Optimal matching in wireless sensor networks

A. Roumy†, D. Gesbert* [1]
† INRIA-IRISA, Rennes, France.
* Institute Eurecom, Sophia Antipolis, France.

***Abstract*— We investigate the design of a wireless sensor network (WSN), where distributed source coding (DSC) for pairs of nodes is used. More precisely, we minimize the compression sum rate for noiseless channels and the sum power for noisy orthogonal channels in a context of pairwise DSC. In both cases, the minimization can be separated into a matching problem and a pairwise rate-power control problem (that admits a simple closed-form solution). Using this separation, we obtain an optimization procedure of polynomial (in the number of nodes in the network) complexity. Finally, we show that the overall optimization can be readily interpreted. For noiseless channels, the optimization matches close nodes whereas, for noisy channels, there is a tradeoff between matching close nodes and matching nodes with different distances to the sink. We provide examples of the proposed optimization method based on empirical measures. We show that the matching technique provides substantial gains in either storage capacity or power consumption for the WSN.**

I. Introduction

We consider a wireless sensor network (WSN) where spatially distributed sensors (or sensor nodes) gather data and send them to a common center (or sink) in order to monitor some physical or environmental phenomenon [1], [8]. A design issue for such a WSN is to maximize the network lifetime while dealing with low-cost sensors exhibiting limited capabilities in terms of processing (computation capabilities, memory) and communication (power).

A naive approach consists in transmitting all the data measured by the sensors directly to the sink. This approach suffers two sub-optimalities: *(1)* First due to spatial correlation between the measured data, the sufficient amount of data to transmit from the nodes to the sink can be reduced (from the sum of individual entropies to the joint entropy). Therefore taking into account the correlation between the nodes, communication power and spectral ressource can be saved. *(2)* Second the Distributed source coding (DSC) (aka. Slepian Wolf coding) theorem [12] states, that this reduced amount of data can be sent without explicit cooperation between the nodes. Therefore using DSC techniques can save not only some ressource (no communication between the nodes) but also some processing (data of other nodes are not processed at a node). More precisely, in DSC, the only knowledge required at each node is the rate at which this node needs to compress its data. Note that all the processing complexity is transferred to the sink, since to achieve optimal compression without encoding cooperation, joint decoding has to be performed.

Therefore, in the context of WSN, optimal strategies has been proposed in the literature based on DSC coding [5], where an optimal DSC coding for all the nodes is assumed. However most existing DSC schemes concern two correlated sources. First attempt to design codes for multiple (binary) sources has been proposed in [14] but it suffers some loss wrt to the optimal compression rate. Therefore it is also of interest to consider DSC coding for pairs of nodes. This strategy is referred to *pairwise DSC* in the following. Note that pairwise DSC is close to the idea of clustering nodes as in in-network aggregation [7]. There is however some difference between the two approaches: in in-network aggregation, nodes need to communicate their data to their neighbors, and then a decision whether to compress or concatenate the data is taken, based on the correlation between the data. In contrast, pairwise DSC avoids transmission between nodes, correlation measurement and strategy optimization at the nodes. The only information required at each node, is the power and rate at which to compress the data but not the global strategy. Another reason for considering pairwise DSC is its flexibility. A system designed with DSC for two sources is more flexible than a multiple source code, since the whole code may not be changed if one node disappears. Therefore, we focus in this paper on pairwise DSC coding. This raises a new question: how to optimally match the paired nodes. We address this problem in two different communication scenarios. *(i)* Perfect node-sink channels. In that context, the goal is to maximize the storage capacity. *(ii)* Orthogonal noisy channels. In that case, source channel separation holds [2] and we optimize the compression rates and the node matching in order to minimize the total used power.

Main contributions of the paper. First we model the design of a pairwise DSC scheme in a WSN. Then we show that the optimization of the pairwise DSC strategy can be separated into a matching problem and a pairwise rate-power control problem (that admits a simple closed-form solution). Using this separation, we obtain an optimization procedure of polynomial (in the number of nodes in the network) complexity. Finally, we show that the overall optimization can be readily interpreted. For noiseless channels, the optimization matches close nodes whereas for noisy channels, there is a tradeoff between matching close nodes and matching nodes with different distances to the sink.

