt}}(\theta) = \frac{P_{\text{tot}}}{R} = \alpha N_0 G_1 d^k \frac{(2^\theta - 1)}{\theta} + \frac{P_{\text{pr}}}{\theta B} \quad (\text{J/bit}) \quad (4)$$

The above equation gives the relation between the energy efficiency E_{bt} as a nonlinear function of the spectral efficiency θ of the whole system. In fact, it determines the energy cost of a single bit for each SE value thus it allows to know the optimal spectral to energy efficiency point. Figure 1 shows how EE changes with respect to SE for different circuit power consumption expressed as $P_{\text{pr}}/(BN_0)$. We notice that the circuit power consumption affects strongly the energy bound, obtained for $P_{\text{pr}} = 0$, in the low spectrum efficiency region. The plot shows that the circuit energy per bit affects the left part of the curve and therefore reduces the achievable region. The Shannon theoretical bound ($P_{\text{pr}} = 0$) delimits the achievable region, above the curve and it shows the set of optimal solutions for energy minimization. This figure reveals the existence of unique minimal energy solution shifting the set to solutions with higher energy consumption. In general, a large transmit power yields to a large spectrum efficiency, however a large spectrum efficiency may affect the energy negatively. Therefore by considering a real power model, there might be a tradeoff between the energy and spectral efficiency for the entire system.

2.1.3 Problem Formulation

As E_{bt} varies greatly with respect to the spectral efficiency θ , we would like to find the optimal θ that minimizes the energy. For that, consider the optimization problem of minimizing (4), then the solution of our objective function is E^\star and the corresponding optimum SE value is denoted θ^\star , defined as

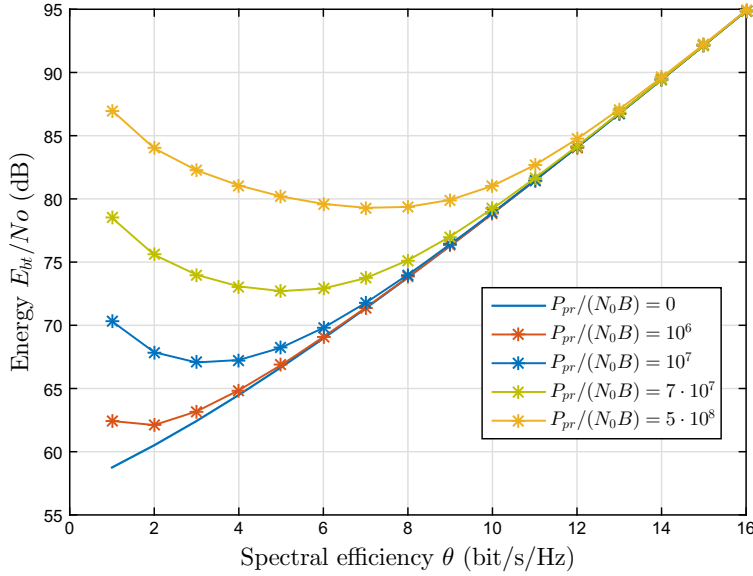


Fig. 1 Impact of circuit power on energy efficiency-spectrum efficiency tradeoff ($d = 5$ m, $G_1 = (\frac{4\pi}{\lambda})^2$, $k = 2$, $\alpha = 3$)

$$E^{\star} = \min_{\theta \geq 0} E_{bt}(\theta), \quad \theta^{\star} = \operatorname{argmin}_{\theta \geq 0} E_{bt}(\theta) \quad (5)$$

Note that if the system is 100% efficient and no power is wasted off the signal path, i.e., $P_{pr} = 0$, then (4) becomes identical to the Shannon's limit in (2). In this case, the energy is strictly increasing with θ and the best SE is always achieved at $\theta^{\star} = 0$. The minimum energy is then the well known ultimate Shannon limit:

$$E_l = \lim_{\theta \rightarrow 0} E_{bt}(\theta) = N_0 \ln(2) \quad (6)$$

This limit defines the minimum energy per bit required to achieve arbitrarily low probability of bit error by allowing the used code to occupy an infinite bandwidth. However, by using the right power model ($P_{pr} > 0$), the traditional conclusion that low spectral efficiency saves energy is not generally valid. As shown in Fig. 1, as P_{pr} grows, the optimal spectral efficiency value increases whereas when θ approaches 0, the energy grows without limit. This yield us to investigate more the real tradeoff between energy consumption and spectrum requirement. The following subsection gives general results about the optimal points θ^{\star} and E^{\star} , their properties as well as the impact of system parameters on their values. This can contribute to unveil the characteristics of SE and EE tradeoff.

2.2 General Properties of $E_{bt}(\theta)$, E^{\star} and θ^{\star}

Based on the relation between energy and spectrum efficiency value from (4), we propose to give a theoretical study to investigate the corresponding properties. To this end, the following lemmas of main importance can be derived:

Lemma 1 Due to the presence of extra circuit energy, (4) highlights two energy regions in high and low spectral efficiency. Therefore an approximation of (4) can be estimated in these regions as follow

$$E_{\text{bt}} \approx \begin{cases} \alpha N_0 \ln(2) d^k G_1 + \frac{P_{\text{pr}}/BN_0}{\theta} & \text{for low SE} \\ \alpha N_0 \ln(2) d^k G_1 2^\theta & \text{for high SE} \end{cases} \quad (7)$$

Proof See Proof of Lemma 1 (Appendix). \square

Lemma 1 brings some insights on how the total energy per bit in (4) behaves. For low SE, the circuit energy dominates over the transmission energy and contributes more to the energy consumption in this case, the energy reduces when SE increases. Therefore higher circuit consumption always lowers down the EE performance (or maximizes the total energy per bit) in the low SE as shown in Figs. 1 and 2. Whereas, in the high SE regime the contribution of the transmission energy dominates due to the increase of transmit power which is monotonically increasing with SE. In this case it is preferable to decrease the SE to save energy. This confirms the intuition that low SE is beneficial only when the transmission energy dominates, typically for large distances.

