Fundamentals of Energy-Constrained Sensor Network Systems

Brian M. Sadler†

Abstract

This article is an overview of energy-constrained sensor networks, focusing on energy-conserving communications and signal processing strategies. We assume battery-driven nodes, employing robust communications, with little or no fixed infrastructure. Our discussion includes architectures, communications connectivity, capacity and scalability, mobility, network localization and synchronization, distributed signal processing, and cross-layer issues. Because energy is a precious system resource, all aspects of the network must be designed with energy savings in mind. In particular, transmissions and idle listening must be minimized, which implies the use of duty-cycling to the maximum extent possible.

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Army Research Laboratory, AMSRD-ARL-CI-CN, 2800 Powder Mill Road, Adelphi, MD 20783, USA. Tel: 301-394-1239, Fax: 301-394-1197, e-mail: bsadler@arl.army.mil

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I. Introduction

Sensor networks have emerged as a new discipline in the last few years [1]-[10]. What is a sensor network? We postulate that, given any definition of a sensor network, there exists a counter example. Fundamentally, there are extremely varied requirements, environments, communication ranges and propagation conditions, and power constraints. It seems that unless the scenario is given in at least some specificity, a general definition may remain too general. Consequently, it is important to at least roughly categorize sensor networks to define the scope of discussion. This article is an overview of *energy-constrained* sensor networks, considering the rich multi-disciplinary interplay between sensing, signal processing and communications, with a focus on energy preserving communications strategies and associated key issues. This spans *ad hoc networking*, *sensing* which includes the physics of the sensor and propagation, *signal processing* which spans communications and sensing and includes a new emphasis on low power and adaptive systems and circuitry, and *controls* which includes actuation in general as well as robotics and avionics. The term convergence might be somewhat over used, but is appropriate to highlight how the combination of technologies is enabling the emergence of sensor networks.

Sensing application domains can be roughly categorized as in Table I. *Point sources* refers to the detection, estimation, geolocation, and tracking of moving sources. An example is the aeroacoustic localization and tracking of vehicles [10]. Associated signal processing includes topics like detection, and angle-of-arrival estimation. *Imaging* implies spatially distributed sampling or measuring of a field, perhaps in 2 or 3 spatial dimensions, with time as an additional dimension. Examples of imaging include environmental monitoring such as air temperature, or moisture content in soil. The term imaging is used to associate issues like sampling and image processing. *Monitoring* is used here to denote dedicated sensor and source groupings as arise, for example, in industrial settings such as assembly lines and machine monitoring, or patient monitoring. *Logistics* is another important sensing domain, namely, where is my stuff, and what is its condition? Finally, *mobility and control* is worth highlighting, such as the combination of robotics and/or unmanned aerial vehicles (UAVs) and sensing, which will generate new and important capabilities in a variety of settings.

Overall the Table I categorization is useful but not necessarily definitive. For example, we could regard the sound field from a point source as a time-varying imaging problem, and intrusion detection is likely best placed in the point source category yet could easily be argued to be a form of monitoring. These observations support the postulate above.

A great variety of sensing modalities and environments are possible, a few of these are listed in Table II, and a little thought will yield additional entries. Note that the typical sensor output bandwidth tends to be relatively narrow, with the exception of imaging sensors (video, IR, and so on). This is an important distinction, and the communication bandwidths needed for video are generally much more demanding so as to be in a class by themselves. In addition to passive sensing, active sensors also fit into the sensor network category, such as radar and active RF tags. It is also quite clear that many future applications will feature multiple sensing modalities on (possibly mobile) platforms with actuators, all supported with a wireless network.

What are the types of constraints which specify the problem? Many of these emerge in the course of this article; we highlight some now. First, energy (battery powered *versus* continuous power supply). Wireless communications brings a significant list of constraints.[1] These include one or multi-hop communications to a fixed infrastructure, *versus* no fixed infrastructure; homogeneous *versus* non-homogeneous nodes (such as including "base stations"); synchronization (via beacons or message passing) and geolocation; the degree of robustness to interference; and highly variable radio propagation conditions. Other constraints include random *versus* deterministic sensor node placement, and sensor field density.

Here, we focus on energy-constrained, battery-driven, robust radio communications with little or no fixed infrastructure. We assume the need for communications waveforms to have inherent robustness to in-band interference and jamming. Robustness is desired for military applications, but this is easily extended to include shared commercial spectrum such as the ISM band. The lack of fixed infrastructure contrasts with many commercial settings. For example, the IEEE Standard $802.15.4$, and associated commercial activity in the ZigBee alliance, provides physical layer (PHY), medium access control (MAC), and associated networking techniques which can be implemented using an access point (AP) with a continuous power supply [90]. As we will describe later, the AP may be leveraged to enable battery-powered nodes with very long lifetimes. This will support many important applications such as monitoring, where the AP, connected to the internet or other fixed infrastructure, may be one or perhaps a few hops away from a battery-

[1] We consider radio, noting that other possible communications approaches include acoustic, or optical.

powered node. In contrast, here we generally focus on the case when a continuous power supply is not available.

Energy consumption will depend on the state of the sensor node, such as transmit, receive, idle, DSP active, and so on, and these states may have sub-states. Some of these will cost considerably more than others, so it is critical to manage the node state in an efficient way. This is especially true for the transceiver, where dramatic energy reductions can be achieved (see Side Bar 1 – Energy Consumption and Duty Cycling). It is likely that the transceiver portion of the node will consume 2-3 times more power on receive than when transmitting, e.g., [80]. More functionality is required on receive, such as acquisition and synchronization, decoding, and so on, and the complexity is further increased when employing robust waveforms such as direct sequence spread spectrum. This does not necessarily imply that $E_{rcv} > E_{tx}$, because E_{tx} depends critically on the path loss. However, the cost E_{tx} is borne only on transmission, whereas E_{rcv} must be paid whenever the node is listening. *Consequently, in the absence of network synchronization and scheduling which enables receiver duty cycling, idle listening can be a dominant energy drain.*

We are all familiar with the various forms of Moore's Law (actually an empirical observation), such as digital processing power requirements dropping by a factor of about 1.6 per year. In contrast, Shannon's theory and Maxwell's equations govern the required receiver signal-to-noise ratio (SNR, or E_b/N_0) and propagation losses, and these values are fixed.[2] Consequently, while DSP may increase in sophistication without an increase in energy requirements, there remains the need to couple energy between transmitter and receiver. We therefore quickly come to the conclusion that, *in energy-constrained sensor networking, maximizing network lifetime implies minimizing the communications.* This has implications for virtually all aspects of the sensor node across the signal processing and communications, and leads naturally to cross-layer issues and design. Various definitions of network lifetime are possible, such as time to first node failure, or time to appearance of the first network partition (i.e., connectivity breakdown). Together with energy consumption models such as (1), these may be used to obtain design guidelines and bounds on system performance [41]-[46].

[2]Receiver sensitivity can be enhanced, e.g., by lowering the thermal temperature, or incorporating multiple antennas. However, these enhancements come at an increased system energy cost, and so must be balanced in the overall design.

The rest of the article is organized as follows. In the next section we consider choice of architecture, and communications connectivity. This is followed by a discussion of capacity and scalability in sensor networks, revealing several desirable network attributes. Achievability of these attributes is the subject of the following sections, and includes network synchronization and node localization, distributed signal processing, hardware, and MAC and routing. Finally, we close with a discussion of cross-layer system design, where significant research challenges remain. With so much interaction and dependence between the many transceiver layers and system components, the systems design and analysis is a very challenging task.

