Collaborating with Correlation for Energy Efficient WSN

Milen Nikolov and Zygmunt J. Haas

Wireless Networks Laboratory (WNL),
Cornell University
Ithaca, NY 14853

{zjh1, mvn22}@cornell.edu http://wnl.ece.cornell.edu

ABSTRACT

This paper describes a novel approach for collaboration in WSN that substantially reduces energy expenditure in the network by exploiting spatial correlation among nodes. The idea behind the scheme is that the whole range of measurements is partitioned into individual intervals, with each interval assigned to a unique subset of nodes. Each node needs only to determine whether its measured value falls within its assigned interval and transmit a binary decision to the sink. The base station, after gathering the responses of sufficiently large number of nodes, calculates the actual measurement value. This division of responsibilities across the network nodes enables our scheme to utilize collaborative transmissions by spatially clustered and highly correlated nodes. While maintaining a similar distortion level, the proposed scheme achieves in the worst case close to a factor of 2 in energy savings, compared to the standard approach of transmission of the measurement by a single node. The results are derived analytically, evaluated numerically, and confirmed by simulations.

Categories and Subject Descriptors

C.2.1 [**Computer Communication Networks**]: Network Architecture and Design - *Network communication, Wireless communication*, *Sensor Networks*;

Keywords

wireless sensor networks; collaboration; division of responsibilities; energy efficiency; reporting;

1. INTRODUCTION

Along with listening to the wireless channel, one of the main causes of nodes' energy depletion in Wireless Sensor Networks (WSN) is radio transmission. Correspondingly, numerous schemes operating at various network layers have been proposed to reduce the amount of required transmissions and thus achieve more energy-efficient network ([1], [7], [8], [9] and references therein). Among the main strategies to this end is the elimination of redundant transmissions by nodes that measure correlated values of the same phenomenon. This approach drastically reduces the amount of energy consumed by radio signaling, especially in dense sensor-nodes deployment with high spatial correlation of observations [1]. Indeed, observed phenomena (e.g., temperature, magnetic waves, bridge vibration, etc.) are often location dependent; i.e., sensor-nodes in close spatial proximity of one another measure similar and highly correlated values.

Typically, measurements of the phenomenon by only a fraction of the network nodes would suffice for a reliable (low level of distortion) measurement. In the context of a network communication scheme, the problem of how to remove as many of the spatially correlated nodes as possible, while still maintain a reliable measurement within some constraint of quality of service has been tackled in [1], which formally casts the problem as:

$$M^* = \arg\min_{M} \left\{ D(M) \le D_{QoS} \right\}, \qquad (1)$$

where M is the number of reporting nodes, $D(M)$ is a distortion metric, and D_{QoS} is the maximum distortion satisfying the quality of service requirements.

In a sense, the reduction in the number of transmitting (i.e., reporting) nodes is the sources of energy savings, and, therefore, minimizing M is viewed as minimization of the energy spent on transmissions (e.g., [1], [10]). However, reducing the number of reporting nodes does not always lead to minimization of energy requirements, as we demonstrate in this paper.

We consider here a practical scheme that attempts to minimize the energy spent via reducing the number of bits, b, sent from the M sensor nodes to a base station (BaS), while exploiting spatial correlation of observations, while maintaining an acceptable level of distortion of. More formally our goal is to determine

$$b^* = \arg\min_{b} \left\{ D(b, M) \le D_{QoS} \right\}. \qquad (2)$$

The main original contributions of this paper towards this goal can be summarized as follows:

- we develop a novel reporting scheme for WSN, dubbed *C*, exploiting *collaborative signaling* (rather than silencing) of spatially correlated nodes;
- we show analytically, numerically, and via simulation that the scheme *C* achieves at least close to a factor of 2 *energy savings* along with similar level of measurement *distortion* compared to the usual approach, dubbed *U*, of silencing spatially-correlated nodes.

1.1 The Intuition behind the Solution

Suppose time is split into time-intervals, referred here to as *rounds,* and let *G* be a *Cluster of Highly Correlated Nodes*

MiSeNet'12, August 26, 2012, Istanbul, Turkey.