II. Sensor network model and problem statement

We consider a network with N nodes all communicating to a single sink. Let $\mathcal{N}$ be the set of sensor indices: $\mathcal{N} = \{1, \dots, N\}$. The data to be sent from node $i \in \mathcal{N}$ to the sink are modeled as the realizations of a discrete random variable denoted X_i taking its value in the alphabet $\mathcal{X}$. R_i [resp., P_i]

[1]This work is supported by the Network of Excellence in Wireless Communications (NEWCOM), E. C. Contract no. 507325.

denotes the rate (in bits per source symbol) [resp., the power] at which node i sends data.

The data of all the nodes are compressed without loss with a pairwise DSC scheme. More precisely the data are encoded separately at each node but decoded (jointly) by pairs of nodes. This approach is suboptimal in comparison to the joint decoding of the data of all nodes but is motivated by the availability of efficient DSC schemes for two sources (see references in [6]). This raises the question of optimally partitioning the nodes into pairs, which can be modeled as the selection of an optimal *2-partition* defined below.

Definition 1: A 2-partition $\mathcal{P}$ is a partition of $\mathcal{N}$ s.t. the cardinality of each subset is 2, except for a set that contains only one element if N is odd. An element of 2-partition is called a pair (even for the left alone node).
Let $\mathcal{S}$ denote the set of all possible 2-partitions.

Property 1: The total number of 2-partitions is:

$$|\mathcal{S}| = \begin{cases} (N-1)!! & \text{if N is even} \\ (N)!! & \text{if N is odd} \end{cases}$$

where $(N-1)!! = (N-1)(N-3)\dots 5.3.1$ [13].

The problem we address in this paper is how to send the data (measured by the sensors) to the sink without loss. In a pairwise DSC scheme, the design parameters are: the 2-partition, the compression rates and for noisy channels the powers used to send the data. The cost function is application and communication dependent. In the following, we consider different communication scenarios (noiseless and noisy) and define the related cost functions.

III. Perfect node-sink channels

In this section, we assume that each node can communicate directly to the sink and that the channels between each node and the sink are perfect. In this context, we want to maximize the storage capacity of each node (sensors and sink) without losing any information. Since pairwise DSC is used, the rates of each pair of nodes are constrained to lie in the so-called Slepian and Wolf region [12]: two nodes i, j can separately code their source symbols without loss of information if their compression rates (in bits per source symbol) belong to the Slepian and Wolf region SW_{ij} defined as:

$$\mathrm{SW}_{ij} \triangleq \left\{ (R_i, R_j) : \begin{array}{rcl} R_i & \geq & H(X_i|X_j) \\ R_j & \geq & H(X_j|X_i) \\ R_i + R_j & \geq & H(X_i, X_j) \end{array} \right\} \quad (1)$$

Fig. 1 represents the set of rate pairs (R_i, R_j) for which lossless compression is possible. The region in dark grey corresponds to separated source coding (separated encoding and decoding). The SW_{ij} region corresponds to DSC (i.e. separated encoding but joint decoding) and includes the dark and light grey region. DSC allows smaller rates (shown in light grey): this reduces the total amount of data to be sent or stored for the same amount of information captured by the WSN.

Hence, from the definition of the DSC rate region (1), the sensor network pairwise optimization for noiseless channels can be rewritten as Problem 1.

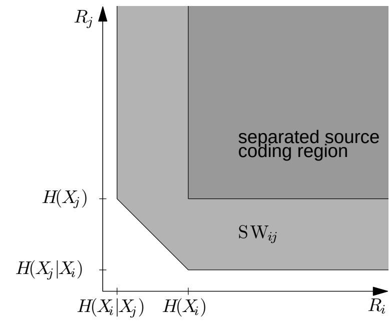

Fig. 1. Slepian Wolf region

Problem 1: The maximization of the storage capacity over all individual rates and over all 2-partitions under the constraint of lossless pairwise DSC coding reads:

$$\left(\{R_i^*\}_{i=1}^N, \mathcal{P}^*\right) = \arg \min_{\{R_i\}_i,\ \mathcal{P}\in\mathcal{S}} \sum_{(i,j)\in\mathcal{P}} R_i + R_j$$
$$\text{subject to} \qquad \forall\ (i,j) \in \mathcal{P}, \quad (R_i, R_j) \in \mathrm{SW}_{ij}$$

At first sight, this problem looks exponentially hard due to the large number of possible 2-partitions (see Property 1). However, Proposition 1 and its Corollary 1 show that in fact it has polynomial complexity.