[Side Bar 1] Energy Consumption and Duty Cycling

One way to assess energy consumption is to employ a radio and signal processing model such as the following, along the lines of, for example [80], [121]. The transmit energy is described by

$$E_{tx} = e_{sp} + d^{\alpha} \cdot e_{out}, \tag{1}$$

where e_{sp} is the energy cost of the signal processing associated with signal generation, e_{out} is the transmitter output energy, and a simple geometric path loss model is assumed, so that propagation loss is proportional to

$$\frac{1}{d^{\alpha}}, \quad 2 \leq \alpha \leq 4 \tag{2}$$

where α is the path loss exponent and d is the distance (meters). At the receiver, let E_{rcv} = receiver energy, and E_{sp} = sensor signal processing energy. The units are Joules / bit, and E_{tx} and E_{rcv} are then scaled by the packet length. In addition, suppose the receiver also has a low energy idle state, with the radio off, such that $E_{idle} = \beta E_{rcv}$, $\beta \ll 1$. The parameter β indicates the degree of energy savings when the receiver is not operating. At a minimum, when idle, the node might continue to operate a clock (see section IV-A).

Eqn (1) is coarse. For example, fading is ignored, e_{out} is not necessarily a linear function of power control (see section VI regarding power amplifiers), and e_{out} should be lower bounded by some non-zero minimum. For specific cases much more detail may be added, but the basic approach leads to insights.

Consider the following example. Let $E_{rcv} = E_{tx} = 1$, and suppose the radio is active ρ percent of the time; we refer to ρ as the *duty cycle*. Figure 1 shows the radio energy consumption versus duty cycle. The baseline case assumes that the radio receiver is on whenever their is no transmission, while the other cases assume the transmissions are precisely scheduled such that the radio is in idle state $1-\rho$ percent of the time, for different values of β. This simple example illustrates how E_{rcv} must be accounted for whenever the receive circuitry is active, even when there is no signal present to be received. At low duty cycles (low message rates), the energy is dominated by E_{idle}, while at high duty cycles E_{tx} dominates.

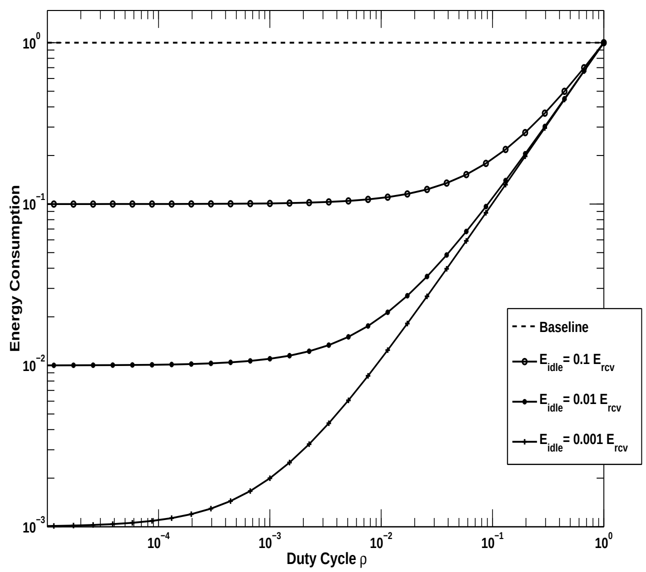

Fig. 1. Duty cycling the transceiver into an idle state can dramatically reduce energy consumption, especially at low message rates. This example assumes perfect scheduling, comparing to a baseline radio whose receiver is always on when not transmitting. The energy consumed in the idle state may be dominated by the node clock.

II. Communication Architectures and Connectivity

The choice of network architecture is quite fundamental, and yet quite variable, given the large variety of applications described above. The choice of architecture is woven into the entire sensor network problem, dictating and being dictated by the sensor density and area, communications rate and quality of service requirements, desired lifetime, and other factors. Architectures might be roughly divided into a few classes. A *flat* architecture implies multi-hop communications, perhaps with one or more collectors (sinks), whereas a *clustered* (hierarchical, perhaps multi-hop) approach might be thought of in analogy with cellular networks (see Figure 4). Clusterheads can be elected, pre-selected, or otherwise chosen perhaps in some optimal and time-varying way. In a homogeneous network (identical nodes), there may be significant advantage in sharing the clusterhead functions so that no undue burden is placed on any specific node, and so prolong network lifetime.

In a heterogeneous network, the clusterheads might have significantly more functionality and energy at their disposal. A continuously-powered access point approach is enabled using the $802.15.4$ communications standard, as mentioned previously. A logical extension is to have *mobile access points* (collectors); these might be unmanned aerial vehicles (UAVs), or ground-based mobile collectors such as robots. This can be viewed as the inversion of a standard cellular approach (the base station moves and the users remain fixed). In these cases the network becomes very asymmetric, and this brings significant advantages and potential simplifications of the nodes (as will be described later), albeit with the cost of the mobile access point.

Hand-in-hand with the communications architecture is the network *connectivity* [11]-[17]. A network is connected when a multi-hop path exists between all (or desired subsets) of nodes. Connectivity is a function of the node locations (density, and coverage area), radio channels, power assignment (power control), and the traffic matrix (the traffic matrix might be such that arbitrary peer-to-peer connectivity is not needed). Initial connectivity could be ensured by careful node placement along with channel measurement and power adjustment, a luxury that might be available in some applications. However, robustness to node failure, as well as time-variation in the radio channels, makes hand emplacement somewhat more complicated. Even in the fully static case, fading channel variation may be significant due to the motion of nearby scatterers (cars, blowing trees, and so on).

Consider a randomly deployed sensor network with n total nodes, as in Figure 5, where the nodes are placed under a homogeneous Poisson distribution with parameter λ into an area of size A. Assume the geometric path loss model of eqn (2), and that any two nodes within distance r are able to close the link. Let $A_r = \lambda\pi r^2$, which is the area covered by a transmission with radius r. Then, $N = \lambda A_r$ is the expected number of nodes in the transmission radius.[3] Given this model we can then ask, what value of N will ensure connectivity, and does this scale with overall area A for fixed density λ? Alternatively, for a given A and λ, what value of r will ensure connectivity? The later question takes the form of a tradeoff; increasing r will increase N and so increase the likelihood of a connected network and decrease the average number of hops needed between two arbitrary nodes, but larger r also implies more transmission interference between nodes and so affects the network throughput.

This problem has been studied at least since the 1970's. Employing a slotted ALOHA model in addition to the above setup, and assuming peer-to-peer traffic (uniform traffic matrix), Kleinrock and Silvester used average throughput analysis to show that $N = \lambda A_r \approx 6$ achieved the best tradeoff, with r the same for all nodes [11]. It was postulated that, if on average each node has 6 neighbors within distance r, then the entire network is connected with very high probability (the value of 6, and later other values, were referred to as "magic numbers"). Of course, under the Poisson model with fixed node density λ, then as the area A grows there is a finite probability of disconnection of one or more nodes (i.e., a network partition exists). This was pointed out by Philips [12], who showed that as $A \longrightarrow \infty$, then probability$\{$connected$\} \longrightarrow 0$, although they recognized that the vast majority of nodes are highly likely to be in a single connected component for N as small as 3. More recent results show that as $A \longrightarrow \infty$, no finite magic number for N exists. Rather, for a network with n nodes, the number of neighbors within range per node should grow as $c \cdot \mathcal{O}(\log n)$,[4] which is shown to guarantee that Prob$\{$connected$\} \longrightarrow 1$ as $n \longrightarrow \infty$ (note however, that this has the undesired potential effect of creating more mutual interference) [17]. For $c \geq 1.5$, simulations show that full connectivity is very highly likely even with relatively small network size, e.g., $n \approx 30$.

