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***Abstract*—This paper addresses the problem of efficient data gathering in wireless sensor networks with a complexity constrained data gathering node. A particular scenario of interest is a cluster of sensor nodes among which one is selected as the cluster head. Distributed source coding allows for exploiting the dependency between the nodes observations and reducing the required rate of communications. We consider a rate allocation structure, which incorporates the decoder complexity constraints, by limiting the number of nodes whose data may be stored and exploited during decoding. Based on this structure, we investigate the problem of rate allocation for the nodes to minimize the total cost, where the cost of a node is a general function of its rate and related parameters. To this end, an optimal dynamic programming solution based on a trellis structure is proposed. Also, a suboptimal yet high performance solution is presented whose complexity grows in polynomial order as the number of network nodes increases. Numerical results demonstrate that the proposed solutions, even with limited complexity, allow for exploiting most of the available dependency and hence the achievable compression gain.**

Keywords-Wireless Sensor Networks; Data Gathering; Cost Optimization; Distributed Source Coding;Slepian-Wolf Coding

I. INTRODUCTION

Wireless sensor networks (WSN) are widely researched and used in different applications recently. A data gathering sensor network consists of many small sensor nodes, which send their data to a data gathering node (DGN). The sensor nodes are restricted in energy, memory and computational capability [1]. Different data aggregation and compression techniques have been developed for efficient utilization of WSNs [2]. In particular, when the data collected by the nodes are correlated, distributed source coding (DSC) can be used to reduce the required rate of communications. The Slepian-Wolf (SW) theorem states that separate encoding of two distributed sources, at the cost of increased complexity at the joint decoder, is as efficient as their joint encoding for lossless compression [3-4]. The SW theorem also holds for the case with multiple sources [5].

Data gathering and aggregation in WSNs are often facilitated via splitting the network nodes to a set of clusters. The nodes within a cluster communicate to a cluster head (CH) node through single-hop wireless links. The CH is often an ordinary wireless sensor node, with similar complexity limitations, while it acts as a DGN within the cluster and communicates the collected and

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possibly aggregated nodes data to a central DGN [2]. This paper considers the problem of cost optimized distributed source coding in such complexity constrained wireless sensor clusters. This is distinct with the classic DSC, in which no complexity constraints are assumed at the DGN. In part of [6], aiming at minimum total cost, optimum rate allocation and transmission structure for a single sink data gathering network are presented. The rates are optimally found to be the corner points of the SW rate region. The cost function is restricted to be a product of a function of rate and a function of path weight. In [7], the problem of finding pairs of nodes and rate allocation to minimize the sum of the nodes rates is considered. The setting is motivated based on this claim that most existing DSC schemes concern two correlated sources. The problem is mapped to a minimum weight matching problem, within the pairwise SW rate region. The setting is also extended to minimizing the sum of the nodes powers for the case of single-hop data gathering over orthogonal noisy channels. In [8], the rate allocation problem within the pairwise SW region is considered in the case, where each node is to encode its data using that of one of the prior nodes as side information. This is shown to outperform the approach suggested in [7] and result in a smaller sum rate. However, the schemes presented in [6] and [8] require that the data of any and all of the prior nodes are stored and available at the DGN for the decoding of the data received from subsequent nodes. As high performance distributed source codes are set up based on large block lengths, this implies a substantial memory requirement at the data gathering node.

In this paper, we consider efficient data gathering in a WSN cluster whose cluster head node is of limited storage and computational complexity. We employ asymmetric SW codes, which optimally compress the data of each node prior to transmission, by exploiting its dependency with those of the prior nodes stored in the CH buffer as side information (SI). Due to the CH memory limitation, it is assumed that it may only store the data of up to β nodes. This in turn allows for decoding of each node data upon reception at the CH with limited complexity. Practical distributed source codes for this purpose are presented e.g., in [9]. For this network, we consider the problem of nodes rate allocation in order to minimize the sum cost of the nodes, where the node cost is an arbitrary function of rate and parameters related to the node. To solve this problem an optimal dynamic programming solution based on a trellis structure is proposed. The presented algorithm determines an optimal order for transmission of the nodes and identifies the corresponding optimal side information, i.e., the consecutive sets of up to β nodes, whose data are to be stored at the CH. The presented algorithm obtains the optimal solution with a substantially smaller computational complexity in comparison to an exhaustive search, at the cost of a modest increase in memory requirement. To reduce the complexity to a polynomial order, we also present a suboptimal yet high performance algorithm, which is set up based on a modified trellis with tied states. Numerical results demonstrate that a limited value of β can capture most of the available dependency and achievable compression gain.

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The rest of this paper is organized as follows. The system model is described in Section II. In Section III, the cost optimized rate allocation problem and the proposed optimal solution are presented. The implementation issues and complexity are discussed in Section IV. Sections V and VI, respectively present the numerical results and conclusions.

II. System Model

We consider a cluster of WSN with N nodes that communicate with a CH. Hereafter, we use the terms WSN or network and WSN cluster interchangeably for simplicity. For each node i, X_i is a random variable, observed at this node, that has a countable alphabet, e.g., following quantization of a continuous random variable. It is assumed that X_i is from a discrete-time random process and is independent and identically distributed over time. The nodes observations are spatially correlated and their joint mass probability function is known as $p(X_1, \dots, X_N)$ [6].