Proposition 1: Separation of rate allocation and 2-partition selection. The storage capacity maximization (Problem 1) can be separated in a rate allocation over all possible distinct unordered pairs and a selection of the best partition. First, the rate allocation: $\forall\ (i,j) \in \mathcal{N}^2$ s.t. $i < j$

$$T_{ij}^* = \arg \min_{T_{ij}\in\mathrm{SW}_{ij}} T_{ij}(1) + T_{ij}(2) \quad (2)$$

where $T_{ij} = (R_i, R_j)$ denotes a rate pair and $T_{ij}(1) = R_i$ [resp., $T_{ij}(2) = R_j$] the first [resp., second] element of the pair. Then, the 2-partition optimization:

$$\mathcal{P}^* = \arg \min_{\mathcal{P}\in\mathcal{S}} \sum_{(i,j)\in\mathcal{P}} T_{ij}^*(1) + T_{ij}^*(2) \quad (3)$$

Proof: See [11]. ■

Corollary 1: The storage capacity maximization under lossless pairwise DSC coding is polynomial in the number of sensor nodes.

Proof: From Proposition 1, the joint optimization separates into a rate allocation with complexity $O(N^2)$ and a partition optimization. The latest is a classical problem in combinatorial optimization, where it is known under the name of weighted matching for non-bipartite graph [9]. Its complexity can be lowered to $O(N^3)$ [4]. ■

IV. Noisy node-sink channels

In this scenario, the channels between the nodes and the sink are noisy. More precisely, we assume independent additive white Gaussian noise (AWGN) channels. We also assume orthogonality in the channel access (no internode interference). This orthogonality can be achieved through protocols (CSMA) or multiple access techniques (such as TDMA, FDMA or orthogonal CDMA). The capacity of the Gaussian channel (between node i and the sink) with transmit power P_i and channel gain γ_i is

$$C_i(P_i) \triangleq \log_2(1 + \gamma_i P_i)$$

where P_i represents the cost of sending C_i bits (per transmission) over the channel with gain γ_i. Notice that the function $C_i(x) = \log_2(1 + \gamma_i x)$ depends on i upon γ_i. We further assume that the channel gains $\{\gamma_i\}_i$ are fixed quantities, known by the sink.

Due to power limitation at the sensors, the transmit power is constrained by a so called peak power constraint: $\forall\ i, P_i \leq P_{max}$. In this context, a natural cost function is the sum power that needs to be minimized. The constraints for this minimization are: the above mentioned peak power constraints and the asymptotically (in the size of the data length) small error probability.

We now detail the vanishing error probability constraint. Under the assumption of orthogonal channels, DSC and channel coding separation holds [2]. Therefore, the achievable (for vanishing error probability) rate region for distributed separated or joint source-channel coding[1] coincide. More precisely, for two sources, it is the set of rates (R_i, R_j) lying in the intersection of the Slepian Wolf region SW_{ij} (1) and of the TDMA capacity region C_{ij} defined as:

$$\mathrm{C}_{ij}(P_i, P_j) \triangleq \left\{ (R_i, R_j) : \begin{array}{ccc} R_i & \leq & C_i(P_i) \\ R_j & \leq & C_j(P_j) \end{array} \right\} \quad (4)$$

This achievable rate region (for distributed separated or joint source and channel coding) is the darker grey region on fig. 2. Hence, the sensor network pairwise optimization for

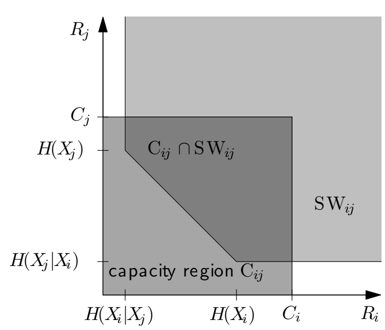

Fig. 2. Slepian Wolf and capacity regions

orthogonal noisy channels can be stated as follows.