Together, these results provide useful guidance on the choice of randomly deployed network density and power control levels, from a communications connectivity point of view, although the analysis ignores fading and non-homogeneous node deployment. This is the first result indicating issues associated with scaling of the network, others will be studied in the next section. We also note that the discussion of architecture and connectivity has focused on the communications,

[3]Kleinrock and Silvester refer to N as the "average degree" [11].

[4]Order notation $\mathcal{O}(x)$ generally indicates that the largest term scales with x.

whereas the underlying sensing application may dictate the sensor coverage (node density) based on criteria such as spatial Nyquist sampling or detection coverage.

III. CAPACITY, SCALABILITY, AND TRAFFIC MODELS

A. Ad-hoc network capacity

A discussion of network performance and performance limits, including capacity and scalability, naturally turns to information theory [18]-[25]. However, it has proven difficult to translate many of the fundamental information theoretic results and bounds from point-to-point communications to ad hoc networking cases [18]. Consequently, when Gupta and Kumar (GK) defined a new notion of network capacity that was analytically tractable [19], it created a large amount of interest. GK put forward the network metric of *transport capacity* in bit-meters / second, which may be the network aggregate, or the per-node average (and the distance may be normalized to obtain transport capacity in bits / second). They obtained the following: for n nodes in a peer-to-peer ad hoc network (scaled into a square-meter area), with a commonly shared channel of bandwidth W Hz, at best the total network transport capacity scales like $\mathcal{O}(W\sqrt{n})$ bits / sec, for large n. The average per-node transport capacity follows by dividing by n, yielding $\mathcal{O}(W/\sqrt{n})$.[5] Thus, as n grows the overall capacity grows, but at a rate such that the per-node capacity decreases. For more on transport capacity, see Side Bar 2 – Transport Capacity in a Fixed Wireless Network.

These results are fundamental, and are due to the limitations imposed by the common access channel. Let us more carefully consider the assumptions that lead to this result; see Table III. In addition to connectedness, a genie is able to establish global timing and scheduling, routing, and power control to facilitate optimal network performance. Using these assumptions GK developed upper bounds on transport capacity. Allowing for optimal placement as well, GK also developed constructive lower bounds on transport capacity. Fundamentally, the global scheduling, routing, and power control bring about efficient network operation. Much of the rest of this paper is directed towards these assumptions in the context of energy-constrained sensor networks, and how they might be at least approximately achieved in practice.

[5]Slightly different results are obtained, depending on the interference model. GK treated two cases. (1) Protocol model: any collision within radius r negates communication, or (2) SINR model: requiring the signal-to-interference plus noise ratio to be above a threshold, with a geometric path loss model.

[Side Bar 2] Transport Capacity in a Fixed Wireless Network

Transport capacity, in bit-meters / second, can be used to characterize the possible overall throughput of a network in the limit as the number of nodes $n \longrightarrow \infty$ [19]. The transport capacity is the total transport length (in meters) of all the bits in the network, per unit of time. This is fundamentally different from Shannon's definition of capacity, which does not involve physical distance.

The fixed node positions are modeled as iid and uniformly distributed in a disk (or sphere) of unit area. A uniform traffic model is assumed; each source i has data intended for a randomly and independently chosen destination j. Under the geometric path loss model as in (2), signal power decays with range r_{ij} as $r_{ij}^{-\alpha}$. Transmission from i to j is assumed successful if the signal-to-interference plus noise ratio (SINR) exceeds a threshold, otherwise the message is lost (which implies there is no form of multi-user reception). Letting P_i be the node i transmit power, then the power received at node j from node i is

$$\mathrm{PR}_{ij} = \frac{P_i}{r_{ij}^{\alpha}} \tag{3}$$

and the SINR criterion can be expressed as

$$\frac{\mathrm{PR}_{ij}}{N_0 + \sum_{k \neq i} \mathrm{PR}_{kj}} \geq \gamma, \tag{4}$$

where the denominator of (4) is the thermal noise plus the interference power from all other concurrent transmissions. Suppose there is only one interfering equal power transmission from node k to node j, then from (4) transmission will not be successful if

$$r_{kj} \leq \gamma^{-\alpha} r_{ij}, \tag{5}$$

i.e., the transmission from i to j is jammed if the interfering node k has range r_{kj} proportional to the range r_{ij}.

From an interference standpoint, high-power long-range communication is undesirable, because the interference area grows as r^2, so that typical transmissions should be limited to nearest neighbors. With random node placement, the nearest neighbors have range that is proportional to $\mathcal{O}(1/\sqrt{n})$. (Note that this range is scaling down as the network size grows due to the assumed square-meter total area.) This implies that, under the SINR model, only one node in a neighborhood may transmit per slot, so that a total network transport capacity upper bound scales like $\mathcal{O}(\sqrt{n})$. Under the uniform traffic model, the average multihop route requires $\mathcal{O}(\sqrt{n})$ hops. As each hop is of length $\mathcal{O}(1/\sqrt{n})$, then the average distance per message is $\mathcal{O}(1)$. Thus, the transport capacity *per source* scales as $\mathcal{O}(\sqrt{n}/n) = \mathcal{O}(1/\sqrt{n})$. While the average distance per message is not changing, the number of hops required per message is also growing as $\sqrt{n}$, creating ever more interference and fundamentally limiting the overall network throughput. From another point of view, the total network transport capacity is *growing* as $\sqrt{n}$, but the per-node share of this capacity is *decreasing* like $1/\sqrt{n}$.

This assumed omni-directional single-channel transmission, but the results do not change if the channel is split (e.g., employing FDMA, or base stations), so long as the total bandwidth W does not change. Similarly, the scaling behavior is unchanged if beamforming is employed, so long as the beamformer has non-zero spatial coverage around the receiver.

B. *Correlated traffic*

We note that the GK traffic model is peer-to-peer; the traffic is randomly generated between arbitrary nodes i and j (uniform traffic matrix model). But, peer-to-peer is not likely to be the appropriate traffic model for most sensor networks. Instead we anticipate traffic flows to collectors (a many-to-one traffic model) [26]-[40]. In addition in many applications (e.g., environmental sampling, source detection) the data will be highly correlated, rather than independent as assumed in GK. In 1973, Slepian and Wolf provided a theoretical limit on distributed coding (compression), when transmitting to a common destination [26]. Remarkably, this theorem indicates that the nodes do not need to communicate among themselves in order to achieve the fundamental limit on data reduction, although the destination node needs to know the underlying source correlation.

Suppose now we consider a flat architecture with a single collector (many-to-one architecture), and assume that optimal Slepian-Wolf compression can be achieved. If the node density increases (e.g., $\lambda \longrightarrow \infty$), then the number of bits per sensor needed to be communicated goes to zero, due to the increasing correlation between sensor measurements. On the other hand, the GK results show that the per-node available bandwidth decreases due to the shared communications channel. Will the required communication bandwidth decrease sufficiently fast per node in the limit to enable successful communication? There is evidence that the answer is no for the case of a single collector as the network density increases [33]. Intuitively, the communications become bottlenecked near the collector, and so more bandwidth is required as the node density grows.