(CHCN), all measuring the value of the *same* phenomenon, for instance temperature, at any given round. To minimize the energy spent on signaling, we'd like to send as few bits as possible from the CHCN to the BaS. According to the usual approach to redundancy elimination (scheme U) only one of the nodes in the CHCN transmits the measurement; i.e., M^*=1 in (1). In our collaborative scheme, C, each node in G is responsible to determine only if the measurement falls within its assigned region (typically a range) of temperatures. Given that the temperature T^o is measured by the nodes in G in round J, exclusively *all* the nodes whose "region of responsibility" includes T^o send a signal, "1", to the BaS, as shown in Fig. 1. The BaS identifies the set of transmitting nodes by the received signals. Note that the set of nodes responsible for each distinct T^o is unique (see discussion in Section 3). Hence, identifying the set of nodes "responsible" for T^o allows recovery of the value of T^o.

Suppose in the example in Fig.1, the measured temperature can take the following values: 0^o, 1^o, …, 19^o. Assume a report of the temperature needs to be sent in each round.[1] According to our scheme C, the 20 different temperatures are associated with $20 = {}^6C_3$ subsets of three nodes chosen from the 6 nodes in G. At each round only 3 bits are sent by the appropriate three nodes. In comparison scheme U would require a single node from G to send $\lceil \log 20 \rceil = 5$ bits, so that T^o is received at the BaS.

In essence, the intuition behind scheme C is based on the "*combinatorial explosion*" formula characterizing the number of subsets of a set, allowing large number of values (e.g., of temperatures) to be mapped uniquely to subsets of nodes in G. In the C scheme, bits are not sent to represent a measurement itself, but rather to indicate a node membership in a subset of G; i.e., a bit is sent to the BaS by each member of the subset. The subset consists of the nodes "responsible" for the particular measurement, and we show that even in the worst case the number of bits sent by such responsible nodes amounts to significant energy savings in comparison with the scheme U.

1.2 Related Work

Accounting for spatial correlation to eliminate the transmissions of redundant nodes, as per the scheme U discussed above, has been considered in [1] and in [10]. Pattem *et al.* ([11]) suggest that cluster-based topologies could be rather efficient, again, in eliminating redundant transmissions in the context of spatial correlation aware routing. In contrast, our scheme C utilizes transmission *across the spatially correlated nodes*.

In [12], [15], and [16] the authors exploit spatial correlation to decrease nodes' energy consumption, and correspondingly introducing predictive probabilistic phenomenon modeling, adaptive data sampling and varying precision of phenomenon estimates based on node distance to the BaS. However, none of these techniques utilize the principle of "responsibility division" inherent in the scheme C and allowing the scheme to benefit from *collaborative reporting* among the correlated nodes.

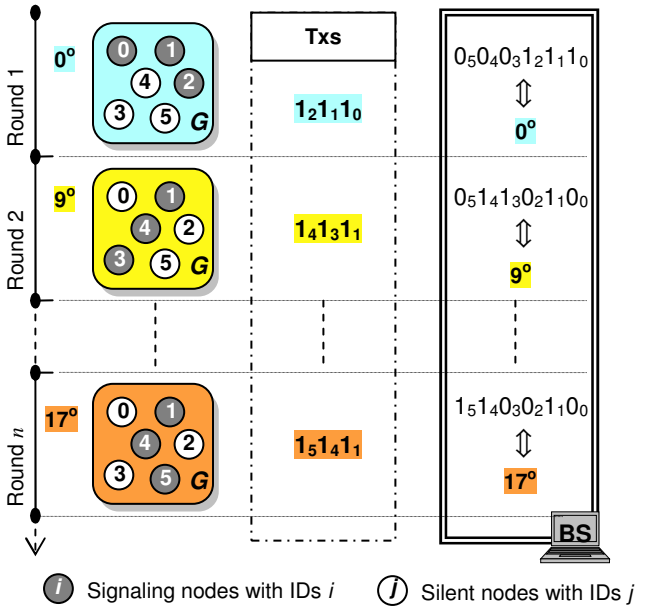

Figure 1: Responsibility division. All nodes in G sense the same temperature T. Only nodes 2, 1, and 0 are responsible for 0^o and signal in round 1; nodes 4, 3, and 1 signal for 9^o in round 2, etc. At each round the BS identifies each transmitting node by its received signal and reconstructs the set of responsible nodes in this round. Each temperature value is mapped to a unique set of responsible nodes and the BS recovers the measurement.

Distributed source coding, joint-routing and compression frameworks for WSN have been proposed in the literature attempting to solve a problem reminiscent in spirit to (2). For instance, source compression based on Slepian-Wolf coding has been studied in [13] and [14], motivated by the goal of reducing energy consumption in WSN by reducing the number of bits sent. However, in contrast, as shown below, the scheme C utilizes a simple trade off between the number of nodes in a CHCN and the amount of bits sent utilizing the *division of responsibility* across the nodes.

