

Optimizing Transmission and Shutdown for Energy-efficient Packet Scheduling in Sensor Networks

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Abstract—Energy-efficiency is imperative to enable the deployment of sensor networks with satisfactory lifetime. Conventional power management in radio communication primarily focuses independently on the physical layer, medium access control (MAC) or routing and approaches differ depending on the levels of abstraction. At the physical layer, the fundamental trade-off that exists between transmission rate and energy is exploited. This leads to the *lazy scheduling* approach, which consists of transmitting with the lowest power over the longest feasible duration. At MAC level, power reduction techniques tend to keep the transmission as short as possible to maximize the radio's power-off interval. Those two approaches seem conflicting and it is not clear which one is the most appropriate for a given network scenario. In this paper, we propose a transmission strategy that combines both techniques optimally. We present a cross-layer solution to determine the best transmission strategy taking into account the transceiver power consumption characteristics, the system load and the scenario constraints. Based on this approach, we derive a low complexity, on-line scheduling algorithm that can be used to optimally organize the forwarding of the sensed information from cluster heads to the data sink (uplink) in a hierarchical sensor network. Results, considering Coded Frequency Shift Keying (FSK) modulation, show that depending on the scenario, a 50% extra power reduction is achieved in a realistic uplink data gathering context, compared to the case where only transmission rate scaling or shutdown is considered.

I. INTRODUCTION

Wireless sensor networks are autonomous networks for monitoring purpose, ranging from short-range, potentially *in vivo* health monitoring [1] to wide-range environmental surveillance [2]. Despite the huge variety of their potential applications, all sensor networks are severely constrained in terms of energy. Sensor nodes are small form factor battery powered devices and size constraints limit the battery capacity. In most cases, the density of the network or the vast environment where they are deployed prohibits a periodic

replacement of the batteries. This makes energy consumption very critical.

In a general way, the task of a sensor network consists of measuring a variable through the sensors, eventually (pre-) processing this information (e.g. to decide to forward it or not), and if opportune, transmitting the data to a data sink. It has already been shown in several design cases [3], [4] that some of the most critical energy consumers in a wireless sensor node are the radio electronics. Reducing the radio power dissipation is hence crucial to enable the deployment of sensor networks with satisfactory lifetime.

Currently, energy-efficient radio communication is tackled differently depending on the level of abstraction. At the physical layer, one tends to exploit the fundamental trade-off that exists between transmission rate and energy [5], [6]. The information theory has shown that the capacity of the wireless channel increases monotonically with the signal to noise ratio [7]. Hence, scaling down the transmission rate, i.e. reducing the required channel capacity allows decreasing the signal to noise ratio and therefore the signal power. This leads to the *lazy scheduling* approach [6], which consists of transmitting with the lowest power over the longest feasible duration.

From the network point of view, the *lazy scheduling* translates into trading-off user bandwidth (in terms of transmission time) for power. As a result, a schedule, energy-optimal for one user (i.e. which maximizes its time share of the wireless channel) might be heavily sub-optimal for the network, since other nodes contending for the channel will have to delay their transmission or speed it up if they have to meet a deadline. Moreover, *lazy scheduling* only optimizes the transmit power.

More specifically, it minimizes only the contribution of the electronics whose power consumption is proportional to the transmit power. Yet, in low- and middle-range radios, as mostly considered in sensor networks, an important part of the power dissipation (i.e. the contribution of the frequency synthesizer, the up-conversion mixers and the filters) is not proportional to the transmit power [8]. This motivates the approaches based on radio shutdown that tend to minimize the duty cycle of the radio circuitry, and therefore transmit as fast as possible. These approaches jointly consider the medium access and routing (topology management) [9], [10] but neglect the physical layer aspects.

At first issue, the *lazy scheduling* and the shutdown approaches seem conflicting. In this paper, we show that actually they correspond to two extreme cases and that most often, the optimal transmission strategy in a multi-user scenario consists of a cross-layer combination of both approaches. We present a solution to determine the best transmission strategy, taking into account the transceiver power consumption characteristics, the system load and the scenario constraints (e.g. the number of nodes and their distance to the Cluster Head). Based on this we derive a new scheduling algorithm that exploits jointly the energy savings that can be obtained from transmission rate downscaling and radio shutdown. The proposed algorithm is general: depending on the traffic constraints and on the relative impact of the transmission power to the circuit energy consumption, more transmission scaling or shutdown is considered. As practical radio implementations only allow a discrete set of transmission schemes, the discrete nature of the problem is taken into account in the system model and solution. Although central control is generally not considered for self-organizing sensor networks, it suits naturally the data gathering or monitoring applications. For instance the proposed protocol can be implemented to organize the forwarding of the sensed information from cluster heads to the data sink (uplink) in a cluster of a hierarchical sensor network (Fig. 1). As the scheduling optimally adapts to the distance and current number of CL's, it achieves the best energy savings for each instance of the hierarchical routing algorithm.

The remainder of the paper is organized as follows. In Section II, a detailed overview of related work is given and the contributions and specific focus of this paper are highlighted. Section III elaborates on the sensor energy and performance radio model. Taking into account all overheads, we present in Section IV the trade-off between rate scaling and shutdown. An algorithm is proposed in Section V to determine a close-to optimal time allocation across all users and give results for a multi-user scenario. Finally, conclusions are drawn in Section VI.