Lemma 2 The energy efficiency function defined in (4) is a strictly quasi-convex function with respect to spectral efficiency θ . It has a unique global solution θ^\star that corresponds to a unique minimum E^\star . That is, $\forall \theta > 0$, E_{bt} is decreasing for $\theta < \theta^\star$ and increasing for $\theta > \theta^\star$.

Proof See Proof of Lemma 2 (Appendix). \square

Then, the following lemma derives the optimal point θ^\star

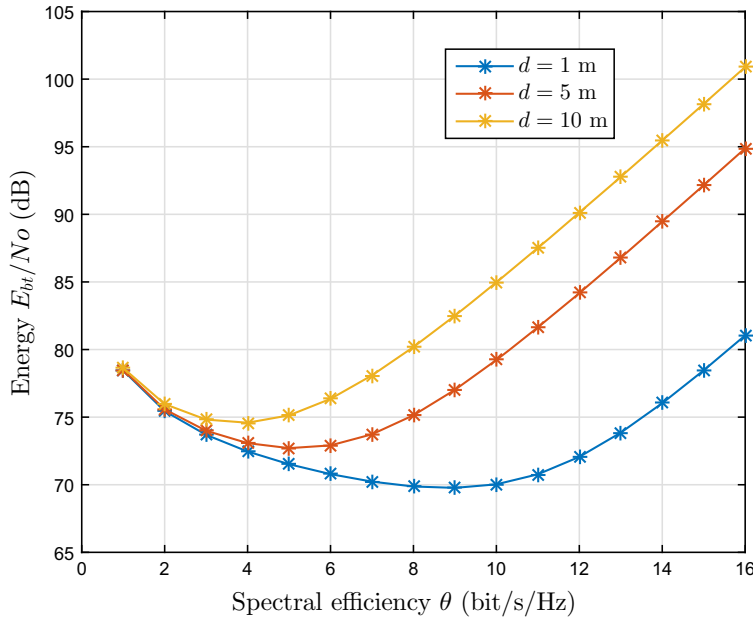


Fig. 2 Energy efficiency-spectrum efficiency tradeoff for different distances, $P_{\text{pr}}/(N_o B) = 7 \times 10^7$

Lemma 3 *The energy-optimal spectral efficiency θ^\star for a system whose energy consumption is described by (4) can be given in a closed form as*

$$\theta^\star = \frac{1}{\ln(2)} \left(1 + W_L \left(\frac{P_{\text{pr}}}{e\alpha B N_0 G_1 d^k} - \frac{1}{e} \right) \right) \quad (8)$$

where e is the base of the natural logarithm and W_L is the Lambert function.

Proof See Proof of Lemma 3 (Appendix). \square

As seen in Lemma 3, the optimum SE behavior depends strongly on system parameters. Let us analyze the impact of varying some parameters, namely d , B , G_1 , N_0 , P_{pr} on θ^\star and the corresponding minimum energy E^\star . With the θ^\star expression provided above, we have the following lemma:

Lemma 4 *By increasing or decreasing one system parameter when the other are kept constant, the following claims are true:*

- *effect of distance:*

$$\lim_{d \rightarrow +\infty} \theta^\star = 0 \quad \text{and} \quad \lim_{d \rightarrow +\infty} E^\star = +\infty \quad (9)$$

- *effect of bandwidth:*

$$\begin{cases} \lim_{B \rightarrow 0} \theta^\star = +\infty & \text{and} & \lim_{B \rightarrow 0} E^\star = +\infty \\ \lim_{B \rightarrow +\infty} \theta^\star = \theta_\ell & \text{and} & \lim_{B \rightarrow +\infty} E^\star = E_{\text{bt}}^\ell \end{cases} \quad (10)$$

- *effect of static circuit power:*

$$\begin{cases} \lim_{P_c \rightarrow 0} \theta^\star = \theta_\ell & \text{and} & \lim_{P_c \rightarrow 0} E^\star = E_{\text{bt}}^\ell \\ \lim_{P_c \rightarrow +\infty} \theta^\star = +\infty & \text{and} & \lim_{P_c \rightarrow +\infty} E^\star = +\infty \end{cases} \quad (11)$$

where

$$\theta_\ell = \frac{1}{\ln(2)} \left(1 + W_L \left(\frac{\varepsilon}{e\alpha N_0 G} - \frac{1}{e} \right) \right) \quad (12)$$

$$E_{\text{bt}}^\ell = \alpha G E_l \cdot \left(\frac{e^{1 + W_L \left(\frac{\varepsilon \ln(2) - G E_l}{e E_l G} \right)} - 1}{1 + W_L \left(\frac{\varepsilon \ln(2) - G E_l}{e E_l G} \right)} \right) + \frac{\varepsilon \ln(2)}{1 + W_L \left(\frac{\varepsilon \ln(2) - G E_l}{e E_l G} \right)} \quad (13)$$

This Lemma reveals important insight of θ^\star and E^\star limits regarding systems parameters and power model. The first claim means that when the distance d increases while all other parameters are fixed, θ^\star approaches 0 and E^\star increases without bound since the transmission energy grows with distance. In such a case, the optimum SE has to be decreased, so the system should slower its transmission to operate in optimal EE mode. When the distance increases, the contribution of the transmission energy dominates over that of circuit energy consumption. For the second claim, reducing the bandwidth allows to increase both SE and energy consumption. However, when the bandwidth growth, the optimal SE converges to a specific value $\theta_\ell > 0$ given by (12) and the minimal energy converge to $E_{\text{bt}}^\ell \geq E_l$ as shown in (13), where it is expressed as a function of the minimal

energy per bit in the signal as defined in (6). Note that if $\varepsilon \rightarrow 0$, we obtain a θ_ℓ that converges to 0 and the minimal energy $E_{\text{bt}}^\ell \rightarrow \alpha G E_l$ as expected. This result agrees with the novel power consumption factor theory carried out in [27]. Hence, Lemma 4 gives an interesting insight about the energy to spectral efficiency relationship since if we do not consider the bandwidth-dependent power, i.e., $\varepsilon = 0$, the result would be 0 for θ^\star and $E^\star = +\infty$, which can bias optimal system setting. Similar observation when bandwidth-independent power consumption P_c decreases to 0. Whereas if P_c go to infinity in (11), the optimal SE will increase boundless as well as the minimal energy.

