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Abstract—**This paper concentrates on characterizing energy, latency and capacity trade-offs in multi-hop wireless ad-hoc networks. Therefore, a multiobjective framework is proposed to derive the Pareto-optimal set of solutions with respect to these three criteria. The work presented in this paper assumes a linear network where transmission powers and relay positions are optimization variables. We study the asymptotic state where the distance between source and destination is very high such that the number of hops tends to infinite. Two types of traffic are considered in the following. First, low rate traffic is analyzed by characterizing the multiobjective performance of a single packet transmission using an interference free multi-hop relaying strategy. Second, a continuous flow of packets from a unique source is considered. In the first case, we show an important theorem which states that all Pareto optimal solutions with respect to delay and energy metrics provide the same target SNR at the receiver side. In the second case, our analytical results highlight how the energy/delay Pareto front moves when considering a capacity constraint and the optimal re-use factor is derived.**

I. INTRODUCTION

Evaluating the capacity of wireless ad hoc networks is an important issue that has triggered a comprehensive research effort under various conditions since the seminal work of Gupta and Kumar [1]. Several works provided ways for increasing the asymptotic capacity bound of $O(n\ log(n))$ [1], [2] by for instance accounting for mobility [3] or introducing multi-user detection techniques [4]. Globally optimizing capacity for two-dimensional networks where routing and resource allocation (i.e. frequency, time or power assignment) are performed concurrently is a very hard problem. Toumpis et al. [5] have proposed an interesting model to derive the capacity by properly scheduling transmissions and hence accounting for a temporal multiplexing directly in a 2 dimensional network model. While the model is appealing, the computation of optimal solutions for large networks is intractable due to the size of the search space.

A more tractable way to optimize multi-hop schemes is to consider a unique path in the network which can be assimilated to a linear network [6]–[10]. This leads to an optimization problem where the main variables are the transmission powers and locations of the relays. Common optimization objectives are energy minimization, latency minimization and capacity maximization.

Such a linear network model offers an important framework to derive a comprehensive analytical study of multihop transmission and has been investigated in the following works.

In [7], the authors have proposed to adapt the selection of the relays and their relative transmission powers to optimize power limited or bandwidth limited systems. Capacity and radiated energy are optimized but solutions using a high number of relays are favored since circuit energy is not accounted for. Further, no latency criterion is addressed. In [6] a circuit energy model is introduced for a direct single hop transmission. The same model is applied in [8] to evaluate multi-hop strategies but for fixed relay nodes. In their latest paper [10], the authors search for the multi-hop strategies maximizing the total throughput that also minimize the energy consumption. However, they do not account for interference in their model. They have extended their work to a spatial multiplexing context [9] but for a fixed set of relay nodes and the problem still concentrates on finding optimal powers.

The work presented in this paper pursues the same objectives and our contribution resides in the derivation of a multiobjective framework to optimize concurrently energy, delay and capacity. Results are here derived for a system where not only transmission powers are variable but also locations of relays can be adjusted. Analytical results rely on an asymptotic model where relays can be regularly positioned on a quasi-infinite line. In the first part of this work, we focus on the optimization of a single packet transmission when no spatial multiplexing is considered as in [10]. We derive the analytical Pareto front for the energy/latency trade-off, extending our previous work [11] which concentrated on computing these bounds only for specific modulations and coding techniques. In this paper, we provide a more general formulation where the achievable bound is characterized for any monotonically increasing capacity function. A specific derivation using the Shannon capacity illustrates the framework. We exhibit an important theorem which states that any Pareto optimal solution verifies the unique condition that the SNR at the receiver side is equal to an optimal SNR $\hat{\gamma}_r$. Our model is further extended to the case where a continuous flow is transmitted in the network. In this case, a channel re-use distance is introduced and interference is modeled as an additive Gaussian noise as in [7]. We first prove that the previous optimal SNR $\hat{\gamma}_r$ still holds as a bound but can be relaxed to target a specific capacity constraint. More specifically, the Pareto optimal set of solutions with respect to capacity maximization and energy/latency minimization is assessed by setting the received SNR in the range $\gamma_r \in [\hat{\gamma}_r; \infty]$.