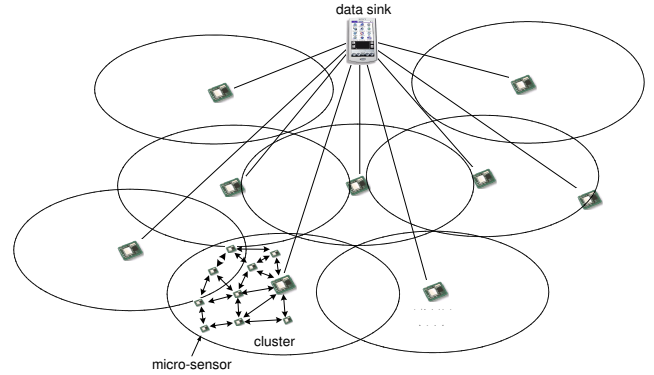


Fig. 1. Hierarchical wireless sensor network topology. The proposed scheduling algorithm can for example be used to organize the data forwarding from the cluster heads to the data sink. The scheduling algorithm is computed on the data sink terminal.

II. BACKGROUND AND FOCUS

A. Related Work

The energy constraint for wireless sensor nodes has already triggered a lot of research including low-power circuits for analog front-end [11], power-aware digital circuitry and embedded software [12] to energy-efficient protocols for medium access control [10], [13], topology management [9], [14] and routing [15], [16]. Each of these works propose solutions that may differ depending on the level of abstraction considered.

At the physical layer, one tries to exploit the fundamental trade-off that exists between the transmission rate and signal to noise ratio [7]. This leads to the so-called *lazy scheduling* approach of Uysal-Biyikoglu et al. [6]. The approach has been extended in [5] to encounter first the discrete nature of the radio settings and second the non-proportionality of the radio circuitry consumption with the transmitted power. Discrete rate scaling is achieved by adapting the constellation size of the modulation, leading to dynamic modulation scaling (DMS), or by changing the code rate (dynamic code scaling, DCS).

From a network point of view, the *lazy scheduling* concept translates in trading off bandwidth (in terms of transmission time) to power. To that extent, it is not trivial to generalize it to the multi-user context. Uysal-Biyikoglu et al. have proposed a generalized version of their algorithm (Right-Flow) for a broadcast channel (downlink) and to the multi-access channel (uplink) assuming a centralized medium access control protocol [17]. In [18], a practical multi-user lazy scheduling scheme called L-CSMA/CA is proposed. This scheme relies on a CSMA/CA distributed medium access control and considers a finite discrete set of possible transmission rates. Raghunathan et al. propose in [19] a centralized *lazy scheduling* algorithm, Energy-Efficient Weighted Fair

Queuing. The modulation is scaled based on the current queue size, which aggregates bursty traffic, exploiting a trade-off between average traffic delay and energy consumption. For applications with periodic traffic and stringent instantaneous delay requirements, real-time energy aware packet scheduling for periodic traffic is proposed in [20], where a share of the channel is allocated to each flow depending on its deadline and worst-case data requirements. Depending on its current data requirements, each node should then make optimal use of its own timeshare, and downscale the transmission rate if possible. Although significant energy gains are achieved, this does not necessarily result in the most energy-efficient schedule from a network point of view as multi-user diversity is not exploited.

Lazy scheduling schemes focus only on this contribution to the node energy consumption that is relative to the transmitted power. However, when considering low and middle range radios, an important part of the power dissipation is not proportional to the transmit power. To reduce this contribution, the sole option is to minimize the duty cycle of the radio, shutting down the RF front-end components as much as possible (sleep mode). However, a node cannot receive data when turned off, hence effective use of the sleep mode requires a significant degree of coordination between nodes. To take care of this coordination at the medium access level, both contention- and schedule-based solutions have been proposed. PAMAS [13] is one of the earliest contention-based energy-efficient protocols that avoids over-hearing among neighboring nodes by using out-of-band paging to coordinate the shutdown. S-MAC, a single-frequency contention-based protocol, takes advantage of the sparse data in sensor networks and packs all messages into short active parts [10]. To organize the active timeslots across sensors, S-MAC needs some synchronization, but not as much as TDMA based protocols. Contention based schemes severely suffer from collisions when the load increases. This is especially the case when considering cluster heads, which aggregate data of many sensors. This motivates the need for establishing transmission schedules that allow nodes to transmit or receive data without collisions. TRAMA is a time slotted, schedule based MAC that allows nodes to switch to a low power mode when they are not transmitting or receiving [21]. It uses a distributed election scheme based on information about the traffic at each node to determine which node can transmit at a particular time slot. This is to avoid the assignment of time slots to nodes with no traffic to send, which can be very valuable for parts of the network where currently no events are monitored. When the density of sensor nodes is sufficient, only a small number of them should be on to monitor or to forward events every time. To take advantage of this, topology management schemes are introduced. They coordinate which nodes turn their radio off and when, such that the data forwarding remains sufficient while minimizing the total network energy dissipation. SPAN [9] and GAF [14] have been proposed for sensor networks

with flat multihop routing. LEAH [15] is an alternative hierarchical approach, where cluster heads are selected to collect local information and forward it to the central data sink. STEM [22] proposes a hybrid wakeup scheme to wake up nodes when they have to participate in data forwarding, and can be used for both flat and hierarchical routing schemes.

To our knowledge, the joint optimization of the a priori contradictory *lazy scheduling* and duty cycle minimization approaches has not been studied yet in the multi-access context. Although, in [5], a general framework is provided to derive the operating regions when a transceiver should sleep or use transmission scaling, a solution to optimize both in a dynamic multi-user scenario is not proposed. In [8], [23], the transmission strategy, combining transmission rate scaling and sleep duration optimization is studied with and without coding. An off-line optimization algorithm is proposed but the scope is limited to a single-user link or a multi-user link with a fixed timeshare for each user. In [24], it is shown that the fixed circuit power consumption has a large impact when optimizing the energy consumption across both physical and MAC layer in IEEE 802.11 DCF wireless LANs. However, no shutdown is taken into account in the optimization. A similar cross-layer optimization, neglecting the shutdown mode, but taking into account the 802.11 PCF, is done in [25].