Problem 2: The minimization of the transmit sum-power that achieves rates with vanishing error probability in a pairwise-distributed separated source and channel coding scheme[2] can be written as:

$$(\{R_i^*\}_i, \{P_i^*\}_i, \mathcal{P}^*) \quad = \quad \arg \min_{\{R_i\}_i, \{P_i\}_i, \mathcal{P} \in \mathcal{S}} \sum_{(i,j) \in \mathcal{P}} P_i + P_j$$

$$\text{subject to} \qquad \begin{array}{ll} \forall\ (i,j) \in \mathcal{P}, & (R_i, R_j) \in \mathrm{SW}_{ij} \cap \mathrm{C}_{ij}(P_i, P_j) \\ \forall\ \ i \in \mathcal{N}, & P_i \leq P_{max} \end{array}$$

[1]*separated* refers to separation of source and channel coding, whereas *distributed* refers to separation of the processing between the sensor nodes.

[2]Recall that for orthogonal channels, this scheme has same achievable rate region as the pairwise-distributed joint source and channel coding scheme

Before we discuss the solution (see Section IV-B), let us first simplify the problem.

A. Optimization separation

Proposition 2: Separation of rate-power allocation and 2-partition selection. The sum-power minimization (Problem 2) can be separated in:
(i) a rate-power allocation over all possible distinct unordered pairs: $\forall\ (i,j) \in \mathcal{N}^2$ s.t. $i < j$

$$Q_{ij}^* \quad = \quad \arg \min_{Q_{ij}} Q_{ij}(3) + Q_{ij}(4) \quad (5)$$

$$\text{subject to} \quad \begin{array}{l} (Q_{ij}(1), Q_{ij}(2)) \in \mathrm{SW}_{ij} \cap \mathrm{C}_{ij}(Q_{ij}(3), Q_{ij}(4)) \\ Q_{ij}(3) \leq P_{max} \\ Q_{ij}(4) \leq P_{max} \end{array}$$

where $Q_{ij} = (R_i, R_j, P_i, P_j)$ denotes the four design parameters. The two first parameters of the quadruple are the rates $Q_{ij}(1) = R_i$, $Q_{ij}(2) = R_j$, whereas the two last represent the powers: $Q_{ij}(3) = P_i$, $Q_{ij}(4) = P_j$.
(ii) a 2-partition optimization:

$$\mathcal{P}^* = \arg \min_{\mathcal{P} \in \mathcal{S}} \sum_{(i,j) \in \mathcal{P}} Q_{ij}^*(3) + Q_{ij}^*(4) \quad (6)$$

Proof: Same proof as for Proposition 1. ∎

Corollary 2: The sum power minimization under lossless pairwise-distributed separated source and channel coding is polynomial in the number of sensor nodes.

Proof: Same proof as for Corollary 1). ∎

B. Sum of 2 powers minimization

In this section, we solve problem (5), a convex optimization problem of four variables. First, we show that the number of variables can be reduced to two (Lemma 1) and then to one (Lemma 2). In order to keep track of the meaning of the variables (which simplifies the proofs of the two lemmas), we shall use the notation R_i, R_j, P_i, P_j instead of Q_{ij}. This introduces no confusion, since the pair (i, j) is fixed in (5).

Lemma 1: The minimum power is achieved on the boundary $P_i = \frac{2^{R_i}-1}{\gamma_i}$ [resp., $P_j = \frac{2^{R_j}-1}{\gamma_j}$].

Proof: (5) is a convex optimization problem. The optimum occurs either at a stationary point or on the boundaries. Since there is no stationary point (linear function), the optimum occurs on a boundary s.t. P_i is minimum. It follows that $P_i^* = \frac{2^{R_i^*}-1}{\gamma_i}$. Similarly, we can show that $P_j^* = \frac{2^{R_j^*}-1}{\gamma_j}$. ∎

From Lemma 1, the rate-power optimization *(ii)* in Proposition 2 can be rewritten as:

$$Q_{ij}^* \quad = \quad \arg \min_{Q_{ij}} \frac{2^{Q_{ij}^*(1)} - 1}{\gamma_i} + \frac{2^{Q_{ij}^*(2)} - 1}{\gamma_j} \quad (7)$$

$$\text{subject to} \quad (Q_{ij}(1), Q_{ij}(2)) \in \mathrm{SW}_{ij} \cap \mathrm{C}_{ij}(P_{max}, P_{max})$$

The following lemma allows to further reduce the number of variables.