Section II introduces the model, assumptions and param-

eters. The energy-per-bit and delay-per-bit objectives are defined. In Section III, the classical Shannon limit is revisited for a single hop transmission providing the latency/energy Pareto bound. In Section IV, the multi-hop transmission problem for a single packet transmission is addressed. The corresponding continuous flow problem is studied in Section V and Section VI concludes the paper.

II. MODEL AND PARAMETERS

A point to point transmission is being considered first. The transmission power density normalized with respect to the receiver noise power is denoted by $\gamma_e = \frac{P_E/W}{N_0}$, with P_E the transmission power and W the frequency bandwidth. On the receiver side, the normalized power density is the classical SNR denoted γ_r and in the rest of the paper, all power and energy densities are normalized with respect to N_0.

The propagation environment is assumed homogenous, i.e. $\gamma_r = A(e,r) \cdot \gamma_e$ with:

$$A(e,r) = A_0 \cdot d_{er}^{-n} \qquad (1)$$

where n is the pathloss coefficient, d_{er} the emitter-receiver distance. The radio link capacity is:

$$C = W \cdot c(\gamma_r) \qquad (2)$$

where the capacity per Hertz function $c(x)$ is supposed continuously derivable and monotonic. This function is noted $c_g(x) = \log(1 + x)$ for the Gaussian channel.

For a given information quantity Q_i, the direct transmission delay D_i is given by $D_i = Q_i/C$, which can be expressed as a delay-per-bit (latency):

$$D_b = D_i/Q_i = C^{-1} \qquad (3)$$

The normalized radiated energy for transmitting Q_i is:

$$E_i = \gamma_e \cdot W \cdot D_i \qquad (4)$$

An additive component E_c is introduced which stands for circuit energy and losses at both transmitter and receiver sides [6], [11]: $E_t = E_i + E_c$. This energy can also be normalized as an energy-per-bit quantity:

$$E_b = E_t/Q_i \qquad (5)$$

III. SINGLE HOP TRANSMISSION OPTIMIZATION

In this section, Shannon's classical limit is revisited to express the energy/latency trade-off for transmitting Q_i information bits. Capacity can be omitted because in a single hop transmission, capacity and latency are directly related to each other by (3). Thus, the following problem is considered: having a transmitter and a receiver at distance d_{er}, what would be the optimal transmission power to concurrently reduce latency and energy consumption?

A. Optimization for ideal transceivers

Let's first consider a null circuit energy (i.e. $E_c = 0$), thus:

$$E_b = \gamma_e \cdot D_i \cdot W/Q_i \qquad (6)$$

Introducing (3) and (2), leads to:

$$E_b = \gamma_e \cdot W/C = \frac{\gamma_e}{c(A(e,r) \cdot \gamma_e)} \qquad (7)$$

Besides, introducing (2) into (3) provides the delay per bit expression:

$$D_b = \frac{1}{W \cdot c(A(e,r) \cdot \gamma_e)} \qquad (8)$$

Equations (7) and (8) give together the closed-form expression of the energy-latency Pareto front. The Pareto front represents the solutions that provide the best possible compromises between the considered performance metrics. In our case, it represents the optimal lower bound on the energy-latency trade-off. The compromise between both constraints is adjusted by setting the transmission power.

The inversion of (8) allows to express γ_e as a function of a given delay constraint D_b:

$$E_b = \frac{W \cdot D_b \cdot c^{-1}(1/W.D_b)}{A(e,r)} \qquad (9)$$

In the Gaussian case, the Shannon's limit is obtained:

$$E_b = \frac{W \cdot D_b \cdot (2^{1/W.D_b} - 1)}{A(e,r)} \qquad (10)$$

This curve delimits the achievable region (above the curve) as represented in Fig.1 for $A(e,r) = 1$. Any solution on this curve is Pareto optimal with respect to energy and latency.