2. THE SYSTEM MODEL

Here we concentrate on the model and assumptions for a single *Cluster of Highly Correlated Nodes* (CHCN). This model is extended later in section 5 to account for multiple CHCNs.

Let G be a set of sensor-nodes in a single CHCN. We assume that nodes are coarse-grained synchronized at a level of a round. Suppose all nodes in G have IDs: 0, 1, …, $|G|$-1, and sense a single modality of the same observed phenomenon. Furthermore, all nodes in G are deployed in close spatial proximity with one another, thus sensing the same state of the phenomenon during each round; a dense

[1] That is, the reporting schemes do not utilize compression of measurements from multiple rounds. Of course, *both* schemes C and U can easily be extended to further benefit from aggregation of multiple measurements and low-duty cycling.

WSN deployment is assumed. In this paper, we consider a single hop communication with a BaS where all nodes have transmission radius *r*.

Typically, the maximum and the minimum measurable values of the observed phenomenon are known prior to network deployment; these values may be dictated by the limitations of sensors on board of the nodes or simply by the nature of the observed phenomenon. Thus, we assume that the phenomenon takes on values from the interval $\Psi = [\psi_{\min}, \psi_{\max}]$. The precision of a sensor-node's measurement (e.g., 1^{o}) is denoted by ε. Then, Ψ could be described as a sequence T of intervals given by $([\psi_{\min}, \psi_{\min}+\varepsilon), [\psi_{\min}+\varepsilon, \psi_{\min}+2\varepsilon), \ldots, [\psi_{\min}+n\varepsilon, \psi_{\max}])$, where T is indexed by the sequence of natural numbers $L=\{0, \ldots, n-1\}$.

3. DIVISION OF RESPONSIBILITY

As noted above we'd like each node in G to signal the BaS only if it measures one of the values in its associated responsibility domain (*RD*). We denote the *RD* of node *i* by RD_i. Here RD_i is simply a subset of the sequence T above (e.g., values of temperature). Furthermore, as noted, the RD_i's need to be associated with nodes under the constraint that each element, ι, in T is mapped only to one unique subset, A_ι, of nodes in G. If that constraint is satisfied the BaS can infer the measurement that triggered the transmission of the particular set of nodes'; i.e., the responsibility association is a *one-to-one* and *onto* function. The following definition formalizes this statement.

DEFINITION 1: *A* valid responsibility association (VRA) *is a set function* $\varpi(A_\iota): 2^G \to T$ *such that for any* $\iota, \iota' \in T$ *:* $A_\iota = A_{\iota'} \Leftrightarrow \varpi(A_\iota) = \iota = \iota' = \varpi(A_{\iota'})$.

Notice that RD_i's are easily obtained given the definition of a VRA. If node *i* is within a subset of G that is associated with element ι according to the VRA, then *i* is responsible for ι and $\iota \in RD_i$, or, $RD_i = \{\iota \in T : i \in A_\iota \wedge \varpi(A_\iota) = \iota\}$.

3.1 The Combinatorial VRA

In the example of Fig. 1, we have hinted that an intuitive responsibility division across nodes in G could result from mapping T to all distinct *m*-subsets chosen out of *K* nodes in G. That would allow the BaS to infer a measurement with only *m* signals sent from G. Next, we show such a mapping is a VRA and describe how to obtain it efficiently. We utilize the following lemma stating that there exists an inherent 1-to-1 relationship between every natural number and a unique *m*-subset chosen out of the *K* elements.

LEMMA 1**:** *For every number* $k \in \mathbb{N}$, $\exists$ *a unique set* $\{n_m, n_{m-1}, \ldots, n_1\}$, $n_i \in \mathbb{N}$ *and* $n_m > n_{m-1} > \ldots > n_1 \geq 0$, *such that for any* $m \in \mathbb{N}$, *where* $m \leq n_m$

$$k = {}^{n_m}C_m + {}^{n_{m-1}}C_{m-1} + \ldots + {}^{n_1}C_1 = \sum_{i=1}^{m} {}^{n_i}C_i \qquad (3)$$

PROOF: See p. 6 in [3].□

Algorithm 1 Map $k \in L$ to *m*-element subset *A* of G

Input: *k, m*
Output: $A = \{n_m, n_{m-1}, \ldots, n_1\}$
Algorithm:
1: $A \leftarrow \{\varnothing\}$
2: **while** $m > 1$ **do**
3: $n_m \leftarrow$ maximum integer such that ${}^{n_m}C_m \leq k$
4: $k \leftarrow k - {}^{n_m}C_m$
5: $m \leftarrow m - 1$
6: $A \leftarrow A \cup n_m$

Now, let Λ be a collection of all distinct sets $A \subset G$ such that $A = \{n_m, n_{m-1}, ..., n_1\}$, where n_i's *are the node IDs* and $n_m > n_{m-1} > \ldots > n_1 \geq 0$.