Now let see the impact of varying distance separation between the transmitter and the receiver from one value to another when all the other parameters are kept constant. For that, assume two different values of distance separation d namely d_1 and d_2 . Denote $E_{\text{bt}}(\theta, d)$ the consumed energy per bit evaluated for an SE value θ at a distance d and by

$$\theta^\star(d) = \arg \min_{\theta \geq 0} \{E_{\text{bt}}(\theta, d)\} \quad (14)$$

the optimal SE value corresponding to the minimum energy per bit evaluated at a distance d . We have the following lemma.

Lemma 5 *Considering $d_2 > d_1$, then $E_{\text{bt}}(\theta^\star(d_2), d_2) \geq E_{\text{bt}}(\theta^\star(d_1), d_1)$ and $\theta^\star(d_2) < \theta^\star(d_1)$*

Proof See Proof of Lemma 5 (Appendix). □

This means that the optimal rate per Hz decreases with the distance and the minimum energy per received bit decreases with the distance. As observed in Fig. 2, the increase in distance leads to an increase in energy consumption and reduces the optimal SE. A similar analysis can be carried out for the other parameters. It appears from (8) that increasing B , N_0 or G_1 has an impact similar to increasing distance, meaning that the optimal SE value decreases when increasing each of these parameters. However, a growth in the circuit consumption P_{pr} , leads to an increase of the corresponding optimal SE value and its minimal energy as well as shown in Figs. 1 and 3.

The above analysis present an attractive basic study to understand the relationship between SE and EE but it ignores some practical details needed for a fair assessment. In the next section, a practical modulation scheme is considered and the energy to spectrum optimization as well as the impact of system parameters are studied in order to corroborate the theoretical analysis.

3 System Description and Energy Model

3.1 Power Consumption Model

In a sensor node, the energy is mainly consumed for communication [18]. To facilitate our study, we assume a generic transmitter and receiver as shown in Fig. 4. The baseband signal is converted to an analog signal by the digital-to-analog converter (DAC), then filtered by the reconstruction filter and modulated by the mixer, then filtered again and finally amplified by the power amplifier (PA) and transmitted to the wireless channel. On the receiver side, the RF signal is first filtered by the RF band selection filter and amplified by the low noise amplifier (LNA), then down converted by the mixer, filtered again and

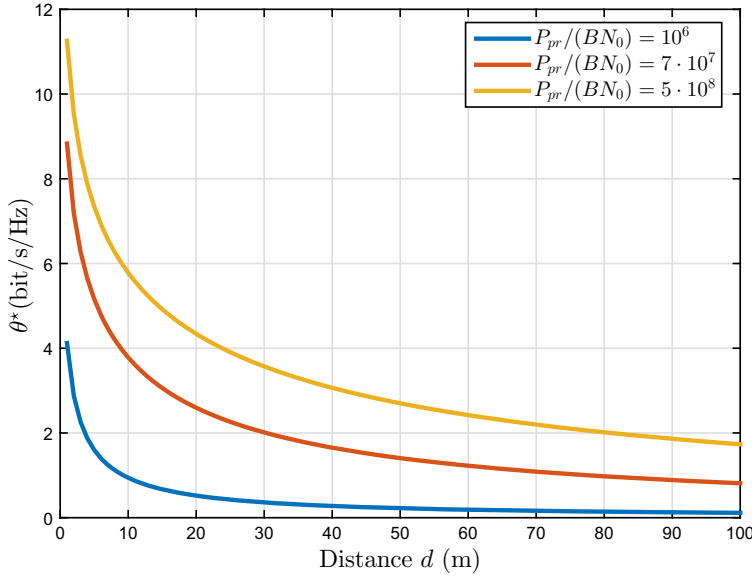


Fig. 3 Optimal SE for different circuit power

amplified by the baseband amplifier before going through the analog-to-digital converter (ADC) to convert back to a digital signal.

In practice the overall power consumption of the link is composed by the transmission power and the hardware-circuitry power. Thus, we adopt in this work a more realistic double linear power consumption model. The power consumption of the power amplifier depends on the transmit power, while the DAC and the ADC power consumption is linearly dependent on bandwidth [17]. In addition to the RF power consumption, the power model includes also the baseband consumption part which is proportional to the bandwidth since the clock frequency scales with the band [28]. This justifies the general power consumption model in (3). Here, P_{pr} is composed of the RF power and the baseband power:

- The RF power includes a constant power consumption part P_c referring to most analog components, e.g., LNA, filters and a bandwidth dependent power consumption part that comes mainly from the DAC and the ADC. The overall RF power is equal to $P_c + \vartheta_t B + \vartheta_r B$, where ϑ_t and ϑ_r are respectively the power coefficients of the DAC and the ADC;
- The baseband power consumption is linearly dependent on bandwidth as $\varepsilon_t B + \varepsilon_r B$, where the coefficients ε_t and ε_r are respectively the power coefficient of the transmitter and the receiver.

Finally, according to the aforementioned explanations, the total power consumption is

$$P_{tot} = \alpha P_t + \varepsilon B + P_c \tag{15}$$

where

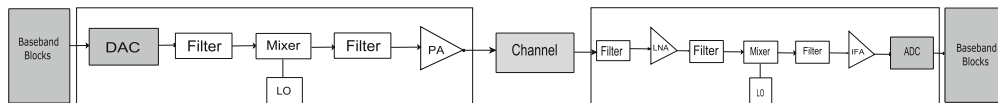


Fig. 4 Communication link model with block diagram of transmitter and receiver hardware

$$\begin{aligned}
P_c &= 2(P_{\text{mix}} + P_{\text{syn}} + P_{\text{filt}}) + 3P_{\text{filtr}} + P_{\text{IFA}} + P_{\text{LNA}} + c_{\text{fa}} + c_{\text{fd}} \\
\varepsilon &= \vartheta_t + \vartheta_r + \varepsilon_t + \varepsilon_r
\end{aligned} \tag{16}$$

The corresponding coefficients values of the total power with their definitions are provided in Tables 1 and 2.