B. Focus

In this paper, we analyze the trade-off that exists between *lazy scheduling* and duty cycle minimization in a multi-access channel. Based on that, we propose a scheduling algorithm that optimizes jointly the transmission rate and the sleep period, considering the dynamic traffic requirements of each node. The total network energy consumption is minimized. Other variations of the scheduling algorithm could aim at extending the network lifetime, and first consider those CL for energy saving with the least battery power left. The solution is general: based on the relative weight of the transmission power to the fixed circuit power, more transmission scaling or shutdown is considered to achieve the most energy-efficient solution in each scenario. We assume the channel is only divided in time, hence the scheduling algorithm computes the transmit opportunities (TXOP) that should be allocated to each user. No spatial reuse or interference are taken into account. Ideally, each user is only awake when allocated a TXOP, to send its queued traffic. Also, it is assumed that sufficient synchronization between the users is achieved. The core of the scheduling algorithm consists of computing per user a set of transmit opportunities that represent optimally the trade-off between channel use and energy consumption. Then, these are combined across users to determine the schedule (i.e. vector of transmission grants) with the minimal network energy consumption. Based on the above considerations, we state the problem explored in this paper: *Given a sensor network with bursty data, in a heterogenous and varying network topology, how does one decide to allocate the time-shared channel to minimize the*

fixed and transmission energy consumption for the network as a whole while assuring a target degree of reliability?

It is important to develop and test the energy-efficient schedule based on a realistic sensor network scenario. Moreover, it is important that the proposed scheme can be implemented with minimal control overhead. We hence state in more detail the application scenario considered, and stress why the proposed optimization is extremely valuable and can be easily implemented online. Most sensor networks are deployed for data gathering or for monitoring and state forwarding to a central data sink (Fig. 1). This is the scenario of interest here. A hierarchical routing scheme is assumed: Cluster Heads (CH) aggregate the sensed data and forward it to the sink. Routing is not the focus of this paper, and forwarding paths from simple sensor nodes to cluster heads are not considered. We assume the hierarchical clusters are formed by a higher layer routing scheme. The focus of this contribution is hence on the forwarding in a single cluster, e.g. the top level cluster where data is forwarded from CL's to the data sink. As such, the scheme could be extended to take into account data-dependencies between different clusters, as done in [26].

Depending on the range of the cluster, the transmission power is more or less dominant compared to the fixed circuit power. However, even for very short distances ($< 5m$) where transmission scaling is less important, the proposed scheme flexibly allocates the just required TXOP to each node maximizing the possibilities to shutdown. We consider ranges from $5m$ to $35m$ in this paper, which are realistic distances from CH to data sink, considering environment monitoring (Fig. 1). We conclude with the following basic observations motivating the proposed optimization and its online implementation:

- 1) The data stream is mainly uplink, from cluster heads to the data sink. As a result, to communicate, the sensor nodes are mainly transmitting, motivating the transmission scaling in the energy optimization.
- 2) The wireless channel is time-shared between a large number of sensor nodes, motivating the transceiver shutdown when other nodes are sending data.
- 3) The cluster heads aggregate sensed data, which can be a lot when they cover a large cluster. Due to this large load, a schedule-based MAC is preferred due to collision risk in contention-based protocols.
- 4) Optimally, each cluster head is awake only when sending its own data towards the central sink, so no communication is possible between cluster heads without waking them up between data communications (here we abstract the data aggregation that should also be done by the cluster head).
- 5) All CH communicate with the central data sink. Therefore, it is possible to piggyback the data requirements of each cluster head on its data exchange towards the

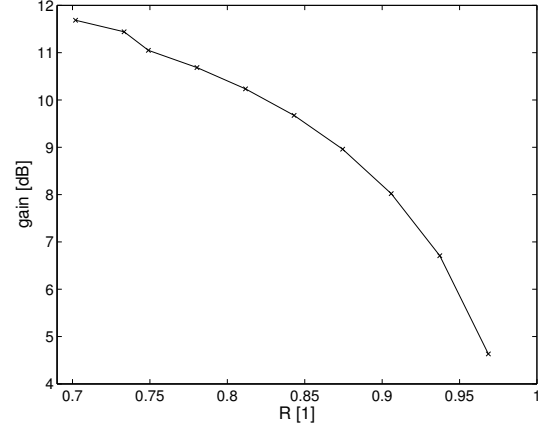


Fig. 2. Asymptotic code rate versus code gain trade-off for BCH codes with $n = 255$.

central data sink. The central sink collects the data requirements across the networks and decides on the optimal allocation vector, which is fed back using the acknowledgement from sink to cluster head.

III. SYSTEM MODEL

Modulation scaling (MQAM) is usually considered to enable transmission rate scaling [8]. Yet, MQAM is not such a good choice for a wireless sensor node radio. Wang et al. have shown that radios based on binary frequency shift keying (2FSK) may be far more efficient because they require less analog components [27]. With less analog components, the sensors are much cheaper and consume less circuit energy. Because of that, FSK is a promising air interface for sensor networks. To enable rate scaling in a 2FSK scheme with a constant radio bandwidth, we rely on code scaling [5]. We consider a set of binary BCH codes. Binary BCH codes may be constructed with following parameters:

$$n = 2^m - 1 \quad (1)$$

$$n - k \leq m \times t \quad (2)$$

$$d_{min} = 2 \times t + 1 \quad (3)$$

where m and t are arbitrary positive integers. n is the codeword size, k the code dimension and d_{min} , the minimum Hamming distance between two codewords. The Hamming distance dominates the code performance (coding gain). A code with a higher Hamming distance will have a higher coding gain and hence less transmit power is required to achieve a given packet error probability. Typically a BCH code can correct any pattern of t errors in a codeword.