The Slepian-Wolf results provide fundamental bounds, but are not constructive. Is it possible to achieve this level of compression? As recently as 1998, it was noted that "the conceptual importance of Slepian-Wolf coding has not been mirrored in practical data compression" [28]. Recent work using iterative turbo and LDPC codes [29], [30], [31], as well as other approaches [32], may yet lead to highly efficient practical distributed compression schemes.

C. *Mobility*

The above results on scalability might be taken as somewhat discouraging, at least with regard to very dense large networks. They do naturally point away from large flat networks, and towards routing and aggregation schemes that exploit clustering and tree-type architectures. How can these fundamental limits be overcome? From a communications perspective, we seek diversity to raise throughput. One powerful way to do this is to introduce mobility. Following up on GK, Grossglauser and Tse showed that dramatic gains in peer-to-peer ad hoc network capacity are possible when mobility is introduced, so that the network topology is time-varying [20]. Using a *store-and-forward*[6] paradigm, and allowing finite but arbitrary delay, they showed that the per-node transport capacity may now scale as $\mathcal{O}(1),$ i.e., *not* decreasing with n. This occurs due to the ultimate availability of good channels between arbitrary nodes, so long as one is willing to wait, and assumes that the channels are globally known to allow for optimal routing and scheduling (and we note that optimal routing may be multi-hop, even with mobility). When the tolerable delay is bounded, then capacity may be reduced, revealing a fundamental capacity - delay tradeoff; see [24] and references therein.

The advantages of mobility also potentially translate to throughput gains in the sensor network and other settings. For example, mobility (time diversity) can greatly increase the throughput in random access schemes such as ALOHA, when channel knowledge and/or multi-packet reception is utilized at the clusterhead [112], [113], [114], [120]. Multi-user reception at the clusterhead

[6]Generally, a message is received, buffered, and then forwarded at a later time.

allows for collision resolution, and the channel knowledge can be used at each node to optimally modify its probabilistic backoff time before retransmission when collisions are not resolved.

As introduced in section II, employing mobile (such as aerial) access points is an interesting way to gain advantage via mobility. By shifting complexity to the mobile node(s), the sensor nodes may be simplified, but of course this comes at the cost of the mobile access point complexity and deployment. Advantages include typical line-of-sight propagation, and facilitating node localization (which is non-trivial, see section IV-B). Employing a mobile access point can greatly simplify the MAC, which now can become many-to-one via a single hop. The mobile access point may use a beacon to facilitate sectorized node wakeup and channel estimation; this in turn can be used in a random access scheme. The per-node energy (ignoring the energy consumed by the mobile access point) can be orders of magnitude lower than that required in a static ground-based network [25], [121].

IV. Network Timing & Node Localization

A. Network Synchronization

Some level of synchronization between sensor nodes will be needed, both from the signal processing and communications viewpoints [47]-[62]. Cooperative sensing, detection, and estimation requires this, so that sensed events can be synchronized across the network. Many proposed sensor network signal processing schemes involve sharing raw data, or various forms of fusion, in which some form of synchrony is implicitly assumed. The degree of synchronization for sensing could vary from coarse synchrony of events (e.g., detection), down to ADC sample time accuracy (e.g., as might be required for cooperative beamforming across nodes, see section V). In addition to the signal processing tasks, synchronization enables scheduling by the MAC layer, allowing for duty cycling of unnecessary hardware components and thereby keeping idle processing and listening to a minimum, which leads to dramatic energy savings and network lifetime extension.

To maintain synchrony across a wireless network, each node may utilize its own clock, and then rely on communications between nodes to account for the unavoidable clock drift between nodes; it is this scenario we will focus on. Before doing this however, a brief discussion of centralized timing is in order. This approach has been used extensively in wired networks, where a single master clock may easily be distributed across the network, e.g., see [48]. This approach has a long history, such as utilizing early telegraph technology to synchronize time across continents in the late 1800's, and the problem was considered by both Einstein and Poincaré.[7] In the context of sensor networks, centralized timing can be maintained via access points and beacons, an approach that is enabled with the previously mentioned $802.15.4$ standard [90]. If the beacon has a continuous power supply available, then the lifetime of the energy constrained nodes can be extended considerably, as we discuss below.

The problem of network synchronization via individual clocks and message passing was studied extensively in the 1970's, e.g., see Lindsey and Kantak [47] and references therein. In the following we focus on the issues of energy consumption and clock technology. Consider two nodes i and j, whose clock times are denoted t_i and t_j, respectively. These can be related by the model

$$t_j = a_{ij} t_i + b_{ij}, \tag{6}$$

where a_{ij} is the skew (relative drift), and b_{ij} is the offset between the two clocks. One way to synchronize the two nodes is to pass messages in order to estimate a_{ij} and b_{ij}, and several protocols have been suggested for this [50], [51], [52], [55], [56], [57], [58]. From an estimation viewpoint, more frequent signaling leads to better estimates, at the cost of additional energy, although one can exploit piggybacking on communications traffic. Interpolation, both forward and backward, may be carried out over reasonable time frames, which facilitates post-event synchronization across the network [51]. While (6) can be exploited between nodes, there remains the larger question of synchrony among clusters or globally across the network. This can be achieved, for example, using an iterative global least squares solution, again at the cost of increased communications (energy). Some experiments have exploited (6) and achieved μsecs accuracies [51], [57]. Such results are relative to the accuracy of the oscillators employed, the degree to which processing latency can be controlled or measured, and the frequency of signaling. In addition, the parameters in (6) will slowly vary with time, e.g., as a function of temperature.

Let us be more specific and consider some relative oscillator accuracies and energy costs, and the impact on the ability to schedule slotted transmissions. Table IV lists several types of

[7] See [61] for an interesting historical perspective on development of international time standards, the use of synchronized time for accurate longitude estimation, and how technology advances in time synchronization over global distances may have spurred the theory of relativity.

oscillators, their rough accuracies, power consumption, and idealized lifetime based on a AA battery. The AA is assumed to have 10,800 Joules (3 Watt-hours) of energy. Actual lifetime depends on the duty cycle rate and other factors, so the lifetimes in Table IV may be quite optimistic, especially for the longer lifetime predictions.

It is clear from the table that more accurate clocks come at the cost of higher energy requirement. Consider a temperature controlled crystal oscillator (TCXO), with an accuracy of 6 parts-per-million (PPM)[8] and energy requirement of 6 mW. If the sensor network is equipped with such oscillators and an AA battery, then simply operating the clocks limits the network lifetime to 21 days, without including any signal processing or communications costs. When communication is a relatively rare event, the clock may become the dominant energy consumer.

Given the range of oscillator accuracies in Table IV, how often must messages be passed in order to maintain network synchrony? A form of worst case analysis proceeds as follows. Consider two nodes whose clocks drift with d (PPM), and assume they drift in opposite directions (the worst case). Assume a slotted system with slot time t_s, and suppose it is desired to maintain a worst case of 90$\%$ slot overlap to keep the probability of reception sufficiently high. We take the drift time to be $t_d = (1/2)(0.10)t_s$, where the factor $1/2$ accounts for the worst case drift in opposite directions. The time to drift t_0 seconds apart is given by

$$t_0 = \frac{10^6\ t_d}{d}, \tag{7}$$

where the factor 10^6 enters because d is expressed in PPM. We plot t_0 versus slot time t_s in Figure 6, parameterized by d (PPM), which gives an idea of how often messages should be passed in order to resynchronize the nodes to maintain the desired 90$\%$ slot overlap. For example, in this worst case, maintaining 1 msec slot timing with 1 PPM accuracy oscillators requires message passing at a rate greater than one per minute. These results do not exploit (6); this or other approaches might allow for significantly reduced communications overhead. While technology will evolve, the breakpoints can be clearly delineated in terms of accuracies and energy consumption. Referring to Figure 6, achieving 0.001 PPM accuracy significantly reduces the synchronization overhead burden, with respect to a slotted system with slots on the order of msecs, but such an accurate clock currently comes with a relatively large power drain.