3.2 Scenario and Energy Parameters

We assume that the transmitter needs to communicate L bits of information at a given deadline T . We assume also that the transceiver circuitry operates on multi-mode basis, i.e., (1) when there is a signal to transmit, the circuits are in active mode, we denote the active duration by T_{on} and the corresponding consumed power by P_{on} ; (2) when there is no signal to transmit, the circuits operate in a sleep mode, we denote the sleep duration by T_{sp} and the corresponding consumed power by P_{sp} ; (3) the circuits are in transient mode during the switching process from sleep mode to active mode, we denote the transient duration by T_{tr} and the corresponding consumed power by P_{tr} . We assume that the transient duration from active mode to sleep mode is short enough to be neglected. But, the transient duration from sleep mode to active mode may be slower due to the settling time of the phase-locked loop in the frequency synthesizer. So, the total transmission period is defined by

$$T = T_{\text{on}} + T_{\text{tr}} + T_{\text{sp}} \tag{17}$$

Hence, the total energy required to transmit and receive L bits is expressed as

$$E = P_{\text{on}}T_{\text{on}} + P_{\text{tr}}T_{\text{tr}} + P_{\text{sp}}T_{\text{sp}} \tag{18}$$

We assume that all sensors are equipped with similar transmitter and receiver circuit blocks and that the power consumption of the active filters at the transmitter and receiver are similar. It is noted that the power consumption during the transient mode is equal to the power consumption of the frequency synthesizer and thus $P_{\text{tr}} = 2P_{\text{syn}}$. In realistic circuit designs, the power consumption of the sleep mode can be considered as negligible compared with the active mode so $P_{\text{sp}} \simeq 0$. P_{on} is equal to the sum of transmitter and receiver circuit power thus $P_{\text{on}} = P_{\text{tot}}$. Based on this, the total energy per information bit is expressed as

Table 1 Coefficients for energy consumption model

Coefficient	Description	Value
ε_t [29]	Coefficient related to the transmitter baseband consumption	4.09×10^{-9} W/Hz
ε_r [29]	Coefficient related to the receiver baseband consumption	1.62×10^{-9} W/Hz
ϑ_t [16]	Coefficient related to the transmitter RF component whose power consumption in bandwidth dependent (DAC)	2.16×10^{-10} W/Hz
ϑ_r [16]	Coefficient related to the receiver RF component whose power consumption in bandwidth dependent (ADC)	7.56×10^{-8} W/Hz
c_{fd} [16]	Constant power of DAC	0.0615 W
c_{fa} [16]	Constant power of ADC	0.0378 W

Table 2 System parameters

Parameter	Value	Parameter	Value
f_c : carrier frequency	2.4 GHz	T : transmission period	100 ms
P_e : BER	10^{-3}	T_{tr} : transient time	5 μ s
N_0 : noise spectral density	-204 dB J	N_f : figure noise	10 dB
α : amplifier's efficiency	2.9	P_{LNA} : LNA power consumption	20 mW
k : path-loss coefficient	3.5	P_{syn} : frequency synthesizer power consumption	50 mW
G_1 : power gain factor	30 dB	P_{IFA} : IFA power consumption	3 mW
M_l : link margin	40 dB	P_{filt}, P_{filtr} : active filters power consumption	2.5 mW
L : packet size	2 kbits	P_{mix} : mixer power consumption	30.3 mW

$$E_{bt} = \frac{P_{tot}T_{on} + 2P_{syn}T_{tr}}{L} \quad (19)$$

3.3 Relationship Between θ , T_{on} and Constellation Size b

We consider in the rest of the analysis an uncoded MQAM system in AWGN channel. Denote $M = 2^b$ the constellation size where b is the number of bits per symbol. Hence the corresponding spectral efficiency is equal to $\log_2 M$. On the other hand, suppose a symbol rate equal to the bandwidth B of the signal. Transmitting L bits requires a bit rate equal to L/T_{on} . Therefore the following equalization can be easily given

$$\theta = \log_2(M) = \frac{L}{BT_{on}} = b \quad (20)$$

In the rest of the analysis, b will be used instead of θ since it is a particular value of the overall spectral efficiency.

4 Spectrum and Energy Efficiency Trade-Off

As established in the previous section, the energy per bit for a variable rate system can be expressed as

$$E_{bt} = \frac{(\alpha P_t + \varepsilon B + P_c)T_{on} + 2P_{syn}T_{tr}}{L} \quad (21)$$

The signal to noise ratio (SNR) per bit γ can be expressed as

$$\gamma = \frac{P_t}{BN_0N_fM_lG_1d^kb} \quad (22)$$

where N_f represents the receiver noise figure and M_l is the link margin compensating the hardware process variations and others additive background noises or interferences. By plugging (22) into (21), we obtain

$$E_{\text{bt}} = \alpha N_0 N_f M_l G_1 d^k \gamma + \frac{\varepsilon + P_c/B}{b} + 2P_{\text{syn}} \frac{T_{\text{tr}}}{L} \quad (23)$$

4.1 Bit-Error Rate (BER) Approximation and Analysis

To formulate E_{bt} as a function of BER, we need to find an analytic expression of the SNR per bit γ which depends on the target BER. The upper bound of the BER for coherently detected MQAM with Gray mapping over an AWGN channel is given by [30]

$$P_e \leq \frac{4}{b} \left(1 - 2^{-b/2}\right) Q\left(\sqrt{\frac{3b\gamma}{2^b - 1}}\right) \quad (24)$$

To estimate the SNR as a function of BER, many works have been yield to make the result more close to the exact one [31–33]. A well-known approximation is based on the Chernoff-bound which has the advantage of being simple and invertible in order to obtain a closed-form expression of the SNR. The correspondent approximation of P_e is then [17]

$$P_e \approx \frac{4}{b} \left(1 - 2^{-b/2}\right) \exp\left(-\frac{3b\gamma}{2(2^b - 1)}\right) \quad (25)$$