B. Effect of circuit energy

For the case of non perfect transceivers, an additional circuit energy is consumed (10):

$$E_b = \frac{W \cdot D_b \cdot c^{-1}(1/W.D_b)}{A(e,r)} + \frac{E_c}{Q_i} \qquad (11)$$

The circuit energy can be approximated [10] by:

$$E_c = E_{c0} \cdot Q_i + E_\delta \cdot D_i \cdot W \qquad (12)$$

where E_{c0} stands for the normalized digital circuit energy-per-bit related to data processing and $E_\delta \cdot D_i \cdot W$ for the RF normalized per-bit-energy. Substituting (12) into (11) we get:

$$\begin{aligned} E_b &= \frac{W \cdot D_b \cdot c^{-1}(1/W.D_b)}{A(e,r)} + E_{c0} + E_\delta \cdot D_b \cdot W \\ &= W \cdot D_b \cdot \left(\frac{c^{-1}(1/W.D_b)}{A(e,r)} + E_\delta \right) + E_{c0} \end{aligned} \qquad (13)$$

The constant circuit energy E_{c0} only shifts the curve along the energy axis and will be discarded in the rest of the paper. On the opposite, the component E_δ strongly affects the Pareto bound in the low power region, as illustrated in Fig.1 for $A(e,r) = 1$. The plot of Fig.1 clearly shows that the RF energy-per-bit affects the right part of the curve and therefore reduces the achievable region. This figure exhibits the existence of a unique minimal energy solution, which limits the Pareto set to solutions with higher energy consumption.
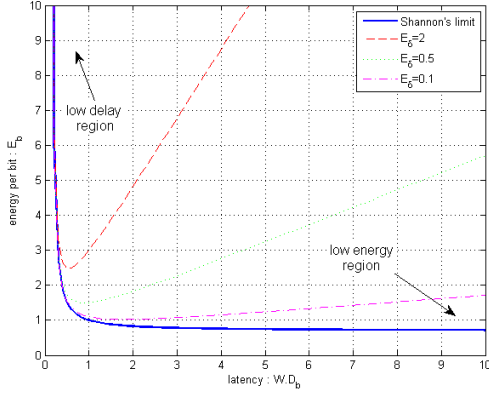
Fig. 1. Shannon's theoretical bound delimits the achievable region (above the curve) and represents the evaluation of the set of Pareto optimal solutions for energy/latency minimization. The RF energy consumption E_δ strongly affects the low energy region, and reveals an energy optimum point.

IV. LOW RATE MULTI-HOP OPTIMIZATION

The previous section just revisited Shannon's well-known limit which is hereafter extended to the case of a multi-hop transmission. The problem is now to find what are the relay positions and their respective transmission powers achieving a Pareto optimal efficiency with respect to latency and energy criteria. This problem has been partially studied in [11] but only for specific transmission conditions where a link is characterized by its packet error rate and not its capacity. We here broaden the proposed formulation to a more general channel capacity model, allowing to derive an analytic expression of the optimal SNR. A similar problem has also been studied in [10] but the authors studied the case of fixed relays where only transmission powers can be optimized. They also consider the problem of energy minimization but without accounting for any latency constraint. Further, their optimal solutions are derived for specific scenarios while we concentrate on giving an asymptotic optimal solution.

A. Theoretical Pareto front

Let's consider that an information quantity Q_i has to be transmitted over a very long distance and that we are free to choose the number and the location of the relays in order to optimize the transmission. The objective is to increase as much as possible the energy/delay feasible region, when compared to a direct transmission. In a homogeneous environment where the attenuation is just a function of the transmitter-receiver distance, the optimal solution corresponds to a regular distribution of the relays [7], [11], [12], providing all relays with the same power. Therefore, the optimization problem relies on finding the couple (d_h, γ_e) where d_h is the inter-node distance, and γ_e the transmission power density. In this section, the transmission is interference free since the relays do not transmit simultaneously and a single packet is considered (see Fig.2).