Consider the function $\varpi(A) = \sum_{i=1}^{m} {}^{n_i}C_i = k$, where $k \in L$. Note that the latter sum has the same properties (and is in fact the same) as the sum given in (3) of Lemma 1. Also, assume $|G|=K \geq n_m$. (This is true since $\max(n_j) \leq K$.)

THEOREM 1: $\varpi(A)$ *as defined above is a VRA.*

PROOF: The proof is trivial and follows from *uniqueness* in *Lemma 1*. Details are omitted due to space limitations. □

That is, defined as above, $\varpi(A)$ maps uniquely all *m*-subsets, A_ι, of nodes in G to a value $k \in L$ and hence to a value ι (e.g., temperature) in T. $\varpi(A)$ is dubbed *Combinatorial Responsibility Association* (CRA).

The communication scheme defined by the CRA is very similar to that described in Fig. 1. Suppose in round *J* all nodes in G measure a value ι (and $k \in L$ indexes the interval to which ι belongs). How would a sensor-node *j* in G know whether $\iota \in RD_j$? The simple Greedy **Algorithm 1** could be run by *j* upon sensing ι. The algorithm is fairly efficient and terminates in time $O(m^2)$. Given input *k* and *m* (the number of responsible nodes) the algorithm outputs the set $A_\iota = \{n_m, n_{m-1}, ..., n_1\}$ containing the IDs of all *m* nodes responsible for the measured value ι, where $n_m > n_{m-1} > \ldots > n_1 \geq 0$. If node *j* is an element of the output A_ι, then $\iota \in RD_j$ and *j* needs to signal to the BaS by transmitting "1". Each of such *m* nodes transmits "1",[2] and after receiving the *m* "1" bits and determining the identities (IDs) of the nodes responsible for the measurement ι, the BaS recovers ι by computing/approximating numerically the sum $\sum_{i=1}^{m} {}^{n_i}C_i$.

3.1.1 An example of a CRA run

Consider a single-round run of the collaborative scheme C utilizing CRA. For instance, at round *J*, $\iota = 5^{o}$, $k = 5$, and

[2] If some readings ι are more likely than others, **Algorithm 1** can be easily extended to allow a round-robin assignment of nodes to ι in order to improve the energy balance of the CHCN.

m=3. The IDs of the nodes that are *responsible* for ι are found using **Algorithm 1**, whose output is n_3=4, n_2=2, and n_1=0. The nodes 4, 2, and 0 signal the bit "1". The base station receives ($1_4 1_2 1_0$) and determines $A_\iota = \{4,2,0\}$. Then the BaS computes the correct measurement $\sum_{i=1}^{3} {}^{n_i}C_i = {}^{4}C_3 + {}^{2}C_2 + {}^{0}C_1 = 5$.

3.1.2 Minimum Density of Nodes in G

For the CRA to work, every ι has to be mapped to a distinct set of responsible nodes, namely

$$|\Lambda| \geq |T| \qquad (4)$$

The minimum number, K^*, of nodes in G needed to satisfy this condition is discussed next.

Let $K = |G|$ and observe that $|\Lambda| = {}^{K}C_m$. Suppose for any fixed K one would like to maximize ${}^{K}C_m$ by varying m, to check if (4) could be satisfied given this K. ${}^{K}C_m$ attains its maximum at $K = 2m$. Hence, we are interested in the values of K (respectively m) for which ${}^{K}C_m = {}^{2m}C_m \geq |T|$.

Using Sterling's approximation one obtains that $m \geq \log(m)/4 + \log(I)/2 + 1/2$. Noting that for practical values of m (up to 16 nodes[3]), $\log(m)/4 < 1$

$$m \geq \lceil \log(|T|)/2 + 1.5 \rceil \qquad (5)$$

Hence, $K^* = 2*(\lceil \log(|T|)/2 + 1.5 \rceil)$. Note that higher values of K allows lower values of m, while still keeping (4) satisfied. $|G|=K^*$ represents the worst case in CRA operation if the goal is to minimize, m, the number of bits sent by responsible nodes in each round.