BCH codes have a good performance for small block sizes and are hence appropriate for short packet transmissions in sensor networks. We consider a block size $n = 255bits$ and vary the code rate assuming a set of values for the code dimension k (Table I), which correspond to the number of data bits in a codeword. From Eq. 2, one can observe that

TABLE I
THE DIFFERENT PARAMETERS USED FOR THE MODEL.

Energy Model	Performance Model	MAC model
$P_{Tx}(dBm)$ [-10 to 20] (step 0.5)	$A_1 = -40dB$	$L = 1000bits$
$k = [247, 239, \dots, 13, 9]$ [29]	$K = -4$	$T_{ifs} = 5\mu s$
$R_s = 1e6$	$d = [5, 15, 25, 35, 45](m)$	$T_{ACK} = 10\mu s$
$P_{elec-tx} = 10mW$	$kT = -174dBm/Hz$	$PER = 10e-3$
$P_{elec-rx} = 10mW$	$N_f = 10dB$	$T_{wakeup} = 100\mu s$
$\eta = 0.3$	$IL = -5dB$	$P_{wakeup} = P_{elec-rx}$

there is a trade-off between the code rate $R_c = k/n$ and the error correction performance t . Thus, varying k allows to trade-off rate and energy. In Fig. 2, the asymptotic coding gain $10\log(R_c \times d_{min})$, which is an image of the transmit power savings, is plotted as a function of the code rate. Knowing the net bitrate and the symbol rate $R_s(baud)$, the time needed to send a packet of L bits is:

$$T_{on} = \frac{Ln}{kR_s} \quad (4)$$

Considering the above BCH-FSK system model, the power consumption to transmit and receive can be found as:

$$P_{on-tx} = P_{elec-tx} + P_{PA} \quad (5)$$

$$P_{on-rx} = P_{idle} = P_{elec-rx}, \quad (6)$$

where $P_{elec-tx}$ represents the power needed by the digital signal processing to produce the base-band signal and the power needed by the analog circuitry to modulate the signal on the required frequencies. The power amplifier P_{PA} drives the current to the antenna. We can assume that P_{PA} is, at first order, proportional to the transmit power P_{Tx} . We define η as the PA power efficiency:

$$P_{PA} = \frac{P_{Tx}}{\eta}. \quad (7)$$

Considering the receiver, its electronic power consumption ($P_{elec-rx}$) consists of the low noise amplifier (LNA) and filters to downconvert the signal to the baseband, where it is processed by the receive digital signal processing (also the coding). The sleep mode power P_{sl} is typically very small when CMOS technology is used [28], so that we neglect it in our model: $P_{sl} = 0$. Also, the receiver energy consumption being dominated by the analog part, we assume that $P_{idle} = P_{on-rx}$.

Further, performance models that reflect the behavior of the FSK signaling scheme and the BCH coding are needed. First, the signal to noise ratio per symbol at the receiver E_s/N_o has to be related to the transmitted power. This requires taking assumptions on the channel. In a wireless sensor network, narrow-band flat fading channels are most often encountered. Also, as a consequence of the relative stationary of the network topology and next to the small packet transmission duration, we can assume that the channel attenuation (due to the path loss and the fading) is constant

during a packet transmission. Hence, the channel is assumed AWGN (additive white Gaussian noise). The received power is typically expressed as a function of the distance d (see Eq. 8). A_1 is the path loss for a distance of $1m$, K is the path loss exponent, α is the random short time fading gain and IL represents the implementation loss. E_s/N_o is given by Eq. 9 where the thermal noise depends on the temperature T , the Boltzmann's constant k and the receiver noise figure N_f . W is the bandwidth.

$$P_r = \alpha A_1 d^K IL P_{Tx} \quad (8)$$

$$\frac{E_s}{N_o} = \frac{P_r}{2WkTN_f} \quad (9)$$

In Eq. 10, the FSK symbol error probability is computed as a function of the signal to noise ratio per bit E_b/N_o . Eq. 11 relates the symbol error probability to the codeword error probability, depending on the parameters of the code (n, k, t) , assuming a *hard decision* decoding. Finally Eq. 12 gives the packet error rate if the packet of size L is made of several codewords:

$$P_b = \frac{1}{2} \text{erfc}\left(\sqrt{\frac{E_b}{N_o}}\right) \quad (10)$$

$$P_w = \sum_{i=t+1}^n \binom{n}{i} \times P_b^i \times (1 - P_b)^{n-i} \quad (11)$$

$$P_e = 1 - (1 - P_w)^{\frac{L}{k}} \quad (12)$$

IV. SYSTEM ENERGY VERSUS TRANSMIT OPPORTUNITY TRADE-OFF

In the previous section, expressions were given to compute the energy to send (E_{tx}) and receive (E_{rx}) a unit of data L , the expected error rate for this P_e and the time needed for this transmission T_{on} . These are a function of the output power P_{Tx} and the scaling parameter k . In this section we show, based on these expressions, how to determine the set of transmit opportunities (TXOP) that can be allocated to a Cluster Head (CH) to transmit a unit of data. Each possible TXOP allocation corresponds to an expected energy that will be consumed by the CH to send its data during the granted transmission time. The optimal Energy-TXOP trade-off curve is derived for the case of code scaling, for a range of distances.