Energy and latency constraints are now differentiated with respect to the distance, to obtain an asymptotic model, as

proposed in [12]:

$$
\begin{aligned}
\partial E_b(d_h, \gamma_e) = E_b/d_h = \frac{\gamma_e + E_\delta}{d_h \cdot c(A_0 \cdot d_h^{-n} \cdot \gamma_e)} \\
\partial D_b(d_h, \gamma_e) = D_b/d_h = \frac{1}{d_h \cdot W \cdot c(A_0 \cdot d_h^{-n} \cdot \gamma_e)}
\end{aligned}
\tag{14}
$$

These parametric equations represent respectively the energy and delay needed to transmit one bit over one meter referred to as the per-bit-per-meter energy, and the per-meter bit latency, as a function of (d_h, γ_e). The total latency and per-bit energy are derived after multiplying with the total distance d_{tot}.
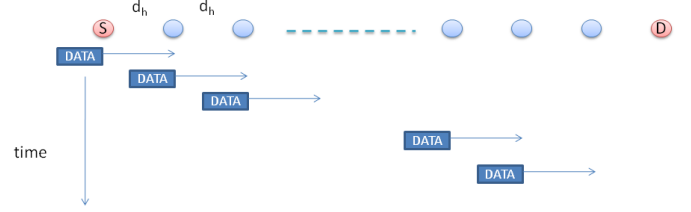

Fig. 2. The first scenario concerns the transmission of a single packet along a line, with a regular multi-hop approach

The achievable region bound can be assessed from (14). The problem relies on finding the couples (d_h, γ_e) that are Pareto optimal. We now change (14) thanks to the attenuation model given in (1) to work with (γ_r, γ_e) instead of (d_h, γ_e). This simple variable change allows to draw very interesting conclusions as stated now.

(14) can be rewritten as such:

$$
\begin{aligned}
\delta E_b(\gamma_e, \gamma_r) = \frac{\gamma_e + E_\delta}{(A_0 \cdot \gamma_e)^{1/n}} \cdot \frac{\gamma_r^{1/n}}{c(\gamma_r)} \\
\delta D_b(\gamma_e, \gamma_r) = \frac{1}{W \cdot (A_0 \cdot \gamma_e)^{1/n}} \cdot \frac{\gamma_r^{1/n}}{c(\gamma_r)}
\end{aligned}
\tag{15}
$$

These equations turn out to be separable with respect to γ_e and γ_r, i.e. $\delta E_b(\gamma_e, \gamma_r) = f_E(\gamma_e) \cdot g_E(\gamma_r)$ and $\delta D_b(\gamma_e, \gamma_r) = f_D(\gamma_e) \cdot g_D(\gamma_r)$. Further, highlighting that g_E and g_R are both equal to $g(\gamma) = \frac{\gamma^{1/n}}{c(\gamma)}$, leads to the following theorem:

Theorem 1: In a homogeneous environment characterized by a power-law attenuation (1) and a capacity function $c(\gamma_r)$ monotonically increasing, a regular linear network is Pareto optimal with respect to energy and latency if and only if :

$$
\hat{\gamma}_r = \arg\min g(\gamma) \tag{16}
$$

$$
\hat{\gamma}_e \geq \frac{E_\delta}{n-1} \tag{17}
$$

If $c(\gamma_r)/c'(\gamma_r)$ is monotonous, the solution of (16) is unique.

Proof: First, the cost functions are separable with respect to γ_r and γ_e. Second, γ_r and γ_e are independent because the inter-node distance is not fixed. Since $g_E()$ and $g_R()$ are equal, the joint minimization of (15) with respect to γ_r is achieved only when $g(\gamma_r)$ is minimal, which prooves (16).