[8]Oscillator manufacturers typically use PPM to specify accuracy. For example, there are 3.6×10^6 msec/hour, so 6 PPM implies an accuracy of 0.6 msec after one hour.

Let us briefly return to the case of an access point (AP) with a continuous power supply. From Table IV, a 200 PPM clock is available with a very low energy requirement of about 1 μW, leading to a potentially very long battery lifetime, but whose inaccuracy must be compensated for. In the AP scenario, the AP may provide a periodic beacon while maintaining its own more accurate clock, whereas the battery driven node uses the 200 PPM clock. When the battery driven node awakens, it has only to listen over one period of the beacon time in order to resynchronize with the AP. This scenario is highly appealing in many commercial settings, especially with very infrequent communication, where the drift of the 200 PPM clock may be quite tolerable. This approach may also be applicable in some energy constrained scenarios, such as when a mobile collector is employed. Referring to our original assumptions in section I, we assume that a beacon would employ a robust waveform to avoid interference or jamming.

Another form of global beacon is to employ GPS receivers at some or all of the nodes. However, as we see from Table IV, current GPS receivers are relatively high energy consumers. This is partly because in addition to timing, GPS receivers generally also estimate position. While positioning is useful, other methods might be employed to obtain this information as described below in section IV-B. It is possible to develop GPS receivers whose sole function is to obtain timing information, reducing the number of parameters to be estimated, and so reducing the required energy. Such a GPS receiver might also be duty cycled, coupling with a continuously-running but lower accuracy clock. Of course, GPS is not available in many scenarios of interest (indoor, urban, foliage).

Another interesting possibility, noted in Table IV, is the advent of a chip-scale atomic clock. Design goals for such devices are high accuracy yet relatively low power requirement, for example see [49], [53], [54], [62].

B. Node Localization

In addition to synchronization, a second fundamental issue arises with deployment, the need for each node to know where it is in 2-D or 3-D, or at least to know relative location with respect to other nodes [63]-[72]. This geolocation task could be solved by careful deployment at known locations, but many scenarios call for random placement, and so the geolocation must be accomplished after emplacement. In addition to (say, 2-D) location, nodes may also require orientation with respect to rotation if any form of directionality is employed in either the sensing or communications (e.g., the node might estimate the angle-of-arrival of the sensed phenomena, or antenna arrays might be employed for communications). Some methods may only provide relative location between nodes, so the network may also require anchoring to nodes that have absolute location information (e.g., they might have GPS). How can we geolocate and determine the orientation of randomly deployed nodes, and what kind of accuracy of location estimation can be achieved? The later question is important, because no matter what method is employed, there will remain some residual uncertainty in the node locations, and this implies some uncertainty in the ability of the sensor network to perform tasks such as target localization and tracking. It may not make sense to provide extremely accurate angle-of-arrival estimation of a target, when the location of the nodes has considerable uncertainty.

Self-localization of the nodes may be either active or passive. A passive scheme would use sources of opportunity, and rely on a relatively sophisticated joint signal processing algorithm to simultaneously solve for the source location and the node locations, e.g., see [67]. An active approach requires beacons (controlled sources), and these may be deployed within or external to the sensor field. An example of an external beacon is GPS, which is appealing due to its world-wide coverage and accuracy. However, as noted in section IV-A, GPS has the significant drawbacks of cost, power consumption, and coverage that is limited to outdoors with generally unobstructed overhead views. Deploying external beacons with the sensor network is an option whose efficacy strongly depends on the application, and is clearly a luxury for many scenarios.

Sensor nodes may inherently have two avenues available for active self-localization, the radio and the sensor itself. For example, an acoustic sensor network could generate acoustic and/or radio signals as beacons. Radio-based geolocation is a long-studied problem, but sufficiently accurate geolocation may require a time-bandwidth product that exceeds that necessary for the sensor network to operate, because many applications require only a relatively low bandwidth radio of modest complexity. One possible radio solution is to employ ultra-wideband (UWB) modulation. However, UWB is inherently an overlay approach, whose complexity may be driven by the need to reject in-band interferers with whom it must coexist. Robust UWB approaches to geolocation are currently under study, e.g., [65]; these are more appealing in indoor and short range environments due to the required low power UWB emissions and the need to overcome the in-band interference.

Active emission may be relatively easy in some modalities, such as acoustics where the fractional bandwidth may be enormous (e.g., 100 Hz bandwidth centered at 100 Hz). The fundamental accuracy limits of such an approach can be studied by employing the Cramer-Rao bound (CRB) [68], [69], [70], [71], and can include heterogeneous nodes with mixed capability such as estimation of received signal strength, time of arrival, angle of arrival, and so on. Interestingly, some CRB results indicate that the best localization accuracy might be achieved when each node is able to exchange information with five or six neighbors, which is in line with connectivity results described in section II.

As an alternative to deploying beacons within the network, one could employ a mobile access point with a beacon [72]. This might be carried out with the same platform used for sensor deployment. The mobile AP can be used to localize many sensors simultaneously in a broadcast mode, without a pre-established sensor network. A multi-modal approach can used, such as using both radio and acoustic signal emission from the AP. The AP radio broadcasts timing, its own location information, and the acoustic signal parameters. The known acoustic emission may be used at the sensor to measure Doppler stretch, time delay, and angle of arrival. These measurements are individually sufficient to localize a sensor node, or they may be advantageously combined. Cases of time delay and Doppler estimation are considered in [72].

V. Distributed and Cooperative Signal Processing

The broad application space (Table I) and environments (Table II) guarantees a great variety of sensor network signal processing tasks [3], [6], [10]. The central issue is to optimize the signal processing performance while minimizing the energy expended to do so, i.e., exploit the opportunities available through the network, and yet minimize the usage of the network to preserve energy. A complete survey of distributed signal processing is beyond the scope of this article, e.g., see [3], [10]. Instead, we consider systems issues, and also provide a specific example (see Side Bar 3 – Distributed Aeroacoustic Source Localization).

In the light of the previous sections focus on communications, we can ask some basic sensing design questions. What is the sensing task (Table I), and what sensor density is needed? We can presumably tolerate oversampling much more readily than undersampling. What is the frequency of sensing, and what level of synchronization is needed for these measurements (i.e., what level of network synchrony is needed from a signal processing point of view)? Perhaps only coarse event-detection synchrony is needed, or maybe very fine synchrony is called for, such as using several sensor nodes in an array processing problem. A need for providing quick updates will force a completely different radio traffic model than slow and infrequent updates. At one extreme, the network can be viewed as a distributed database to be polled (the “pull” scenario). Where should the “answer” appear, e.g., at all nodes or at a single node? If all the nodes need to have the results of a networked computation, then distributed iterative algorithms that employ message passing may be a useful option, although the energy consumption of such an approach may outweigh simply aggregating the data, performing the computation, and passing the answer back to all the nodes. When a single node needs the answer, e.g., for exfiltration, then aggregating tree structures, successive compression and computation, or other schemes may be incorporated along the data route to the central node.