4. ENERGY EFFICIENCY OF CRA

In each round J, the scheme C employing CRA requires the transmission of m bits. The energy consumed per bit transmission, E_b, depends on the modulation scheme employed. Also, each node that sends a bit needs to be identified by the BaS. Standard Direct Sequence Spread Spectrum (DSSS) modulation can be employed. (A variant of DSSS is part of the 802.15.4 standard; a practical DSSS architecture for low-powered WSNs has also been discussed in [17].) With DSSS, node j transmits on a multi-access channel a signal (bit) $b_j \in \{-1, 1\}$ multiplied by unique pseudo-noise (PN) sequence of length n chips [4]. The energy E_b is spread over the n chips. Via a bank of $|G|$ matched filters, the BaS determines the identity of node j and the identities of the rest of the responsible nodes based on their associated PN sequences during the PN sequence acquisition stage of DSSS [see 4, Ch. 3].

Suppose given T and $|G|=K^*$, C operates in its worst case scenario in terms of the number of signals m. Here, $m = K^*/2 = \lceil \log(|T|)/2 + 1.5 \rceil$ from (5). In contrast, the conventional scheme U, which utilizes single-user DSSS techniques to modulate its signals antipodally, would require $b = \lceil \log(|T|) \rceil$ transmissions with consumed energy per bit of E_b.

Assume U and C are operating under the same total energy budget of E. In every round J the schemes need to transmit a measurement to the BaS. The available budget E will last $\tau_U = E/(E_b b)$ rounds under U and $\tau_C = E/E_b m$ rounds under C: $\tau_C / \tau_U \Leftrightarrow \tau_C = 2\tau_U/[1 + 3/\log(|T|)]$. Thus, scheme C is close to 2 times as efficient as U for practical values of $|T|$ in the worst scenario of its operation: $|G|=K^*$.

5. MULTIPLE CLUSTERS

Until now, we have only considered collaboration across nodes within single cluster. However, the scheme C can also be readily be applied to multiple CHCNs in a WSN deployed throughout a larger area. In such a case, the observed phenomenon is now location-dependent, which needs to be accounted for in our system.

5.1 Phenomenon Model

In the model introduced next, the WSN consists of N nodes placed in an event area $\mathcal{A}$ according to some spatial distribution Γ. Here, temporal correlation in the observed phenomenon's nature id not considered. Thus, the phenomenon can be modeled as a discrete memoryless point source: $\mathbf{S} \triangleq \{S[l]\}_l$, where $\{S[l]\}_l$ is assumed to be a sequence of *i.i.d.* Gaussian random variables and $l \in \mathbb{N}$.

According to a spatial correlation model, the source gives rise to a space-time random field $s(l, x, y)$ defined in the l-th round as $\{S_j[l] = s(l, x_j, y_j): (x_j, y_j) \in \mathcal{A}\}$. The instances $S_j[l]$ are modeled as joint Gaussian random variables (JGRV). Considering a single discrete-time interval sample, without loss of generality, the time index l can be dropped and the JGRV characterized as follows:

$$E[S_j] = 0,\ Var[S_j] = \sigma_S^2,\ \rho_{i,j} = E[S_i S_j]/\sigma_S^2,$$

where $\rho_{i,j}$ is the correlation coefficient of the JGRV.

Often physical phenomena's values at different points in space are related via some function of the distance between them. Formally, this function is represented by a parameterized spatial covariance model which reflects the nature of the specific phenomenon and determines the correlation coefficient. Here, the model is assumed to be the *Power Exponential*[4] since different phenomena monitored by sensor networks could be approximated that way ([1]):

$$K_\theta(\|\mathbf{i} - \mathbf{j}\|) = e^{(-\|\mathbf{i}-\mathbf{j}\|/\theta_1)^{\theta_2}} = \rho_{i,j}. \qquad (6)$$

At any round, a sensor node j with coordinates (x_j, y_j) obtains a distorted measurement, X_j, of S_j due to inherent sensing noise/imprecision W_j, where $W_j \sim N(0, \sigma_W^2)$. Thus a node's measurement is given by $X_j = S_j + W_j$. The W_j's are assumed to be *i.i.d.*

[3] For $m = 16$, ${}^{K}C_m = {}^{2m}C_m \approx 6*10^8$ distinct ι's can be mapped.

[4] The following discussion is independent of the specific correlation function of choice.