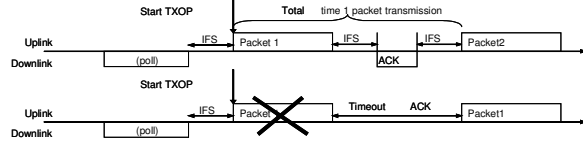


Fig. 3. Timing of successful and failed uplink packet transmission under a MAC polling scheme.

A. Derivation of the Energy-TXOP trade-off

The time and energy to send a packet with given error rate, depending on the setting of the modulation or output power, is known. However, when considering communication in a realistic setup, protocol overhead should be taken into account too, as considered in Fig. 3 for a centralized MAC polling scheme. Even if we can suppress the overhead of the poll message (if the node is informed of the schedule during the previous data exchange and no stringent time synchronization is needed), time spaces between transmissions (IFS), acknowledgements (ACK) for each data packet should be taken into account (See Table I). Moreover, the packet error probability and the resulting retransmissions should be considered. The overhead to wake-up the radio depends on the group of packets, and is not included in the per packet analysis. It should be added later. This leads to the following expressions for energy and time for a successful and failed packet transmission¹ (not considering the poll and wake-up overhead):

$$E_{good} = E_{bad} = E_{Tx} + ((2 \times T_{ifs} + T_{ACK}) \times P_{on-rx}) \quad (13)$$

$$T_{good} = T_{bad} = T_{on} + (2 \times T_{ifs}) + T_{ACK} \quad (14)$$

When targeting a certain degree of reliability, i.e. Packet Error Rate (PER) depending on the specific application, potential packet retransmissions must be considered in the timeslot. The resulting PER when sending a packet with error rate P_e and maximum m retransmissions is:

$$P(m) = P_e^{m+1} \quad (15)$$

Knowing the target degree of reliability, the transmit opportunity (TXOP) to be allocated to a CH is determined taking into account the worst case number or retransmissions m needed (Eq. 16).

$$TXOP(m) = T_{good} + m \times T_{bad} \quad (16)$$

This might result in channel idle time if a retransmission is not needed. However, we want to determine in advance a schedule that guarantees for each packet the target PER. As a result, this potential allocation of unneeded transmission time to a CH cannot be avoided. Indeed, if probabilistic events would cause the schedule to vary, it would be impossible to determine an optimal schedule in advance and put the

¹ $E_{good} = E_{bad}$ because the assumption that idle and receive energy are the same

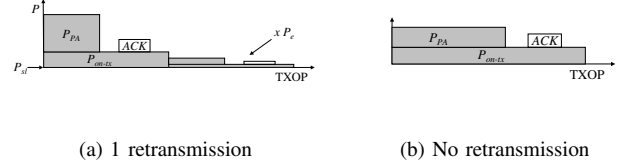


Fig. 4. Expected energy consumption and TXOP as a function of variable and fixed energy consumption and the number of retransmissions.

nodes to sleep² the time they are not allocated transmit time (Fig. 4). Considering that the CH is only awake to transmit or retransmit a packet, and sleeps immediately after successful transmission of all queued packets, we can calculate the expected energy consumption for one packet. We consider the expected values, as the number of retransmissions that will be needed is a random variable. Eq. 17 scales the energy due to retransmissions with the probability a retransmission would happen if the $(j-1)$ th transmission failed (Fig. 4).

$$E(m) = E_{good}(1 - P(m)) + E_{bad}(1 - P(0)) \times \left(\sum_{j=1}^m P(j-1) \times (jE_{bad}) + (m+1)P(m) \right) \quad (17)$$

Determining the expected energy and worst case TXOP for each configuration (k, P_{Tx}) , results in a cloud of discrete points in the Energy-TXOP plane (Fig. 5). However, we are only interested in those points that represent the optimal trade-off between Energy and TXOP, i.e. the points that are closest to the origin (lowest energy and timeslot). Consider e.g. point A on Fig. 5. It should never be allocated, because there exists a point B that needs a smaller share of the channel and will result in a lower energy consumption. As such, if point A can be chosen, it will always be better to use point B instead. We approximate this optimal trade-off with the piecewise linear interpolation of the convex minorant of the cloud of points. The considered trade-off is then the part of the minorant that is monotonically decreasing (Fig. 5). This pruned piecewise linear interpolation of the convex minorant will be called the Energy-TXOP trade-off curve in the remainder of this paper. Only the discrete points can however be allocated, and in the next section we propose a discrete optimization scheme that determines the set of points that achieve an energy consumption within a fixed bound from the (unachievable) optimum. We note that the points of the optimal Energy-TXOP trade-off curve do represent the optimal trade-off between rate scaling and shutdown, as all effects are considered to determine the values.

The energy range spanned by this Energy-TXOP curve depends on the distance (which represents the relative impact of the transmission power to the fixed power) (Fig. 6). When the distance is lower, the gain of scaling down the

²It is possible to share retransmission time for packets of the same cluster head. This additional optimization is not considered in this paper.