Lemma 2: The minimum power is achieved on the line $R_i + R_j = H(X_i, X_j)$.

Proof: By contradiction. See [11]. ∎

Finally, the rate-power allocation can be reformulated as a convex optimization problem of one variable:

$$Q^*_{ij}(1) = \arg\min_{R_i} \frac{2^{R_i}-1}{\gamma_i} + \frac{2^{H(X_i,X_j)-R_i}-1}{\gamma_j} \quad \text{subject to } \mathrm{lb} \leq R_i \leq \mathrm{ub} \tag{8}$$

where

$$\begin{aligned} \mathrm{ub} &\triangleq \min\Big(H(X_i), \mathrm{C}_i(P_{max})\Big) \\ \mathrm{lb} &\triangleq \max\Big(H(X_i|X_j), H(X_i,X_j) - \mathrm{C}_j(P_{max})\Big) \end{aligned}$$

From $Q^*_{ij}(1)$, all other variables can be deduced:

$$\begin{aligned} Q^*_{ij}(2) &= H(X_i,X_j) - Q^*_{ij}(1) \\ Q^*_{ij}(3) &= \frac{2^{Q^*_{ij}(1)}-1}{\gamma_i} \\ Q^*_{ij}(4) &= \frac{2^{Q^*_{ij}(2)}-1}{\gamma_j} \end{aligned}$$

Moreover, (8) admits a closed form explicit solution:

$$Q^*_{ij}(1) = \begin{cases} \mathrm{lb} & \text{if} \quad r < \mathrm{lb} \\ r & \text{if} \quad \mathrm{lb} \leq r < \mathrm{lb} \\ \mathrm{ub} & \text{if} \quad r < \mathrm{ub} \end{cases} \tag{9}$$

where

$$r \triangleq \frac{1}{2}\left(H(X_i,X_j) + \log_2 \frac{\gamma_i}{\gamma_j}\right)$$

a) Case without peak power constraint.: Notice that the solution detailed above encompasses the case without peak power constraint by letting P_{max} tends to $+\infty$.

b) Solution interpretation.: This results admits a nice interpretation. If we don't take into account the rate constraints (Slepian Wolf and capacity region) and peak power constraints, the optimal rate allocation reads

$$\begin{aligned} R^*_i &= \tfrac{1}{2}\left(H(X_i,X_j) + \log_2 \tfrac{\gamma_i}{\gamma_j}\right) \\ R^*_j &= \tfrac{1}{2}\left(H(X_i,X_j) + \log_2 \tfrac{\gamma_j}{\gamma_i}\right) \end{aligned} \tag{10}$$

Moreover, if these rates are feasible, the optimal sum power is

$$2\sqrt{\frac{2^{H(X_i,X_j)}}{\gamma_i\gamma_j}} - \frac{1}{\gamma_i} - \frac{1}{\gamma_j} \tag{11}$$

Therefore the 2-partition optimization matches pairs in order to minimize:

$$\mathcal{P}^* = \arg\min_{\mathcal{P}\in\mathcal{S}} \sum_{(i,j)\in\mathcal{P}} \sqrt{\frac{2^{H(X_i,X_j)}}{\gamma_i\gamma_j}} \tag{12}$$

In general, the joint entropy $H(X_i, X_j)$ decreases with the internode distance. Therefore, the minimization of an increasing function of joint entropies would rather match close pairs. On the other hand, the minimization of $\sum_{(i,j)\in\mathcal{P}} \frac{1}{\sqrt{\gamma_i\gamma_j}}$ tends to match pairs with different γ, where the channel gain γ depends on the distance between a node and the sink. It follows that this would rather match nodes that have different distances to the sink.