5.2 Constructing Multiple CHCNs

The network is partitioned into M disjoint groups, with K nodes in each group, utilizing the algorithm underlying the CC-MAC protocol presented in [1]. Given Γ and the spatial correlation model (e.g., K_θ) as input, the algorithm selects M *representative* transmission nodes out of the available N nodes. The selected M nodes are chosen so that the spatial correlation between their measurements is reduced to minimum, while the distortion $D(M) \approx D(N) \le D_{QoS}$ (†). All nodes within distance $r_{corr} < r$ (where r_{corr} is an output of the node selection algorithm) of each *representative* node have highly spatially-correlated observations of the phenomenon **S**.

Consider a disk, Θ_i, with radius r_{corr}, centered at a representative node i. A group of K nodes, G_i, situated in disk Θ_i is called a *Representative Group*[5]. Each Representative Group forms a CHCN.

5.3 Estimation Distortion

The estimate of the source $\boldsymbol{S}$ at the BaS, produced utilizing either scheme C or U in each CHCN, would be distorted due to channel noise, assumed to be AWGN, $Z_j \sim N(0, \sigma_Z^2)$ added to the inherent sensor imprecisions in X_j. For both schemes the distortion is given by the standard Minimum Square Error (MSE) distortion metric: $D(M) = E[(\boldsymbol{S} - \hat{S})^2]$. For the scheme U, the measurement X_j is transmitted most efficiently using uncoded transmission [2] subject to power constraint P per node and per measurement. The received signal at the BaS is $Y_j = \sqrt{P/(\sigma_S^2 + \sigma_W^2)}(S_j + W_j) + Z_j$ and the optimal decoder at the BaS, is given by the standard MMSE estimator ([2], [1]).: $\widehat{S_j} = Y_j (E[S_j Y_j] / E[Y_j^2])$ and $\hat{S} = (1/\mathrm{M}) \sum_{j=1}^{M} \widehat{S_j}$.

The resulting distortion is

$$D_U(M) = D(M,P) = \sigma_S^2 - \sigma_S^4 [(\sigma_S^2 + \sigma_W^2)(1 + \sigma_Z^2 / P)]^{-1} \times \left[\frac{1}{M} \left(2 \sum_{i=1}^{M} \rho_{S,i} - 1 \right) - \frac{\sigma_S^2}{M^2} \sum_{i=1}^{M} \sum_{j=1, j \neq i}^{M} \frac{\rho_{i,j}}{\sigma_S^2 + \sigma_W^2} - \frac{(1 - 1/M)\sigma_Z^2}{P} \right].$$

For the scheme C, measurements are transmitted by m nodes. Assuming, that for all representative groups G_i the system operates at DSSS acquisition capacity, the probability of misidentifying a node approaches to 0 [5]. Also, the values that can be sensed for a given physical phenomenon are captured as described before, by the interval T where $\varepsilon = 2x\sigma_W$, $x > 0$. x is set so that all nodes in G_i read the same ι despite the measurement imprecision W_j. Hence, per each group G_i, the estimation of measurement at the BaS is $\widehat{S_i} = S_i + 2x\sigma_W$. The overall distortion of scheme C then can be found to be:

[5] It is assumed that i can estimate the distances to its neighboring nodes, as in [1].

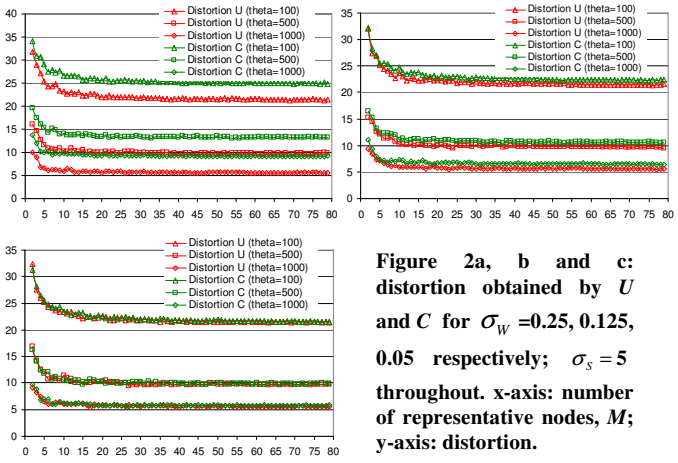

Figure 2a, b and c: distortion obtained by U and C for σ_W =0.25, 0.125, 0.05 respectively; $\sigma_S = 5$ throughout. x-axis: number of representative nodes, M; y-axis: distortion.

$$D_C(M,b) = \sigma_S^2 \left[1 - \frac{1}{M} \left(2 \sum_{i=1}^{M} \rho_{S,i} - 1 \right) + \frac{1}{M^2} \sum_{i=1}^{M} \sum_{j=1}^{M} \rho_{i,j} + \left(\frac{2x\sigma_W}{\sigma_S} \right)^2 \right]$$