On the other hand, a tighter approximation of Q based on series expansion is given in [32], and yields to

$$P_e \approx \frac{2}{\sqrt{\pi}} \frac{(1 - 2^{-b/2})}{b} \sqrt{\frac{(2^b - 1)}{3b\gamma}} \exp\left(-\frac{3b\gamma}{2(2^b - 1)}\right) \quad (26)$$

This equation gives an exact expression for $b = 2$ and a very good approximation for $b > 2$ for a BER lower than 10^{-2} . Figure 5 plots the BER approximation (25) (referred by *approx 1*) and our proposed approximation (26) (referred by *approx 2*) as a function of SNR. It can be seen from Fig. 5 that *approx 2* is more close to the exact BER [33] than *approx 1* for BER lower than 10^{-1} . By the use of the Lambert W function we can express the signal-to-noise ratio per bit and obtain

$$\gamma = \frac{2}{3} W_L \left(\frac{8}{\pi} \left(\frac{1 - 2^{-b/2}}{bP_e} \right)^2 \right) \frac{2^b - 1}{b} = \Gamma(b) \frac{2^b - 1}{b} \quad (27)$$

where $\Gamma(b)$ refers to the SNR per bit gap.

Finally by exploiting (27), (23) can be expressed as

$$E_{\text{bt}} = \alpha N_0 N_f M_l G_1 d^k \Gamma(b) \frac{2^b - 1}{b} + \frac{\varepsilon + P_c/B}{b} + 2P_{\text{syn}} \frac{T_{\text{tr}}}{L} \quad (28)$$

Note that the rightmost factor of (28) has exactly the same scaling behavior $(2^b - 1)/b$ as the Shannon limit in (2). Moreover, the additional gap $\Gamma(b)$ which depends on P_e leads to increase the energy expenditure of the system. Hence apart energy consumption, the QoS introduced by P_e can be of main impact on the global optimization when studying the EE–SE tradeoff.

Further, we can see that the first term in (28) is monotonically increasing function of b for each value of d and k , while the second term is monotonically decreasing function of

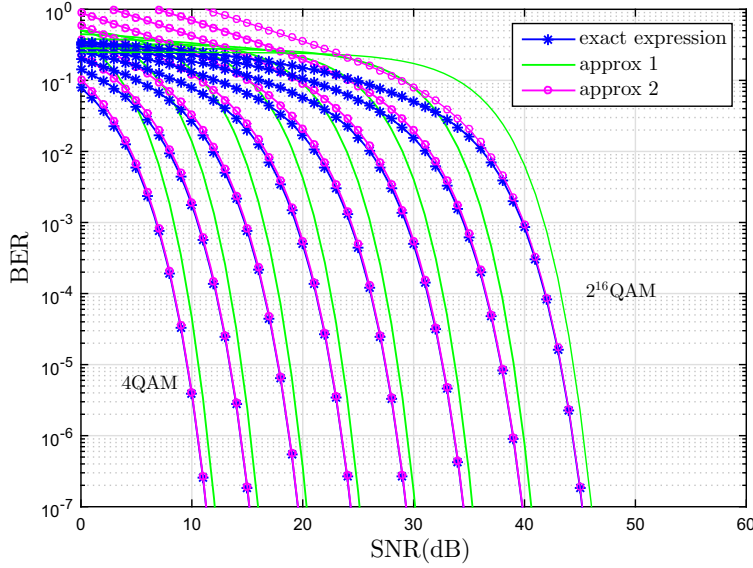


Fig. 5 Comparison between different BER approximation with the exact one

b and L which is independent of d and k . In this case, there exist two scenarios based on the distance d :

- For large values of d where the first term in (28) is dominant, the objective function E_{bt} is a monotonically increasing function of b and is minimized at $b = 2$, equivalent to 4-QAM scheme;
- In the case of a small distance d , there is one possible situation that may happen when the total transmission energy for small size of b is dominated by the second term in (28). For such situation, there are two regions. The first is when b is small. The energy behaves as a monotonically decreasing function of b . The second region is for large value of b , when b grows. The total energy becomes monotonically increasing, meaning that the first term is dominant over the second one.

Thus, the optimal constellation size should provide a balance between these effects.

4.2 Optimal Spectral Efficiency Expression

Trying to find a closed form of b^* for uncoded MQAM in the case of AWGN, the following assumptions can be made. We first assume that $2P_{syn} \frac{T_{tr}}{L}$ can be neglected compared to the two others quantities. Then (28) becomes,

$$E_{bt} = \alpha N_0 N_f M_l G_1 d^k \Gamma(b) \frac{2^b - 1}{b} + \frac{\varepsilon + P_c/B}{b} \quad (29)$$

the above equation reveals the difference between the Shannon-limit case (4) and the practical case when the BER is introduced within the system gap term.

As we seek to provide a closed-form solution of (29), we apply the approximation $\Gamma(b) \approx \frac{2}{3} \ln(\frac{1}{3.10^{-1} P_e})$. In fact, the relative looseness caused by this approximation is less than 0.7 dB when b is in the range of $[2, 18]$, which is reasonable range for practical MQAM systems. This result shows that the gap is independent of b . Note that this gap adds

a fairly constant distance to the Shannon-limit compared to the exponential behavior of $(2^b - 1)/b$. Thus the optimization results for MQAM will correspond closely to the Shannon-limit optimization. Consequently the different lemmas and interpretations derived in Sect. 2 remain valid for MQAM modulation. Based on that, (28) can be rewritten as

$$E_{bt} \simeq \frac{2}{3} \alpha N_0 N_f M_l G_1 d^k \ln \left(\frac{1}{3 \times 10^{-1} P_e} \right) \frac{2^b - 1}{b} + \frac{\varepsilon + P_c/B}{b} \quad (30)$$

Note that the above equation has almost the same form as (4). Having resolved that for a general form in Lemma 3, the solution of (30) w.r.t b is

$$b^* \simeq \left\lfloor \frac{1}{\ln 2} \left(1 + W_L \left(\frac{3(\varepsilon + P_c/B)}{2e\alpha N_0 N_f M_l G_1 d^k \ln \left(\frac{1}{3 \times 10^{-1} P_e} \right)} - \frac{1}{e} \right) \right) + \frac{1}{2} \right\rfloor. \quad (31)$$

5 Numerical Results

In this Section we present different numerical results in order to evaluate the previous analysis and to corroborate the insight about the impact of system parameters in Sect. 2. The considered system parameters are summarized in Tables 1 and 2. Most of them followed those in [16]. By varying some system parameters according to (28), when both transmit energy with the corresponding QoS constraint and circuit energy consumption are taken into consideration, the interpretations can be made as follows.