Given the basic sensing task and some particulars along the lines of the above questions, the specific signal processing approach(es) can be formulated. A solution will find a balance between localized and centralized processing, and may result in a tradeoff between the amount of communication and the signal processing performance. An ideal solution will minimize communications while preserving near optimal performance. In Side Bar 3 we show one such case.

[Side Bar 3] Distributed Aeroacoustic Source Localization

Consider the problem of localizing a source using distributed aeroacoustic sensors [73]-[76]. Acoustic sensing is a mature technology and is appealing in many applications. However, while many array processing techniques are now textbook, significant challenges remain due to outdoor acoustic propagation, as well as the distributed nature of the processing.

Suppose that each node has a calibrated sensor array, enabling angle-of-arrival (AOA) estimation (see Figure 2), and consider three signal processing (SP) solutions:

1) Triangulation
2) Centralized Processing
3) Combined AOA and Time-Delay Estimation (TDE)

Method (1) is conceptually straightforward: the ith node observes the source for T seconds, and estimates the AOA θ_i. The θ_i's are communicated to a central node, and triangulation is used to estimate the source location. This method uses minimal communications, and requires only coarse synchronization across the network.

Intuitively, much better accuracy might be achieved if all the sensors are treated as elements of a single super-array, because of the significantly larger effective array aperture, which leads us to method (2). For example, in Figure 2, the source may be in the near field of the super-array, but in the far field with respect to any individual array; exploiting this can lead to dramatic improvement in localization. So, for method (2), all the raw data samples from each node are communicated to a central node, and an appropriate (near-field) array processing method is applied. While this enables optimal AOA estimation, (2) also maximizes the communications load. In addition, very fine network synchronization and calibration is required.

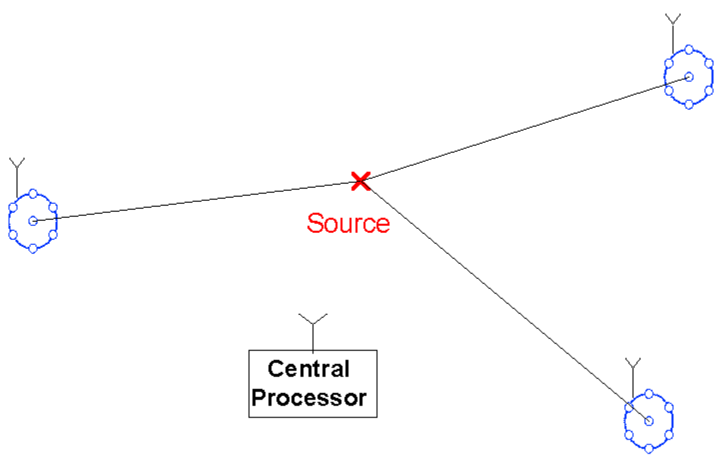

Fig. 2. Energy-constrained distributed signal processing tasks attempt to balance the communications load against performance. In this case source localization might be achieved with high accuracy, without communicating all the raw data to the central processor.

From a communications load perspective, the above two schemes appear to bracket the job, but also present two largely different achievable localization accuracies. This leads us to the intermediate approach of (3). Here, like method (1), the AOA's θ_i are computed at each node. In addition, the raw data from a single array element from each node are communicated, and cross-correlation based TDE is performed between pairs of such elements. The TDE is thus performed over the large baseline separation between nodes, and can be combined with the AOA

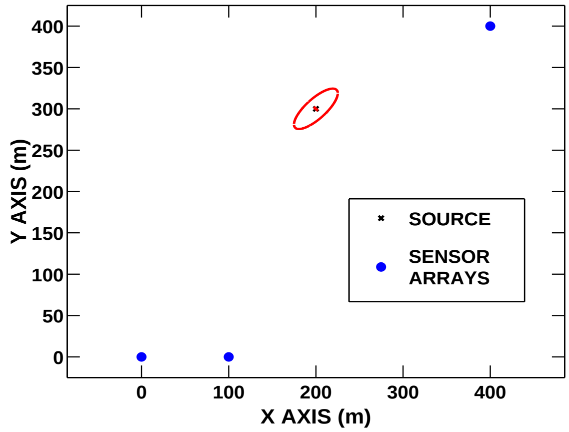

Fig. 3. Cramer-Rao bound ellipses for distributed source localization example, for the three distributed signal processing schemes suggested. When acoustic coherence supports time delay estimation, method (3) achieves optimal performance, whereas triangulation alone has much poorer performance.

estimates. This approach has been shown via Cramer-Rao bound analysis to be nearly equivalent to communicating and processing all the raw data [74], [75]. From a systems perspective, method (1) can be used and, if further accuracy is required, TDE can then be used as needed at an additional cost in communications. An example is shown in Figure 3, using three arrays. The large ellipse bounds achievable source localization accuracy based on triangulation (method (1)), whereas the small ellipse bounds the performance of methods (2) and (3). Results of some outdoor experiments are given in [74], [75].

The use of TDE to augment AOA requires two fundamental conditions to be met. First, the time-bandwidth product (TBP) of the source must be sufficient, i.e., the source must have sufficient bandwidth and duration to provide an unambiguous peak in the cross-correlation. Second, there must be sufficient spatial coherence in the signal at any two measurement points. This second condition arises due to spatial coherence loss that occurs due to acoustic propagation in the turbulent atmosphere (such a coherence loss does not typically occur in electromagnetic propagation, where fading and multipath are the dominant channel effects). The condition on coherence can be coupled to the source TBP condition, leading to a *threshold coherence* for a given TBP [75]. The coherence can be readily estimated experimentally as a function of frequency. In some cases, quite small reductions from perfect coherence are sufficient to make accurate TDE unachievable, even at high SNR. In these conditions, method (2) will generally not improve on method (1), so that a better strategy is to employ method (1), and then attempt method (3) if conditions warrant.

VI. Hardware Trends

To conserve energy, all aspects of the hardware and circuitry need to be considered in sensor network system design [77]-[90]. This includes the sensing, signal processing, and radio, and can be further broken down in terms of functionality to include geolocation, clocks and synchronization, and so on. The sensor node can benefit from energy reduction in virtually all components; here we mention a few key elements. The overall system can allow for duty cycling into various states, such as idle (clock only), signal processing, listening, and transmitting. The state transitions are not instantaneous; there may be a significant energy cost (and associated delay) in order to transition to an on-state. For example, oscillators generally have a settling time that may be 1 msec or more. This implies that the overall system control and timing is an important aspect of saving energy, and arbitrarily fast state transitions will not necessarily result in an energy savings.

In addition to clocks, described previously, the analog RF circuitry, power amplifier (PA), and analog-to-digital (ADC) converter are important components from an energy perspective. It is interesting to note that there has been no form of Moore's Law type behavior when it comes to advancements in the analog circuitry, yet such circuitry is fundamental to the operation of radios. While advances are being made, the analog mixing and filtering, and ADC circuits, require significant energy for operation. The PA exhibits two key attributes that affect its use; see Figure 7. First, the PA output will saturate at high input levels, and the resulting nonlinearity generates undesired out-of-band signals. To remain in the linear region a modulation format that has low or constant peak-to-average power ratio (PAPR) can be employed, such as phase-only modulation (PSK). Alternatively, when other non-constant modulus modulations such as OFDM are employed, some combination of circuitry or DSP may be utilized to reduce the PAPR [78]. The second notable PA issue is that the efficiency of the PA increases with input level, so that low power signaling can be very inefficient from an energy consumption perspective [85].