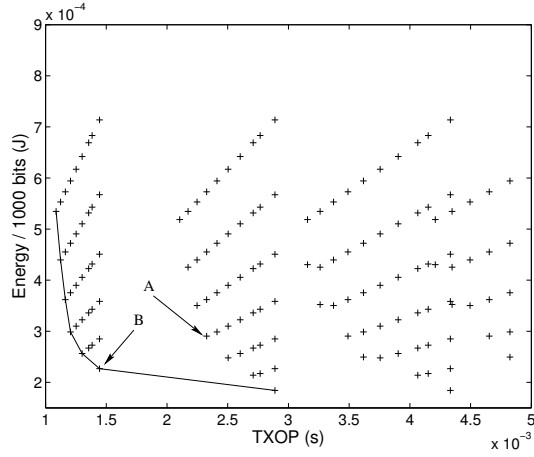


Fig. 5. Optimal energy versus TXOP to send a unit L of data compared to all discrete achievable points in the Energy-TXOP plane, obtained by varying k , P_{Tx} and m ($d = 50m$). The different cloud zones represent the different number of retransmissions.

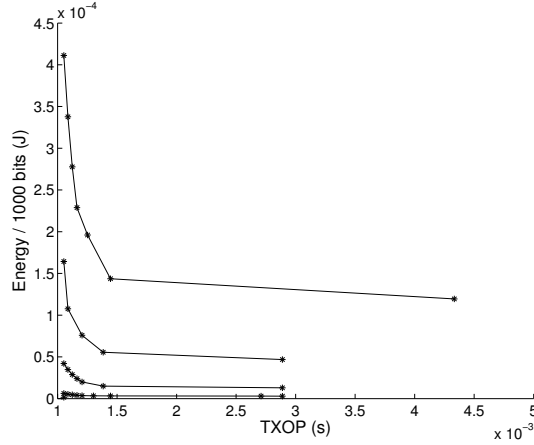


Fig. 6. Optimal energy versus TXOP to send a unit L of data for a range of distances ($d = [5, 15, 25, 35, 45]$ - from bottom to top on the figure). Depending on the distance, significant savings can be obtained by applying BCH code scaling.

transmit energy is dominated by the resulting increase in transmit duration and hence circuit energy consumption. As a result, the Energy-TXOP trade-off curve for these distances spans a much smaller range in TXOP (i.e. downscaling is not beneficial). On the other hand, when the circuit energy dissipation is small compared to the transmission energy, a large gain in energy can be achieved using different code rates, hence the trade-off curve spans the whole range of possible TXOPs. As a result, it should be clear that in a scenario where the Cluster Heads are at different distances from the central data sink (which is a realistic scenario), the TXOP allocation to each of them should reflect this difference in distance. This not only optimizes the aggregate network energy consumption, it also results in more *energy fairness* across the Cluster Heads.

V. NETWORK OPTIMAL TRANSMISSION ALLOCATION

Based on the Energy-TXOP trade-off for each cluster head, we have to determine the set of transmission opportunities that minimizes the total network energy consumption for the current aggregate data requirement X , which denotes the number of L -sized packets to be transmitted during the next scheduling period D . In a first subsection we derive an algorithm to compute, based on the per packet trade-off curve, a solution that deviates by a small and bounded offset from the optimal solution. Second, we show how the scheme is communicated in a way that enables nodes to sleep maximally. Finally, some results are given.

A. Network TXOP Allocation

To determine the transmission strategy for all nodes, we build the aggregate Energy-TXOP trade-off curve for the whole network, taking into account the aggregate traffic load X and the Energy-TXOP trade-off curve that is relevant at that time for each CH . To know this load X and the current distance (database index to current optimal curve), the exchange of control information is needed, prior to the establishment of the schedule. If the channel coherence time allows it, this can happen during the previous data exchange, as explained in the next subsection. If not, some additional poll messages need to be included. Assume a network consisting of N Cluster Heads CH_i , each with data requirement X_i (hence $X = \sum X_i$). Each CH_i has, depending on its distance, its own trade-off curve, representing a set of energy versus TXOP points. Each curve is a set of maximal Q (minimal 0) segments with a negative slope. Within a trade-off curve, the segments are ordered according to decreasing negative slope, i.e. the energy that can be gained when increasing the allocated timeslot with a time unit decreases. This is a result of the convexity of the pruned trade-off curve. Based on the per CH_i trade-off curves and data requirements X_i we determine the network Energy-TXOP trade-off using the following greedy algorithm (See Fig. 7 for $X_i = [1, 2, 3]$ for 3 CH s with $distance = [5, 25, 35]$):

- 1) Allocate to each CH_i the minimal required transmit time, which is the point from the trade-off curve with the smallest TXOP and largest energy, and multiply with the total load for this CH_i : $TXOP_{i,start} = X_i \times TXOP_{i,min}$. This corresponds to an expected energy consumption $E_{i,start} = X_i \times TXOP_{i,min}$. We call *Network TXOP Allocation* the vector $\{E_{i,start}, TXOP_{i,min}\}$ resulting in a total aggregated time allocation $TXOP_{network,start}$ and energy consumption $E_{network,start}$. The total number of points in the aggregate curve, j' , is 1^3 so far. For each CH_i the first segment to be considered is s_1 , and the set of current segments is $\{CH_i, s_1\}$. CH_i with no such segment s_1 are removed out of the list, as their *minimal energy TXOP* ($= TXOP_{min}$) has already been allocated.

³We assume it is always possible to construct this first point, hence no overload is taken into account.