The overall optimization (12) is therefore a tradeoff between matching close nodes and matching nodes with different distances to the sink. A way to achieve this is to place nodes on a radius emanating from the sink. This fact is fully illustrated by our experiment later.

V. A SENSOR NETWORK EXAMPLE

In order to illustrate, the gain achieved by a pairwise sensor network optimization, we consider a WSN in a bounded square area where sensors are randomly placed. A sink is placed at the center. We consider AWGN channels between the nodes and the sink and assume that the channel gain is inversely proportional to the square distance between the nodes communicating together.

We consider the entropy model of [10] based on empirical measure of daily rainfall precipitation. All individual entropies are assumed equal. The joint entropy of two sources is a function of the individual entropy, of a coefficient c that captures the correlation, and of the distances d_{ij} between the sources:

$$H(X_i,X_j) = H(X_i) + \left(1 - \frac{1}{1+\frac{d_{ij}}{c}}\right)H(X_i) \tag{13}$$

The sensors lie in a bounded area such that the coordinates of each sensor are in $[0,1]^2$. The coefficient c captures the correlation. We choose $c = 1$, such that if 2 sensors are distant by 1 (2 corners of the area), then the joint entropy is $\frac{3}{2}$ the individual entropy. We therefore consider a highly correlated sensor network.

Reduction of compression sum rate and sum power. Figure 3 shows the optimization results for 200 sensors and a sink placed at the center of the area. The numerical results (in terms of rate or power) are given in the title of each figure. For perfect channels, Fig. 3(a) shows that the pairwise optimization helps to reduce by half the sum rate: 104 instead of 200, for the naive case (all nodes communicate to the sink). This result is independent of the individual entropy $H(X_i)$, since $H(X_i)$ is a scaling factor in the model (13) of the joint entropy. For noisy channels (Fig. 3(b) (c)), the reduction of sum power is even more important than the reduction of rate due to the exponential behavior of the power wrt to the rate (from 36727 to 1261 for $H(X_i) = 10$ (b), and from 36 to 13 for $H(X_i) = 1$ (c)). The effect of the peak power constraint is illustrated in (d) (compare (b) with (d)). In this case, the constraint is so low that no communication is possible between some nodes and the sink: more precisely, for some nodes, there exists no other node s.t. the achievable region (see Fig. 2) is non-empty. Therefore, these nodes are not connected in (d).

Matching result. For perfect channels, the minimization of the compression sum rate rather matches closest neighbors (see Fig. 3(a)), which is very intuitive since the joint entropy $H(X_i, X_j)$ decreases with the internode distance.

For noisy channels, due to the tradeoff between matching close nodes and matching nodes with different distances to the sink, the matched pairs are located on a radius emanating from the sink, as explained in section IV-B.b). Fig. 3 (b) and (c) highlight this observation. In these figures, we decrease the value of the entropy $H(X_i)$, s.t. the matching is more due to the influence of the γ (in (c) than in (b)) and therefore distant nodes are matched together in (c).

VI. Conclusion

We investigated the design of a wireless sensor network, where distributed source coding (DSC) is used in order to compress the data. Since most existing DSC schemes concern two correlated sources, we focused on pairwise DSC, where the compression is performed for pairs of nodes. This raised a new problem: the optimal matching of nodes in order to save the resources of the network. More precisely, we minimized the compression sum rate for noiseless channels and the sum power for noisy orthogonal channels in a context of pairwise DSC and obtained an optimization procedure of polynomial (in the number of nodes in the network) complexity. Finally, we showed that for noiseless channels, the optimization matches close nodes whereas, for noisy channels, there is a tradeoff between matching close nodes and matching nodes with different distances to the sink. Numerical results showed that the pairwise strategy can save about half the amount of data to be sent.

References

[1] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. "Wireless sensor networks: a survey." Computer Networks, 38(4):393422, April 2002.

[2] J. Barros, S. D. Servetto, "Network Information Flow with Correlated Sources," IEEE Transactions on Information Theory, Vol. 52(1), pp. 155-170, 2006.

[3] S. Boyd, and L. Vandenberghe, *Convex optimization*, Cambridge University Press, 2004.