From a DSP perspective, there are energy - performance tradeoffs. Different signal processing algorithms and associated hardware may be employed, providing different performance levels as needed. An interesting example is the use of adaptive modulation and coding, along with power control. The SNR at the receiver can be enhanced by increasing transmit power; on the other hand more powerful coding can be employed that requires more decoding DSP at the receiver but less power at the transmitter. This can be analyzed using eqn (1) and E_{rcv}.

DSPs may employ multiple bit-widths (e.g., execute FLOPS at different quantizations), allowing a tradeoff between computational accuracy and energy consumption. More generally, modularized domain-specific DSP suites can be developed. Dynamic voltage scaling has also been suggested, which yields variable latency but saves energy, slowing the DSP clock to accommodate the time allowed for the computation at hand. Such tradeoffs involve several system parameters, and a design that is adaptable might achieve the lowest energy consumption.

We note that specialized hardware may also be employed to harvest ambient energy, and thereby recharge the battery. Possible energy sources include vibration [89], solar [82], RF [86], and thermal. Another intriguing possibility is to employ radioactive thin-films that generate high energy particles (effectively a miniature atomic battery [88]), to drive RF circuitry [87].

VII. MAC and Routing Issues

A. Medium Access Control

Perhaps the most central question in radio networking is, how do we efficiently share the common medium (in an energy conserving manner)? Many approaches are possible [91]-[98]. In Table III, perfect scheduling is assumed, which as we have seen fits into the framework of a slotted system employing duty cycling to eliminate idle listening and thereby save energy. Node i knows in which slot it should listen for a potential message from neighboring node j. TDMA scheduling can be deterministic, or based on pseudo-random slot assignments, and perhaps uniquely assigned only within a local cluster. Scalability is a key issue; a low density network might rely solely on a deterministic peer-to-peer schedule between neighbors. However, a dense network might require multiple nodes to be actively listening in a given slot, otherwise the latency between any two nodes might be unacceptable. Generally, there is a latency - energy tradeoff, for decreased latency implies more frequent idle listening. The schedule must also be flexible to accept time variation in the network, including new joins, dropouts, channel variations, and possibly mobility. Additional adaptability may be required, e.g., to accommodate broadcasting.

An alternative is to employ random access, such as an ALOHA-type scheme, and slotted ALOHA may employ scheduling. Random access implies collisions and energy loss, and can lead to increased idle listening. However, from the point of view of energy consumption, an optimal choice of duty cycle is possible. With infrequent random listening, the energy spent to find a neighbor dominates, whereas with more frequent listening the idle-listening energy eventually dominates. Thus, some form of hybrid slotted random access with scheduling is appealing in terms of flexibility with reasonable complexity, although such judgments are highly application dependent.

What is an optimal MAC design, what are the optimality measures, and how will a design scale? Optimality depends on several variable factors, including the application and traffic models, node density (which in reality may be highly varying in the same sensor network), and the quality of service (QoS) and latency required. The desired QoS may be time-varying, and cover a broad range in the same network. For example, a high-density network may be highly redundant from a sensing standpoint, implying that the message from any given node is not critical, and an ACK-less MAC might be employed. At the other extreme, high reliability might be required for every message, and so the overhead of extensive handshaking might be unavoidable. It is easy to envision networks where both behaviors might be desirable at various times.

Even the type of channel access, such as random versus scheduled, can be optimal for the same application, depending on such variable factors as the sensor measurement SNR or sensor density. As an example, if a mobile access point is used to collect sensor measurements, then the choice of MAC impacts the efficiency with which a suitably rich set of samples can be communicated. The efficiency is a function of several factors including sensor density and quality of the measurements, so that the optimal choice of random versus scheduled transmission to the mobile AP depends on the operating conditions [118], [119].

A MAC design typically comes with a large range of tunable parameters. Consequently, analysis is very challenging, and we instead rely on simulations and small (often expensive) experiments. One systems approach is to employ a finite state machine (Markov) model; such an approach is used by Zorzi and Rao to study energy consumption [96], [97]. Adaptability and flexibility in MAC design are important if the network is to support a variety of services, and different solutions provide for various tradeoffs, but provable performance remains elusive.

B. Routing

Incorporating energy consumption into routing algorithms is a relatively old idea. Many types of routing algorithms have now been proposed for sensor networks [99]-[111]. One very common approach is to employ a cost function

$$\min_{\Omega} J(a, b, c, \cdots, z) \tag{8}$$

where the parameters may include some combination of delay, range, hop count, battery level, and so on. This approach can rely on variants of classical distributed optimization algorithms such as Bellman-Ford or Dijkstra, and has the flexibility to incorporate heterogeneous nodes with highly variable energy resources. The choice of weights on the various parameters is an interesting question, e.g., see [110].

Several other routing approaches have been suggested with regard to various sensor network applications, and may or may not explicitly include energy use as a factor to be minimized. These include *directed diffusion*, developed for a query-based network and incorporating data-dependent routes, it is a form of controlled flooding based on "gradients" [105]. *Clustering* algorithms naturally occur in the sensor network context and support hierarchical signal processing; various approaches are possible based on connectivity [106], [107].

There are many routing issues, including route discovery, global versus local routing, and communications load (including load sharing via route diversity to avoid prematurely exhausting the energy of specific nodes). Accomodation of time-variation (e.g., addition of new nodes, dead nodes) and mobility add significant complications. Fundamental energy tradeoffs exist between proactive routing (pre-establishing and then continuously maintaining routes) versus reactive routing (discovering routes on demand). This is a basic problem in general ad-hoc networks, and hybrid proactive / reactive protocols for mobile ad-hoc networks have been suggested, e.g., see [111]. In the static case, routes ideally only need to be established once. However, energy fairness and node failures or additions create the need for more dynamic behavior. Reactive protocols may be more energy efficient at low message rates, or with high mobility. Needed are protocols that adaptively balance proactive / reactive behavior in a provably optimal way that preserves overhead (and therefore energy) while achieving a desired time-varying QoS.

VIII. Concluding Remarks: Cross-Layer Design

Energy-constrained sensor networks must carefully conserve the limited Joules available, and the savings may come throughout the entire design, including such elements as MAC design to enable duty cycling and reduce idle listening, new adaptive DSP hardware, accurate low-power clocks, and efficient distributed signal processing algorithms. It is clear that the signal processing, PHY, MAC, and routing are all fundamentally interrelated with regard to energy-saving strategies as well as overall system performance and lifetime. Recent experiments with large, high QoS, mobile ad hoc networks, reveal that only about 1% of the transmitted bits convey information, while the other 99% support networking functionality [115], [116]. As we have seen, new energy-conserving cross-layer designs for sensor networks can lead to significant (orders of magnitude) energy savings, especially for static networks.

Despite the large variety of applications, consistent cross-layer design principles are needed. A layered architecture view, along the lines of the OSI model for wired networks, has significant advantages. These include taking the long term view, facilitating parallel engineering and ensuring interoperability, lowering development cost, and leading to wide implementation [117]. What should a layered architecture model be for energy-constrained sensor networks? And, should this model be specific to the energy-constrained case as opposed to, for example, those that might have access points with continuous power supplies? There are many aspects to the wireless network space; see Table V. Whether and how these pieces should be incorporated into a layered model remains open.