As shown in Fig. 2, due to spatial correlation, the distortion saturates for some M (around 18 representative nodes). As σ_W decreases, the distortion obtained by the scheme C converges to that of the scheme U.[6] Analytically this is true as the ratio $(\sigma_W / \sigma_S)^2$ vanishes. In this case, $D_U(M) \approx D_C(M,b)$ and both distortions are less than D_{QoS}, per (†) in section 5.2. If, K is large enough, depending on $|T|$, m could be set to 1 as long as (4) holds, while $D_C(M,b) \le D_{QoS}$. That is, asymptotically as $(\sigma_W / \sigma_S)^2 \to 0$, CRA satisfies (2).

6. PERFORMANCE EVALUATION

The schemes C and U are simulated and compared in terms of two metrics: *energy consumption* and *estimate uncertainty* at the sink. *Energy consumption* is given by the average energy consumption, E, per node in the network for τ reporting rounds. *Estimate uncertainty* is given by the average imprecision, $\overline{V}$, of the source estimate at the BaS over τ rounds. That is, $\overline{V} = (1/\tau) \sum_{i=1}^{\tau} V_i$, where at round i, $V_i = 100 \,|\, s_i - \hat{s}_i \,| \,/\, |T|$, s_i is the true value of $\boldsymbol{S}$ at (x_j, y_j), and $\hat{s}_i$ is the estimated measurement at the BaS given measurements of group G_i.

6.1 System Setup

The simulation code is written in JAVA and utilizes the Bayesian Logic (BLOG) Inference Engine ([6]). In each simulation run, N nodes are placed uniformly at random within a square area of 100[m] × 100[m].

The phenomenon event source is simulated per the model in section 5.1 with covariance model K_θ. Here, the covariance model parameters are θ_1 =10000 and θ_2 =2.

[6] In practice, with non-zero probability, some nodes in G_i might read different ι, even if x is large, possibly leading to additional distortion. Scheme C's simulations in section 6 account for that.

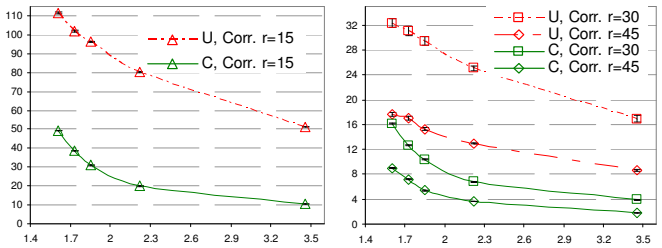

Figure 3: Energy consumption of the two transmission schemes; *x-axis*: density of the network [nodes/m^2]; *y-axis* average energy, *E*, per node in the network [mJ], consumed for 150 rounds and different correlation radii [m].

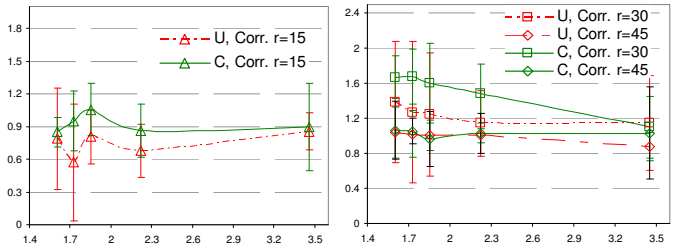

Figure 4: Estimate uncertainty of the two schemes; *x-axis*: density of the network [nodes/m^2]; *y-axis*: average estimate uncertainty in the network [%] for a given round and different correlation radii [m]

The BLOG Inference Engine is used to generate the S_j's.

For all simulations runs, $\varepsilon = 1$, $\sigma_S = 625$, $|T| = 5000$, and $T = \{[-4\sigma_S, -4\sigma_S + \varepsilon), \ldots, [4\sigma_S + 4999\varepsilon, 4\sigma_S]\}$. The transmit power per bit, E_b, is standard and the same for both schemes *U* and *C*: E_b= 14[dBm]=25[mW]. Finally, on the physical layer both schemes utilize DSSS with processing gain $F = 512$ and with transmission radius $r = 100[m]$.

6.2 Energy and Estimates Uncertainty

The average energy consumption per network node, *E*, for the Scheme *C* tends to be substantially less than that of the Scheme *U* as shown on Fig. 3, for the studied range of radii and network densities. As more nodes are added to the network (in effect increasing its density), as expected *E* decreases for both schemes. However, in the case of the Scheme *C*, larger network density allows for larger values of *K* leading to a low number of actively transmitting nodes *m* required to convey a measurement. This trend confirms the analytical results, implying that higher density networks could be more advantageous to scheme *C*.