Concerning (17), the achievable bound varies with different parameters (e.g. $E_\delta, n, ...$) but always looks like the curve in

Fig.1. Thus, due to circuit energy, a minimal energy point exists. Therefore, the Pareto optimal set corresponds to the part of the achievable bound that is on the left of the minima, since on the right, both energy and latency increase. The minima correspond to $\hat{\gamma}_e = \arg\min f_E(\gamma_e)$. ∎

This result asserts that any solution on the Pareto front is obtained by jointly tuning γ_e and d_h to maintain $\hat{\gamma}_r$ constant. Therefore, the inter-node distance d_h can be used as a tunable parameter to fit with transmitter and receiver SNR constraints. Energy and latency are then balanced thanks to γ_e. A corollary of the previous theorem follows:

Theorem 2: In a homogeneous environment characterized by (1) and a capacity function $c(\gamma_r)$ monotonously increasing, a regular linear relaying network is Pareto optimal with respect to energy and delay if and only if γ_e and d_h are related by:

$$d_h^n = \frac{A_0}{\hat{\gamma}_r} \cdot \gamma_e; \forall \gamma_e \geq \frac{E_\delta}{n-1} \qquad (18)$$

Proof: Since γ_r is constrained by theorem 1, theorem 2 follows from (1). ∎

B. Energy minimization

The minimal per-bit-per-meter energy corresponding to $\hat{\gamma}_e$ is given by :

$$\partial E_b = \frac{n \cdot g_0}{(n-1)^{(n-1)/n}} \cdot \frac{E_\delta^{(n-1)/n}}{A_0^{1/n}} \qquad (19)$$

where $g_0 = g(\hat{\gamma}_r)$. One can highlight that the minimal per-bit energy depends only on the pathloss coefficient and the circuit energy. The corresponding per-meter bit latency is :

$$\partial D_b = \frac{(n-1)^{1/n} \cdot g_0}{W \cdot (A_0)^{1/n}} \cdot E_\delta^{-1/n} \qquad (20)$$
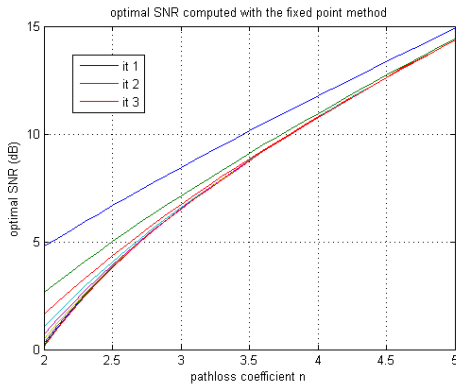

Fig. 3.   Optimal SNR $\hat{\gamma}_r$ as a function of the pathloss coefficient, and computed with the fixed point method which converges in a few iterations.

C. Application to Gaussian channels

Results can be evaluated for an ideal Gaussian channel.Solving (16) leads to:

$$n\gamma_r = (1 + \gamma_r) \cdot \log(1 + \gamma_r) \qquad (21)$$

The solution exists, is unique and is only a function of the pathloss coefficient n as shown in Fig.3. For instance, $n = 3$, $\hat{\gamma}_r = 6.5dB$ corresponds to $g_0 = g(\hat{\gamma}_r) = 0.67$. The minimal energy is $\partial E_b = 1.266 \cdot E_\delta^{2/3}/A_0^{1/3}$. The achievable region is depicted in Fig.4.
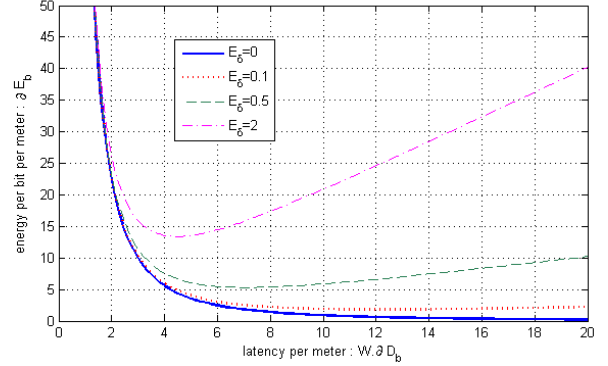