- 2) Search across the set of current segments those with the largest negative slope s , and add their respective CH_i to the set of best segments to be considered during this pass of the algorithm. Add, for each CH_i in the best set, the ΔE and $\Delta TXOP$ corresponding to this slope s , until each packet X_i is downscaled⁴. Each $\Delta TXOP$ increment can be understood as increasing the time allocated to one packet of one Cluster Head, resulting in a network energy decrease ΔE . This results in a set of *Network Allocation Vectors* with lower aggregate expected energy, but a larger time allocation:

$$(E_{network,j}, TXOP_{network,j}); j' < k \leq (j' + \sum_{bestCH} X_i)$$

$$\begin{aligned} E_{network,j} &= E_{network,j'} - (j - j') \times \Delta E \\ TXOP_{network,j} &= TXOP_{network,j'} + (j - j') \times \Delta TXOP \end{aligned}$$

where j' denotes the number of points after the previous pass. The sum of the number of packets across the selected CHs corresponds to the number of points added in this pass. After adding all points in this pass, the current set of segments is updated. This means that for each CH that was treated in this pass, the next segment of its trade-off curve (if it exists) is considered.

- 3) Repeat step 2 until all segments s for all CH_i are treated. A network trade-off curve with maximum $Q \times X$ points is constructed, Q denoting the maximum number of segments per Energy-TXOP curve for each CH_i .

Based on the aggregate Energy-TXOP curve, the network allocation vector corresponds to the point with the largest aggregate TXOP that is smaller than the scheduling period D , as illustrated in Fig. 7 for $D = 10ms$. It is clear that for larger data requirements, less downscaling is possible. The figure represents a set of aggregate Energy-TXOP curves for 3 users with distances 5, 25 and 35 and a data requirement each of 1 to 3 packets. The complexity to construct the aggregate curve is $O(NQ \log(N))$, which is low as a *mergesort* is possible thanks to the convex properties of the curves.

It can be shown that solving this kind of discrete optimization problems with a greedy approach (e.g. according to steepest decreasing slope) based on the convex piecewise-linear interpolation of the trade-off results in a solution that is bounded sub-optimal [30]. This can be understood intuitively, as shown in Fig. 7. As the solution relies on the convex piecewise-linear interpolation of the trade-off, each discrete point of the aggregate curve corresponds to an optimal allocation, for a scheduling period D , that is exactly equal to the aggregate transmission time of the discrete point. However, most often, a point has to be taken with a $TXOP_i$ that is slightly smaller than D . The greedy search based on pruned convex trade-off curves however does not guarantee that there is no solution with $TXOP_{optimal}$ that is larger

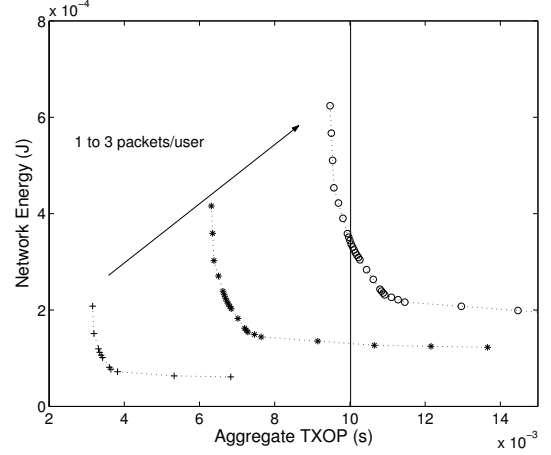


Fig. 7. Aggregate Energy-TXOP for 3 cluster heads with distances 5m, 25m and 35m, data requirement X_i from 1 to 3 and scheduling period $D=10ms$.

than $TXOP_i$ but smaller than D (and has a smaller energy consumption $E_{optimal}$). However, due to convexity, this point has to be above the piecewise linear trade-off curve. Consequently, it can be seen that the worst case difference between $E_{optimal}$ and E_i is bounded by the ΔE_{max} across all segments, which is relatively small and depends on the granularity of the scaling k and the packet size L .

B. Delay Look-ahead Implementation

In general, future traffic arrivals cannot be predicted. This can however be solved by introducing a look-ahead buffer, during which traffic to be scheduled in the future, is captured. This is indeed also the solution proposed in [6], [18]. However, as shown in [18], to be practical in a multi-user context, this requires a communication step after each look-ahead period to communicate the data requirements of each user. It is obvious that when considering shutdown, this approach is not optimal as it requires users to wakeup and communicate in between data exchanges. It would however be much more practical, considering the data gathering application where each node communicates with the central sink, to piggyback the control information on the periodic data and acknowledgement exchange (see Fig. 8). The central sink can then collect the data requirements from each node during period $[D, 2D]$ and take a scheduling decision for all nodes at time $2D$. The data sink can communicate the schedule only during the next data exchange for each node $([2D, 3D])$, as wake-up for control information only should be avoided. The schedule can be piggybacked on the ACK, send from sink to Cluster Head when reliable communication is considered. The communicated schedule can only be used during the next period $([3D, 4D])$. Each data is hence delayed by an amount ranging from $2D$ at the minimum to $4D$ at the maximum. When large scheduling periods are used, this can result in a significant delay. However, the delay is bounded in all cases to $4D$.

⁴The exact order to add extra time for each packet of different Mobile Users should be random to achieve fairness.

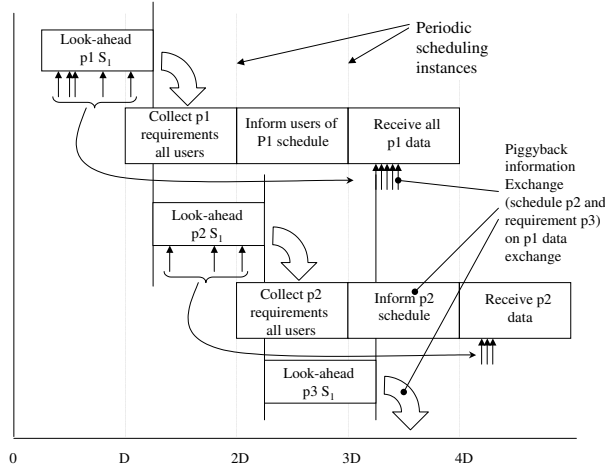


Fig. 8. The three phases of the delay look-ahead to obtain optimized transmission rate scaling and shutdown for multiple users: 1. collect data requirements of all users $[D, 2D]$, 2. inform users of schedule $[2D, 3D]$, 3. receive data $[3D, 4D]$. All control information exchange is piggybacked on the periodic data transfer to eliminate control communication overhead.