Figs. 4 demonstrate that the achieved estimates uncertainty is similar for both schemes *C* and *U*: approximately 1% to 2%. This is expected, since as shown in Fig. 3 the distortion of the two schemes numerically converges as $(\sigma_W / \sigma_S)^2$ becomes smaller.

7. CONCLUSION

In this paper, we investigated a novel WSN reporting scheme, scheme *C*, based on *division of responsibility* and *collaboration* across spatially-correlated nodes, as to reduce energy consumption in the network. It is shown analytically and confirmed through simulations that the scheme *C* based on *CRA conserves* more energy (in the *worst case*, close to 200%) compared to the standard approach in recent literature. The scheme *C* provides a novel avenue of research towards graceful degradation of WSN's distortion of measurement as nodes failures increase over time. Due to the *division of responsibility*, the failure of one node does not necessarily obliterate the entire measurement.

8. ACKNOWLEDGMENTS

This work was supported in part by the NSF grant numbers ANI-0329905 and CNS-0626751 and by the AFOSR contract number FA9550-09-1-0121/Z806001. We would also like to thank the anonymous reviewers for their constructive critique and suggestions.

9. REFERENCES

[1] M. C. Vuran and I. F. Akyildiz, "Spatial correlation-based collaborative medium access control in wireless sensor networks," *ACM/IEEE ToN*, April 2006.

[2] M. Gastpar and M. Vetterli, "Source-channel communication in sensor networks," *IPSN'03*, vol. 219, pp. 162-177, 2003.

[3] D. E. Knuth, *The Art Of Computer Programming*, Volume 4, Fascicle 3: Generating All Combinations and Partitions, Addison-Wesley Profesional, 2005.

[4] A. Viterbi, *CDMA: Principles of Spread Spectrum Communication*, Addison-Wesley Wireless Communications Series, 1995.

[5] U. Madhow and M.B. Pursley, "Acquisition in direct-sequence spread-spectrum communication networks: an asymptotic analysis," *Information Theory, IEEE Transactions on* , vol.39, no.3, pp.903-912, May 1993.

[6] Bayesian Logic (BLOG) Inference Engine. [Online]. Available: http://people.csail.mit.edu/milch/blog/index.html

[7] B. Krishnamachari, D. Estrin, and S. Wicker "The Impact of Data Aggregation in Wireless Sensor Networks," *ICDCS*, 2002.

[8] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: a scalable and robust communication paradigm for sensor networks," *ACM MobiCom* 2000

[9] E. Shih, S. Cho, N. Ickes, R. Min, A. Sinha, A. Wang, and A. Chandrakasan, "Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks," *ACM MobiCom'01*, July, 2001, pp. 272–286.

[10] F. Bouabdallah, N. Bouabdallah, and R. Boutaba, "On Balancing Energy Consumption in Wireless Sensor Networks," *Veh. Technol., IEEE Trans.*, July 2009

[11] S. Pattem , B. Krishnamachari, and R. Govindan, "The impact of spatial correlation on routing with compression in wireless sensor networks", *IPSN'*, 2004.

[12] C. Liu, K. Wu, and J. Pei, An energy-efficient data collection framework for wireless sensor networks by exploiting spatiotemporal correlation, *IEEE Trans. Parallel Distrib. Syst.*, vol. 18, no. 7, pp. 1011-1023, 2007.

[13] K. Yuan, B. Li, and B. Liang, "A distributed framework for correlated data gathering in sensor networks", *IEEE Trans. Veh. Technol.*, vol. 57, no. 1, pp. 578-593, 2008.

[14] J. Barros and S. D. Servetto, "Network information flow with correlated sources", *IEEE Trans. Inf. Theory*, vol. 52, no. 1, pp. 155-170, Jan. 2006.

[15] D. Chu, A. Deshpande, J.M. Hellerstein, and W. Hong, "Approximate Data Collection in Sensor Networks using Probabilistic Models," ICDE , 2006.

[16] X. Tang and J. Xu, Optimizing lifetime for continuous data aggregation with precision guarantees in wireless sensor networks, IEEE/ACM ToN, 2008.

[17] C. Chien, I. Elgorriaga, and C. McConaghy, "Low-power direct sequence spread-spectrum modem architecture for distributed wireless sensor networks," *ISLPED*, 2001.