Fig. 4.   The Shannon's based frontier for the achievable region is represented for $A_0 = 1, n = 3$ and for different circuit energy values

V. HIGH RATE MULTI-HOP OPTIMIZATION

In the previous scenario, a relay transmits only one after the other and thus the capacity tends to 0 for an infinite linear network. Now, a continuous data flow transmission (see Fig.5) is studied thanks to a spatial re-use policy. We here aim at getting a picture of the compromises existing between the per-bit-per-meter energy, the per-meter bit latency and the capacity of the system.
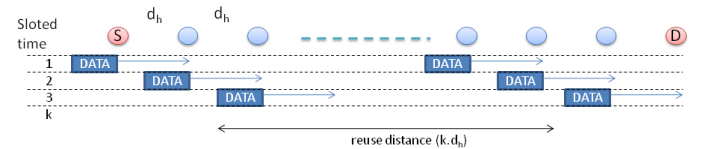

Fig. 5.   The second scenario corresponds to a transmission of a continuous flow along an infinite linear network using a regular spatial multiplexing

A. Problem formulation

Without loss of generality, let's consider a TDMA multiplexing scheme using k slots. The new optimization problem relies on finding the set of triplets $(k, \gamma_e$ and $\gamma_r)$ that achieves a Pareto optimal solution with respect to energy, latency and capacity.

For the link capacity, SINR Γ_I now replaces γ_r:

$$\Gamma_I = \frac{\gamma_r}{1 + I(k) \cdot \gamma_r}, \qquad (22)$$

where $I(k)$ is the relative received interference (see Fig.6) given by [7]: $I(k) = \sum_{i=-\infty}^{\infty} \beta_i(k)$. From simple geometric rules, one have:

$$I(k) = \sum_{i=1}^{\infty} \left((i \cdot k - 1)^{-n} + (i \cdot k + 1)^{-n} \right) \qquad (23)$$

The first and second terms in the sum correspond respectively to the forward and backward interference. A coarse approximation of (23) will be used for the sake of simplicity by considering only the first k interfering signal, i.e. $I(k) > (k-1)^{-n}$. The link capacity as a function of γ_r is obtained by putting (22) in $c(x)$:

$$c^{(k)}(\gamma_r) = c(\frac{\gamma_r}{1 + I(k) \cdot \gamma_r}) \qquad (24)$$

The system of equations (15) of Section IV still holds for the energy/latency trade-off and when there is no capacity constraint, the Pareto bound is achieved when $\hat{\gamma}_r^{(k)} = \arg\min g^{(k)}(\gamma_r)$.

The multi-hop capacity of the system is:

$$C_{mh}(\gamma_r, k) = \frac{c^{(k)}(\gamma_r)}{k} \qquad (25)$$

The maximal capacity is obtained for an infinite power:

$$C_\infty(k) = \lim_{\gamma_r \to \infty} C_{mh}(\gamma_r, k) = c(I(k)^{-1}) \qquad (26)$$

which can be bounded by $C_\infty(k) < \frac{c(1+(k-1)^n)}{k}$, thanks to the first order approximation of $I(k)$.
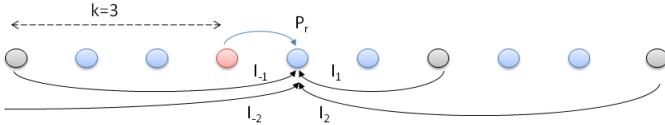

Fig. 6. The interference strength relies on the re-use factor in a periodic structure.

B. Optimization with a constant re-use factor

Let's now study how to trade between capacity, latency and energy for a specific re-use factor k.