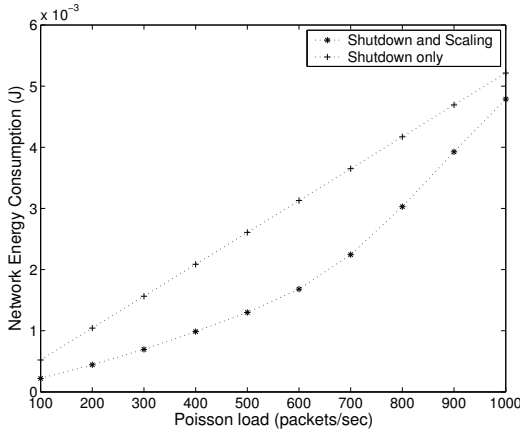


Fig. 9. The energy consumption of 'Shutdown only' and 'Shutdown and Scaling' for a range of load scenario's, 6 CH, $d = 35m$, $D = 15ms$.

C. Results

We have presented a technique to optimally combine code rate scaling and shutdown in a multi-user system with channel (distance) and traffic diversity. Depending on its current situation (distance and circuit power consumption), each CH has a set of points that represent its optimal working points. Depending on the current data requirements of each CH, the central data sink determines the optimal timeslot for each CH. As shown in Fig. 6, each node can have a different optimal curve depending on its distance, and more time should be allocated to those nodes that can use it best to decrease the total energy consumption. This is taken into account in the algorithm proposed in Section V-A. Next, the gains that can be achieved by downscaling depend on the current traffic. This is illustrated in Fig. 9, where for a scenario

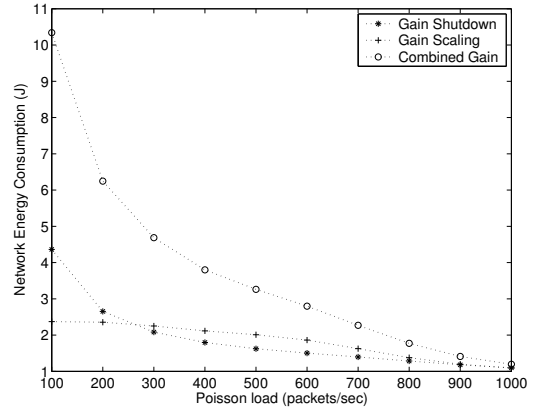


Fig. 10. The energy consumption of 'Shutdown only' and 'Shutdown and Scaling' for a range of load scenario's, 6 CH, $d = 35m$, $D = 30ms$.

of 6 CH at a distance of 35m the Poisson load (in L size packets/sec) is varied. When shutdown only is considered, the energy consumption increases linearly with the load. However, considering rate scaling, the energy consumption for the lower loads is significantly lower (a factor 2.6 for the lowest load in this example). For higher loads, points should be chosen with a small TXOP which decreases the scaling energy gains.

The proposed algorithm combines the gains that can be achieved by scaling and shutdown, as illustrated in Fig. 10 where the performance is compared to a scenario where no energy management is employed (i.e. where only transmit power scaling is performed to adapt to the distance, but no code rate scaling or shutdown). When the load is extremely low, shutting down the system results in significant energy gains. For this low load case, scaling down however also decreases the energy consumption significantly. As a result, the largest energy gains are achieved for low load scenario's (Fig. 9). For larger loads, the gains of scaling decrease as points with large TXOP are no longer schedulable. The relative gain is however always larger than 1, because of the bursty Poisson traffic. For those loads the relative gains of shutdown also decreases, but never reaches 1 as shutting down is always beneficial in a multi-user scenario. The proposed scheme however optimally exploits the gains that can be achieved by scaling and shutting down, over a range of scenarios.

VI. CONCLUSIONS

In this paper, we propose a transmission strategy that combines close to optimally *lazy scheduling* and shutdown, two energy management techniques that seem contradictory. The former exploits the fundamental trade-off between the time and energy needed to send a unit of data, and hence maximizes the transmission duration to minimize the transmit energy consumption. The latter minimizes the fixed circuit energy consumption, hence decreasing the transceiver on time as much

as possible. We show that the optimal transmission strategy in a multi-user scenario is a combination of both approaches. First, we derive a solution to determine a transmission strategy with a worst-case deviation from the optimal strategy that is bounded. As practical radio implementations only allow a discrete set of transmission schemes, this discrete nature of the problem is taken into account in the system model and solution. The proposed algorithm is general: depending on the traffic constraints and on the relative impact of the transmission power to the circuit energy consumption, more transmission scaling or shutdown is considered. We show that the algorithm indeed results in significant energy savings for a range of traffic loads and topologies. It flexibly combines and trades off the gains that can be achieved when scaling or shutting down only, and hence significantly outperforms those energy management techniques in each scenario. Moreover, the algorithm can easily be implemented when considering data gathering applications, making it extremely valuable for deployment in energy-constrained sensor networks. Interesting future work could be to extend the scheme exploiting also the degrees of freedom offered by the routing algorithm. Also, in contrast to this centrally controlled scheme, a fully distributed solution could be developed.

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