Figure 6 plots the total energy with respect to the constellation size b for different distances. The figure clearly shows that there exists an optimal constellation size that minimizes the total energy per bit for each distance. We observe that the energy per bit decreases first from the right side of the optimal point then it increases as the constellation size gets larger. The reason is that, for small constellation size, the transmission time T_{on} decreases and hence the circuit energy dominates over the transmit energy. On the other hand, when the constellation size gets larger, the system sends the information faster decreasing T_{on} thus the transmission energy becomes dominant over the circuit energy. This is in agreement with Lemma 1. As a result the optimal constellation size should provide a balance between these effects. We note also that the optimal point reduces when the distance increases. This agrees with Lemma 5. From an energy point of view, larger constellations sizes are preferred at small distances while small constellation sizes are performing well for large distances.

In Fig. 7, we illustrate the impact of bandwidth on the energy to spectral efficiency tradeoff for two different distances. For both cases, the behavior of the curves is the same. As we observe the energy decreases first until an optimal point of spectral efficiency and increases again. For the case of short distances $d = 5$ m, the influence of bandwidth is more obvious than of the larger distance. The interpretation is that when the distance is small, the circuit energy is predominant over that of transmission energy. Besides, as the bandwidth decreases, the transmission time T_{on} increases which increases also the circuit energy. This implies first a growth of the total energy and a shift of the optimal constellation size to larger values. On the other hand, when the distance becomes large, $d = 50$ m, the transmit energy becomes dominant. Then the optimal constellation size shifts to smaller values. This agrees with the discussion of Lemma 5.

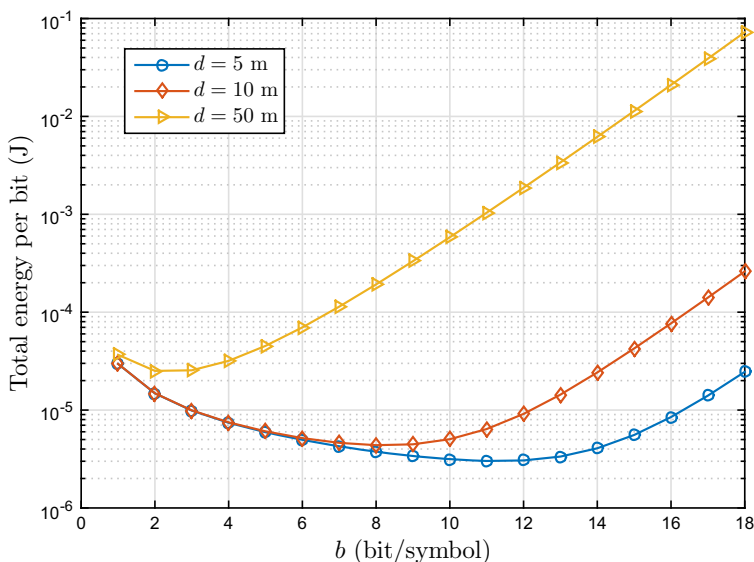


Fig. 6 Impact of distance variation ($B = 10$ kHz)

Figure 8 shows the energy to spectral efficiency tradeoff for $d = 5$ m and $d = 50$ m for different BER constraints. For short distance case, when the constellation size is small, the circuit energy dominates. As a result, the decrease of P_e from 10^{-2} to 10^{-3} does not affect this region whereas as the transmission energy becomes dominant, lower BER induces higher energy but reduces the optimal constellation size as deduced from (31). Intuitively, when the distance becomes larger, the energy per bit scales with the transmission energy that dominates over the processing one. Hence, when P_e decreases, we observe that the energy consumption increases. In that case, small constellation size achieves minimal energy consumption.