Theorem 3: In a homogeneous environment characterized by (1) and a capacity function $c(\gamma_r)$, the Pareto optimal solutions with respect to capacity, energy and latency for a given re-use factor $k > 1$ are defined by the following constraints :

- the received SNR verifies: $\hat{\gamma}_r^{(k)} < \gamma_r < \infty$,
  with $\hat{\gamma}_r^{(k)} = \arg\min g^{(k)}(x) = x^{1/n}/c^{(k)}(x)$
- the transmitted power density γ_e verifies : $\gamma_e \geq E_\delta/(n-1)$.

Proof: First, note that capacity only depends on the received SINR Γ_I and is not affected by the couple (d_h, γ_e) if (18) is fulfilled. Obviously, the higher γ_r, the higher Γ_I and the higher the capacity. On the contrary, γ_r should be kept close to $\hat{\gamma}_r$ to cope with energy/latency constraints. Thus, γ_r allows to balance between capacity and energy/latency. For $\gamma_r < \hat{\gamma}_r$ the solution is not Pareto optimal since capacity decreases while energy and latency increase.

Second, (γ_e, d_h) values do not affect the capacity and can be used to balance latency and energy only. Note that the receive SINR Γ_I is bounded by $\hat{\gamma}_r/(1 + (k-1)^{-n} \cdot \hat{\gamma}_r) < \Gamma_I < (k-1)^n$ ∎

Note that the optimization problem was shown separable with respect to γ_e and γ_r. Besides, without latency constraint, the optimal transmitted power and inter-node distance are respectively $\tilde{\gamma}_e = \frac{E_\delta}{n-1}$ and $\hat{d}_h = \left(\frac{A_0 \cdot \tilde{\gamma}_e}{\tilde{\gamma}_r}\right)^{1/n}$ Thus, all energy/capacity optimal solutions are achieved with the same transmission power which means that adapting the node density instead of the transmission powers is the optimal strategy.

The two extrem cases corresponding to the minimal energy solution and to the maximal capacity are:

a) minimal energy solution: The minimal per-bit-per-meter energy is obtained for $\gamma_r = \hat{\gamma}_r^{(k)}$ and is proportional to $g_0^{(k)}$:

$$\partial E_b = \frac{n \cdot g_0^{(k)}}{(n-1)^{(n-1)/n}} \cdot \frac{E_\delta^{(n-1)/n}}{A_0^{1/n}} \qquad (27)$$

The corresponding capacity is $C_{mh}(\hat{\gamma}_r^{(k)}, k)$.

b) maximal capacity solution: The maximal capacity C_∞ (as defined in (26)) is achieved for an infinite SINR, and corresponds to an infinite per-meter-per-bit energy.
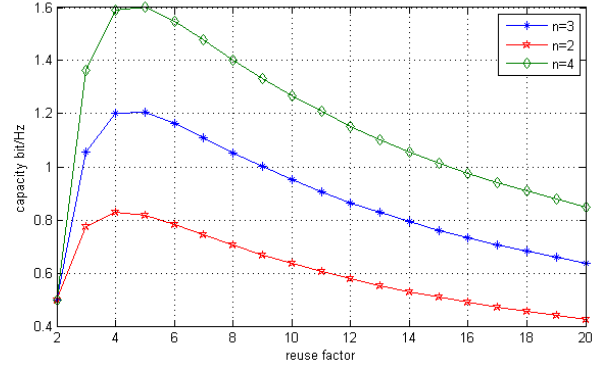

Fig. 7. Maximal capacity in bit/Hz in a Gaussian channel as a function of the attenuation factor n and the re-use factor k

C. Re-use factor optimization for Gaussian channels

The optimal re-use factor is the one corresponding to the maximal capacity under a given energy/latency constraint. We first consider the capacity bound $C_\infty(k) < \frac{c(1+(k-1)^n)}{k}$ which is a ratio of two mononitically increasing functions and the optimal value depends on the capacity function (see Fig. 7). This plot represents the maximal capacity that can be achieved with a non-limited transmission power. In a Gaussian channel, the optimal solution is $k \in \{4, 5\}$. Now the capacity objective has to be balanced with the energy/latency objectives.