[4] W. Cook and A. Rohe, "Computing Minimum-Weight Perfect Matchings," INFORMS Journal on Computing, Vol. 11, pp. 138-148, 1999.

[5] R. Cristescu, B. Beferull-Lozano, M. Vetterli, "Networked Slepian-Wolf: theory, algorithms, and scaling laws", IEEE Transactions on Information Theory, 51(12):4057- 4073, Dec. 2005.

[6] J. Garcia-Frias, Zixiang Xiong, "Distributed source and joint source-channel coding: from theory to practice," Proceedings of IEEE ICASSP, March 2005.

[7] L. Krishnamachari, D. Estrin, S. Wicker, "The impact of data aggregation in wireless sensor networks," Distributed Computing Systems Workshops, pp. 575- 578, 2002.

[8] F. L. Lewis. "Wireless sensor networks." In D. J. Cook and S. K. Das, editors, Smart Environments: Technologies, Protocols, and Applications, New York, 2004. John Wiley.

[9] C. H. Papadimitriou, and K. Steiglitz, *Combinatorial Optimization : Algorithms and Complexity*, Dover Pubns, July 1998.

[10] S. Pattem , B. Krishnamachari , R. Govindan, "The impact of spatial correlation on routing with compression in wireless sensor networks," Proceedings of the third international symposium on Information processing in sensor networks, April 26-27, 2004.

[11] A. Roumy, D. Gesbert, "Optimal matching in wireless sensor networks," in preparation.

[12] D. Slepian and J. K. Wolf, "Noiseless coding of correlated information. sources,". IEEE Trans. Inform. Theory, pp. 471-480, July 1973.

[13] N. J. A. Sloane. Sequence A001147, in "The On-Line Encyclopedia of Integer Sequences."

[14] V. Stankovic, A. Liveris, Z. Xiong, and C. Georghiades, "On code design for the general Slepian-Wolf problem and for lossless multiterminal communication networks," IEEE Trans. Inform. Theory, Vol. 52, Issue 4, pp. 1495-1507, April 2006.

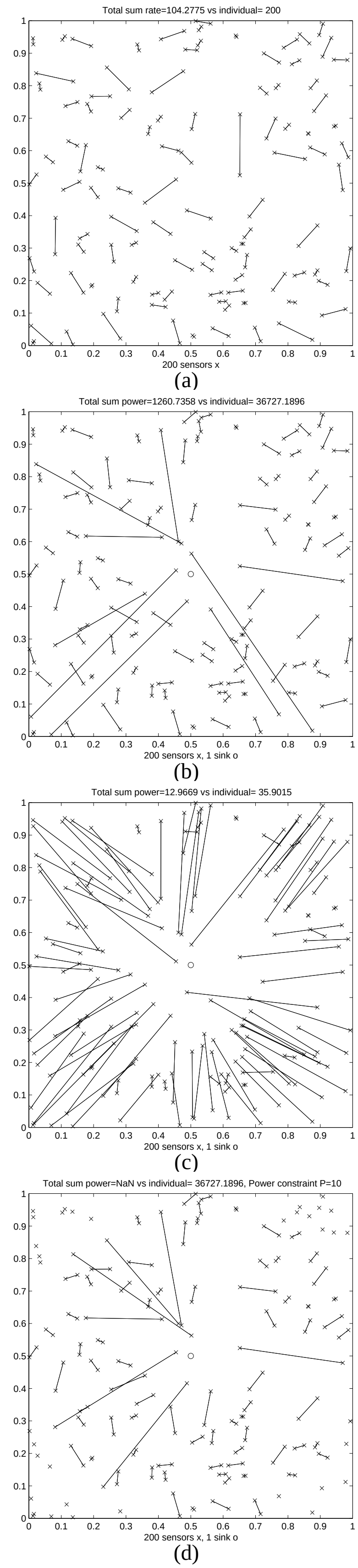

Fig. 3. WSN with 200 sensors (x) and 1 sink (o) placed at the center. 2 matched nodes are linked by a line. Matching results for (a) perfect channel. Then, noisy channel without peak power constraint, and individual entropy is 10 in (b), and 1 in (c). Then, noisy channel with peak power constraint 10, and individual entropy 10, in (d).