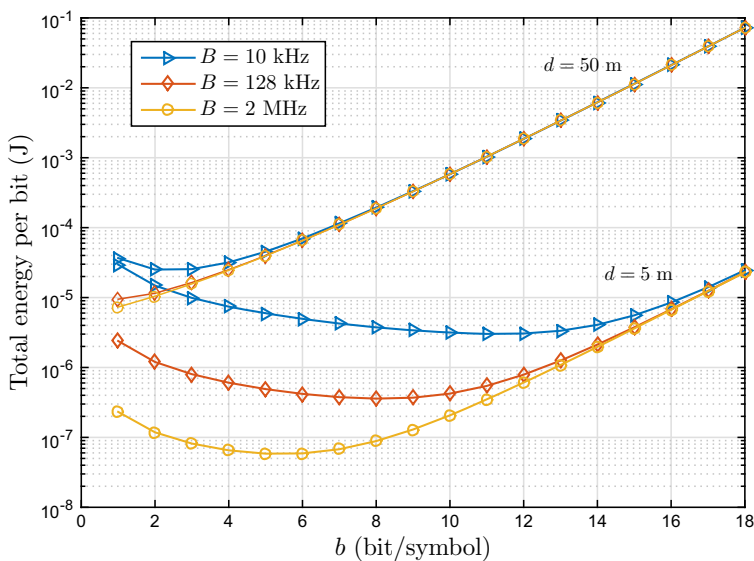


Fig. 7 Impact of bandwidth variation

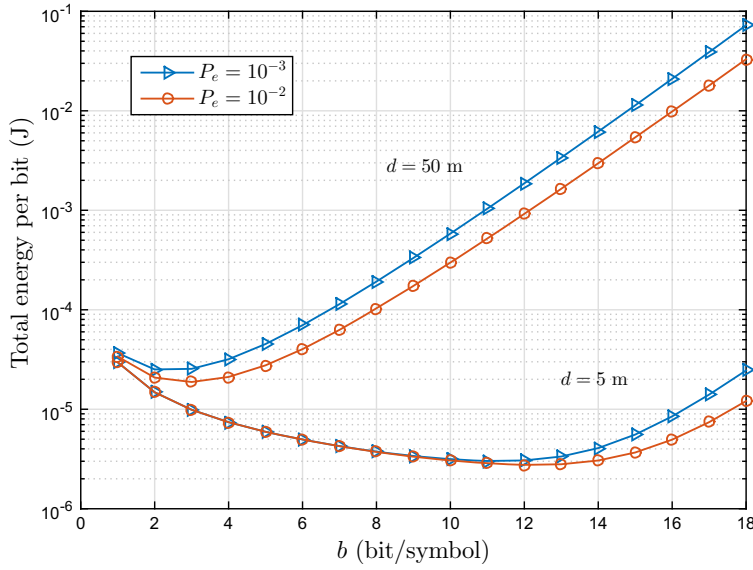


Fig. 8 Impact of BER (P_e), $B = 10$ kHz

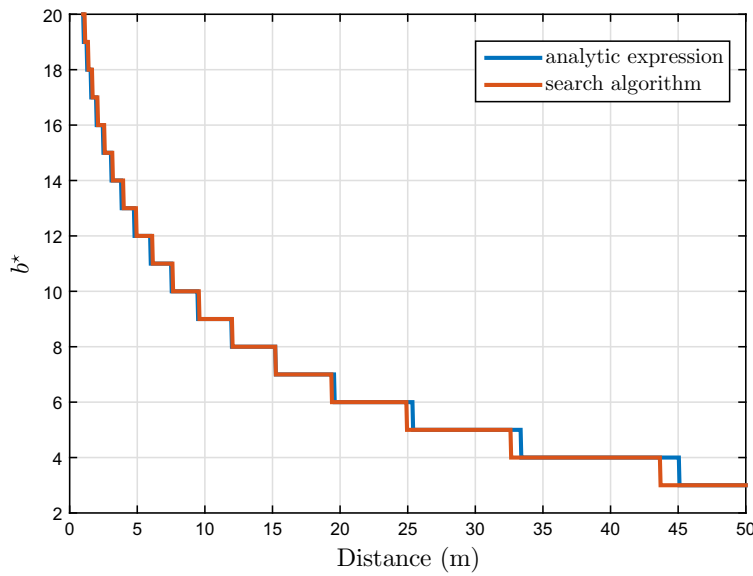


Fig. 9 Comparison between the analytic expression of b^* and the numerical one

Figure 9 plots the discrete value of the optimum SE b^* for each distance. This figure shows analytic and simulated results for b^* . We perform a Newton-Raphson method to find the optimum value from (28). As seen, our closed-form expression in (3) matches well with the numerical results.

6 Conclusion

In this paper, we have investigated the energy per bit and SE performance in the wireless short-range communicating systems. To formulate the energy expenditure, we show the importance of considering a real power consumption model for the system analysis. The link circuit power is modeled as a sum of bandwidth-dependent part and another part which is proportional to the transmission power. Theoretical analysis has been made to study the energy and SE tradeoff using the Shannon capacity in AWGN channel when a simple circuit power model is used. In that case, the total energy per bit as a function of SE is proven to be quasi-convex. We have also addressed the optimization of MQAM constellation size and the consumed energy per bit under BER constraint. A more accurate expression of the SNR as a function of BER has been developed and supported numerically. Then, the energy per bit as a function of the spectral efficiency was formulated. Through numerical results, several interesting observations with practical implications were made. It is seen that, from an energy point of view, large constellation size are preferred at short distances while small constellation size are favorable for large distances communication. But, short distances offer high energy and spectral efficiency conditions. In addition, we show that the bandwidth variation is more remarkable for the short distance case and that the optimal constellation size reduces when allocating larger bandwidth. We show also that higher power consumption lowers down the energy efficiency of the system but also increases the optimal spectral efficiency. Moreover, when varying the BER as a QoS parameter, it is observed that it impacts more the high SE region. Finally, a closed-form expression of the optimal constellation size and hence of the spectral efficiency is obtained and supported by numerical results.

Appendix

Proof of Lemma 1

The objective function E_{bt} can be bounded as follow: $\forall t \in]0, \theta]$ we have $1 \leq e^t \leq e^\theta$ so

$$\theta \leq \int_0^\theta e^t dt \leq \theta e^\theta \quad (32)$$

$$\theta \leq e^\theta - 1 \leq \theta e^\theta \quad (33)$$

$$1 \leq \frac{e^\theta - 1}{\theta} \leq e^\theta \quad (34)$$

$$\text{Hence,} \quad A \ln 2 + \frac{C}{\theta} \leq E_{bt}(\theta) \leq A 2^\theta \ln 2 \quad (35)$$

Finally, E_{bt} can be approximated to the right hand expression for low θ values and to the left hand expression for high θ values.

Proof of Lemma 2

First we express a general form of (4) as follow

$$E_{\text{bt}}(\theta) = A \frac{2^\theta - 1}{\theta} + C \frac{1}{\theta} \quad (36)$$

To prove the quasi-convexity of (4), we recall that for $\theta \geq 0$ a function is strictly quasi-convex if

$$S_\beta = \{\theta \geq 0 \mid E_{\text{bt}}(\theta) \leq \beta\} \quad (37)$$

is a strictly convex set for any real number β . Note that when $\beta \leq 0$, S_β is empty since $E_{\text{bt}}(\theta) > 0$. Hence S_β is strictly convex as no point exist on the contour. Now we investigate the case when $\beta > 0$. In such case, S_β is equivalent to $S_\beta = \{\theta \geq 0 \mid g(\beta, \theta) = A(2^\theta - 1) - \beta\theta \leq 0\}$. Since $g(\beta, \theta)$ is strictly convex in θ , if we take θ_1 and θ_2 two points of the contour of S_β ($\theta_1 > 0$ and $\theta_2 > 0$) then we have $\forall \theta \in (\theta_1, \theta_2)$, $g(\beta, \theta) < \max\{g(\beta, \theta_1), g(\beta, \theta_2)\} \leq 0$. The first inequality comes from the strict quasi-convexity of $g(\beta, \theta)$ w.r.t θ [34]. Hence, S_β is strictly quasi-convex set when $\beta > 0$. Thus we have the strict quasi-convexity of $E_{\text{bt}}(\theta)$.