From our previous analysis, the minimal SINR that allows to reach the energy/latency Pareto front is known but leads to a sub-optimal capacity $C_{mh}(\hat{\gamma}_r^{(k)}, k)$. This trade-off is illustrated on Fig.8 for a pathloss exponent $n = 3$. The achievable region bound between energy/latency and capacity is represented through $g(\gamma_r)$ and $C_{mh}(\gamma_r, k)$. The highest capacity is achieved for $k = 5$ but for a high SNR. We see on this figure how increasing k allows to decrease $g_0^{(k)}$ at the price of a reduced capacity. From $k = 2$ up to $k = 5$,

the achievable region increases significantly. For higher k values, the achievable region shifts to the left and thus favors energy/latency upon capacity. As a conclusion, we show that for $n = 3$, the smaller re-use factor is $k = 5$. When the energy constraint is very strong, k can be increased up to 10, but leads to a capacity loss of about 60%. Note that the minimal per-bit-per-meter energy is equal to the one computed with no multiplexing.
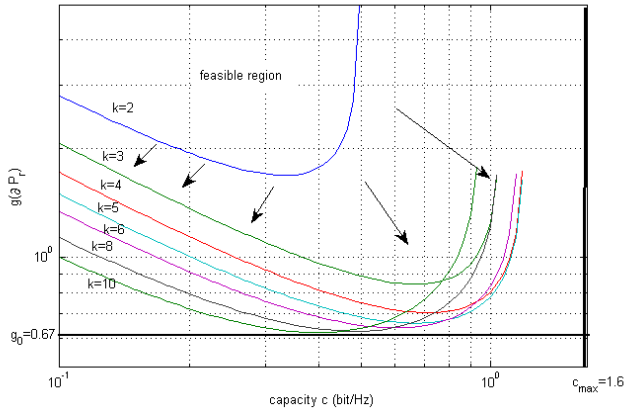

Fig. 8. The achievable region in terms of capacity vs energy/latency is given for different re-use factors. The highest capacity is achieved for $k = 5$.

VI. CONCLUSION AND DISCUSSIONS

In this paper, we derived a general approach to analyze how energy, latency and capacity are linked together. We have first evaluated the energy/latency trade-off for a single packet transmission over a regular linear network and derived optimal transmission power and inter-node distance accordingly.

From a practical point of view, we have proved that all optimal solutions with respect to latency and energy are achieved for a constant received SNR $\hat{\gamma}_r$ that is related to the capacity function and the path-loss coefficient only. On the other side, the optimal transmission power is obtained as a function of the circuit energy. The inter-node distance is then chosen to comply with the transmitting and receiving SNR constraints.

We have also extended this framework for a continuous flow by introducing a re-use factor. We have obtained the optimal re-use factor and derived the Pareto bound with respect to the three constraints of energy, latency and capacity. We proved that Pareto optimal solutions with respect to energy and capacity are obtained for a constant transmission power that is related to the circuit energy and the pathloss coefficient only. Then, the received SNR and the re-use factor k are set to fulfill a target capacity constraint, and the inter-nodfe distance is again used to comply with both sides constraints. The knowledge of the optimal inter-node distance can be exploited in real deployments, to optimize the nodes' density and thus to ensure a good probability of having some nodes at a right distance, or to define a good wake-up policy for a dense network.

These results claim that an optimal routing approach in a wireless sensor network, whatever the optimization constraints, should be rather based on selecting the relays located at the optimal inter-node distance, instead of changing the transmission powers if the environement is homogeneous. Further, it seems that controlling the received SINR to be constant is probably very efficient to comply with inhomogeneous environments.

These results are very complementary to those obtained previously in [7] and offer a very comprehensive framework to represent the performance of relaying approaches. Future works could propose to evaluate other relaying strategies within the same multi-objective framework such as:

- Interference mitigation or avoidance techniques can be evaluated by removing the forward interference in 23 [7].
- Amplify-and-Forward could be introduced in the model to allow several nodes on the line to cooperate.
- virtual MIMO techniques could be considered.

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