Despite its advantages, a layered model inherently brings some limits on performance. A “point design” for a specific application will achieve the best performance. On the other hand, arbitrary cross-layer designs may lead to undesired consequences [117]. The optimal layer interaction and feedback is not clear. What information should be passed between layers to achieve high performance with provable stability? In fact, should we preserve the layered concept, or consider new component-based interactive system designs with feedback between the components? Emerging answers to these questions will be key to developing wireless-based energy-constrained systems across the large range of applications in Table I.

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Point sources	detection, estimation, geolocation, tracking
Imaging	sampling a field
Monitoring	dedicated sensor-source groupings
Logistics	maintenence, transportation, location
Mobility & control	robotics, UAV's, actuation

TABLE I

SENSOR NETWORK APPLICATION DOMAINS.

SOME SENSING MODALITIES
acoustic, seismic
vibration, tilt
thermal, humidity, barometer
nuclear, biological, chemical (NBC)
magnetic, radio frequency (RF)
light
video, infrared (*high bandwidth*)
ACTIVE SENSING
radar
RF tags
ENVIRONMENTS
home, office, factory
toxic, inhospitable, remote

TABLE II

SENSING MODALITIES AND ENVIRONMENTS.

Random, peer-to-peer traffic model
Connected network
Node locations known (geolocated nodes)
Global routes known
Perfect slot timing and scheduling
Power control
Interference = noise (no multi-user detection)
Arbitrary delay

TABLE III

ASSUMPTIONS IN THE RESULTS OF GK [19] AND OTHERS.

Device	Accuracy	Power	Lifetime with AA battery	comments
GPS	10^{-8} – 10^{-11}	180 mW	16.7 hrs	beacon, outdoor, $ cost
DARPA chip-scale atomic clock	10^{-11}	$<$ 30 mW	100 hrs	*program goals*
MCXO	3×10^{-8}	75 mW	40 hrs	large, aging drift
TCXO	6×10^{-6}	6 mW	500 hrs (21 days)	$>$ 1 PPM
Watch clock	200×10^{-6}	1 μW	342 yrs	temperature & aging drift

TABLE IV

REPRESENTATIVE OSCILLATOR TYPES AND ASSOCIATED ACCURACIES AND POWER CONSUMPTION. AA BATTERY ASSUMED TO HAVE 10,800 JOULES (3 WATT-HRS), WITH IDEALIZED BATTERY DRAIN.

Geolocation
Hierarchical and distributed signal processing
Mobility
Variable QoS
Routing metrics
Non peer-to-peer
random vs. deterministic scheduling
Multi-antenna
Multi-user detection
Synchronization
Beacons and robust communications
Adaptive modulation and coding

TABLE V

ASPECTS OF THE WIRELESS SENSOR NETWORK CROSS-LAYER DESIGN SPACE.

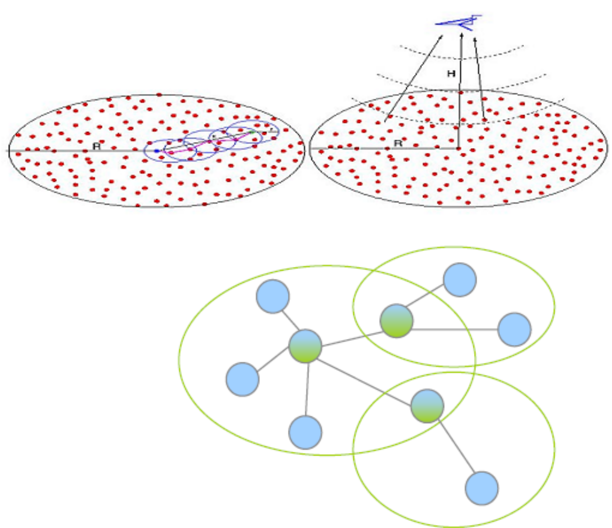

Fig. 4. A variety of wireless sensor network architectures are possible, including flat and clustered, and might even employ mobile access points.

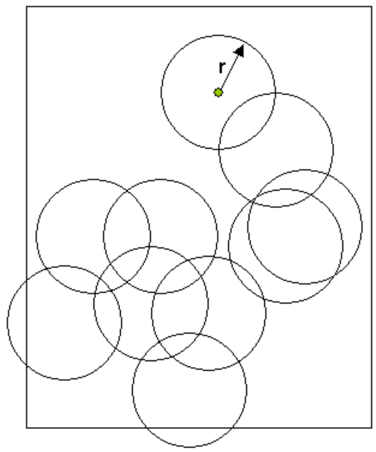

Fig. 5. The network connectivity problem has been studied since the 1970's, assuming random homogeneous Poisson node placement and radius r communications range. This work has produced useful guidelines; see section II.

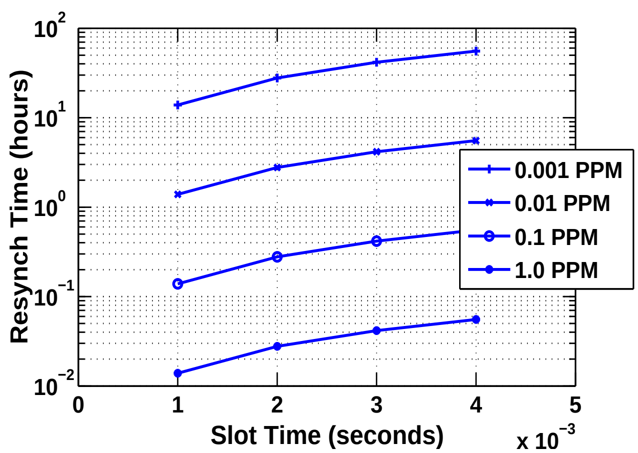

Fig. 6. Maintaining slot synchronization requires messaging to account for clock drift. An unsophisticated scheme may have an unacceptably high message rate.

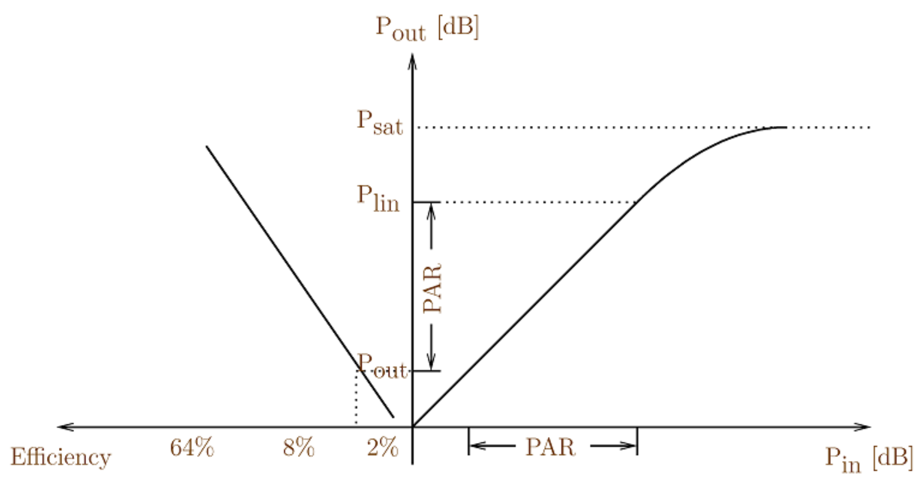

Fig. 7. Power amplifier characteristics. Right-hand-side: input-output response showing characteristic nonlinear response after saturation. Left-hand-side: input versus efficiency, showing typical efficiency loss with low output levels.