Proof of Lemma 3

Setting the derivative of $E_{\text{bt}}(\theta)$ with respect to θ to zero we try to find the optimum spectral efficiency θ^\star . After rearranging the terms, we take the following steps

$$A \frac{\ln(2)e^{\ln(2)\theta} - e^{\ln(2)\theta} + 1}{\theta^2} = \frac{C}{\theta^2} \quad (38)$$

$$e^{\ln(2)\theta-1}(\ln(2)\theta - 1) = \frac{C - A}{eA} \quad (39)$$

by using the Lambert function W_L since it is the solution to $x = W_L(x) \exp(W_L(x))$ we have

$$\ln(2)\theta - 1 = W_L\left(\frac{C - A}{eA}\right) \quad (40)$$

$$\text{therefore} \quad \theta^\star = \frac{1}{\ln(2)} \left(1 + W_L\left(\frac{C - A}{eA}\right)\right) \quad (41)$$

Proof of Lemma 5

We begin by establishing the first inequality. Suppose that P_{pr} is independent of d then

$$\begin{aligned} E_{\text{bt}}(\theta^\star(d_2), d_2) &= \alpha N_0 G_1 d_2^k \frac{2^{\theta^\star(d_2)} - 1}{\theta^\star(d_2)} + \frac{P_{\text{pr}}}{\theta^\star(d_2)B} \\ &= \left(\frac{d_2}{d_1}\right)^k \alpha N_0 G_1 d_1^k \frac{2^{\theta^\star(d_2)} - 1}{\theta^\star(d_2)} + \frac{P_{\text{pr}}}{\theta^\star(d_2)B} \\ &> \alpha N_0 G_1 d_1^k \frac{2^{\theta^\star(d_2)} - 1}{\theta^\star(d_2)} + \frac{P_{\text{pr}}}{\theta^\star(d_2)B} > E_{\text{bt}}(\theta^\star(d_2), d_1) \geq E_{\text{bt}}(\theta^\star(d_1), d_1) \end{aligned} \quad (42)$$

The last inequality is due to the fact that $\theta^*(d_1)$ minimizes $E_{\text{bt}}(\theta(d), d_1)$. To prove the rest of lemma we set the derivative of (4) w.r.t θ and let $q(\theta(d)) = \frac{2^{\theta(d)}-1}{\theta(d)}$. By exploiting the fact that $\theta^*(d_1)$ is the solution of $E'_{\text{bt}}(\theta(d), d_1) = 0$, the following equality hold

$$\alpha N_0 G_1 d_1^k q'(\theta^*(d_1)) = \frac{P_{\text{pr}}}{\theta^{*2}(d_1)B} \quad (43)$$

By setting the derivative of $E_{\text{bt}}(\theta, d)$ w.r.t θ and using (43) it can be shown that

$$\begin{aligned} E'_{\text{bt}}(\theta^*(d_1), d_2) &= \alpha N_0 G_1 d_2^k q'(\theta^*(d_1)) - \frac{P_{\text{pr}}}{\theta^{*2}(d_1)B} \\ &= \left(\frac{d_2}{d_1}\right)^k \frac{P_{\text{pr}}}{\theta^{*2}(d_1)B} - \frac{P_{\text{pr}}}{\theta^{*2}(d_1)B} = \frac{P_{\text{pr}}}{\theta^{*2}(d_1)B} \left(\left(\frac{d_2}{d_1}\right)^k - 1 \right) > 0 \end{aligned} \quad (44)$$

As $E_{\text{bt}}(\theta, d)$ is strictly quasi-convex so $E'_{\text{bt}}(\theta, d) > 0$ when $\theta > \theta^*(d)$ and $E'_{\text{bt}}(\theta, d) < 0$ when $\theta < \theta^*(d)$. Therefore $\theta^*(d_1) > \theta^*(d_2)$.

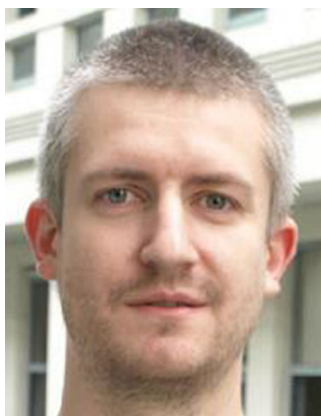
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Randa Jaouadi received a degree in telecommunication engineering from Ecole National d'ingénieurs de Tunis (ENIT) in 2013. Since then, she has been working towards a Ph.D. degree in Electronics at IETR (Institute of Electronics and Telecommunications of Rennes) Laboratory at the Université of Nantes.



Guillaume Andrieux received the M.S. degree in telecommunications and the Ph.D. degree in electrical engineering from the University of Nantes, France, in 2000 and 2004, respectively. He is currently an Associate Professor with the Networks and Telecommunications Department, University of Nantes. His current research interests are digital communications, antenna processing, energy efficiency in wireless networks and channel estimation.



Jean-Yves Baudais received the M.Sc. degree, and PhD degree in electrical engineering from the National Institute of Applied Sciences of Rennes (INSA), France, in 1997 and 2001 respectively. In 2002, he joined the French National Centre for Scientific Research (CNRS), where he is now researcher in the Institute for Electronics and Telecommunications of Rennes (IETR), Communication systems (SYSCOM) team. In 2014, he received the “habilitation à diriger les recherches” from the University of Rennes. His general interests lie in the areas of signal processing and digital communications: transmitter design, resource allocation, receiver diversity processing (space, time, frequency), multiuser and multicarrier processing, network performance measure with point process model, energetic performance evaluation and radar signal processing.



Jean-François Diouris received the Ph.D. from the University of Rennes in 1991. From 1991 to 2000, he was an Assistant-professor in IRESTE, Université de Nantes. He is currently a Professor in Ecole Polytechnique de l'Université de Nantes. His research interests mainly concern digital communications. Since 2012, he has been the vice-director of the Institute of Electronics and Telecommunications of Rennes (IETR).