A. Rate Allocation Structure

For the network described, we consider allocation of an order and rates to nodes within the SW region. It is assumed that the CH has a limited-size buffer, in which it can only store the data collected from $\beta, 1 \leq \beta \leq N$ nodes. A specific transmission order is identified by a permutation of nodes indexes $\{1, \dots, N\}$ and is denoted by $\boldsymbol{\pi} = [\pi(1), \dots, \pi(N)]$.

In general, the SI for node $\pi(i)$ can be considered as any subset of the set $\{X_{\pi(1)}, \dots, X_{\pi(i-1)}\}$. Given the buffer constraint β, we have

$$\begin{cases} SI\big(\pi(i)\big) = \{X_{\pi(1)}, \dots, X_{\pi(i-1)}\}, & 0 \leq i \leq \beta \\ SI\big(\pi(i)\big) \subset \{X_{\pi(i-1)} \cup SI\big(\pi(i-1)\big)\}, & \beta < i \leq N \\ \quad\quad\quad \big|SI\big(\pi(i)\big)\big| = \beta - 1. & \end{cases} \tag{1}$$

Consider the pair $(\boldsymbol{\pi}, \boldsymbol{SI})$, where $\boldsymbol{SI} = \{SI(\pi(1)), \dots, SI(\pi(N)\}$, the rate of the node $\pi(i)$ is given by

$$R_{\pi(i)} = H\big(X_{\pi(i)} \big| SI(\pi(i))\big), \qquad 1 \leq i \leq N. \tag{2}$$

We refer to this Rate Allocation structure with Constrained buffer and parameter β as β-RAC. Note that $\beta = 1$ corresponds to the case, where the rate of each node is equal to its entropy, and no SI is exploited. When $\beta = N$, the rates coincide with SW region corner points.

B. Cost Function

For node i that transmits with the rate R_i, a cost is assigned that is denoted by $F_i(R_i)$. The objective is to minimize the sum cost for the network nodes, i.e.

$$\sum_{i=1}^{N} F_i(R_i). \tag{3}$$

For each node $i, F_{\pi(i)}(.)$ is considered as an arbitrary function of rate of the node and related fix parameters of that node and independent of rate of other nodes in section III. For case orthogonal channels this condition is satisfied. However, for numerical results in section V, we focus on the following two specific cases of interest.

Case 1- A desired objective in data gathering sensor networks is to minimize the sum of the nodes rates. In other words, for node i the cost function is defined as,

$$F_i(R_i) = R_i, \tag{4}$$

and the total cost of the network nodes is given by

$$\sum_{i=1}^{N} R_i. \tag{5}$$

Case 2- Another important design objective is to minimize the total energy consumption of the nodes. We consider orthogonal noisy channels between the nodes and the CH within a single-hop network setting. The capacity of each channel is given by [5],

$$C_i(P_i) = \frac{1}{2}\log\left(1 + \frac{\gamma_i P_i}{N_i W_i}\right) \text{ bit/sample}, \quad 1 \le i \le N \tag{6}$$

in which, P_i is the transmission power in watts, constant γ_i denotes the channel gain, N_i is the noise variance, W_i indicates the channel bandwidth and the sampling time is $\frac{1}{2W_i}$. Therefore, R_i is to satisfy $R_i \le C_i(P_i)$. For a given R_i, the minimum required power is then given by

$$P_i = (2^{2R_i} - 1)\frac{N_i W_i}{\gamma_i}. \tag{7}$$

Considering that the described channel is used in the time interval $[0, T_i]$, in which the channel gain and noise variance are constant, the energy consumption or the cost function of the node i is defined as:

$$F_i(R_i) = P_i T_i, \tag{8}$$

where P_i is given in (7). Therefore, the total cost of the network nodes is described as follows:

$$\sum_{i=1}^{N}(2^{2R_i}-1)\frac{N_iW_iT_i}{\gamma_i}. \tag{9}$$

III. Cost Optimized Rate Allocation

We consider cost optimized rate allocation for nodes of network based on the structure presented in section II-A. Specifically, the problem is to find the optimal pair of permutation and SI of the nodes, such that the corresponding rate allocation with β-RAC structure results in minimum total cost. Note that for $\beta=1$ the solution is trivial. Consider Π as the set of all pairs of permutation and SI for the nodes corresponding to β-RAC. The optimal pair $(\boldsymbol{\pi},\boldsymbol{SI})^o$ is the solution of the following optimization problem:

$$(\boldsymbol{\pi},\boldsymbol{SI})^o=\arg\min_{(\boldsymbol{\pi},\boldsymbol{SI})\in\Pi}\sum_{i=1}^{N}F_{\pi(i)}(R_{\pi(i)}), \tag{10}$$

in which $F_{\pi(i)}(.)$ denotes the cost function of the node $\pi(i)$ with the rate $R_{\pi(i)}$ based on the pair $(\boldsymbol{\pi},\boldsymbol{SI})$.

In order to solve this optimization problem efficiently, we propose a dynamic programming solution based on a trellis structure. Different paths in the trellis simply correspond to different pairs of permutation and SI within the β-RAC structure. A metric is assigned to each branch of the trellis and subsequently a cost is associated with each trellis path. The objective is to find the path with minimum cost, which identifies a specific pair of permutation (transmission order) and SI for the nodes. This consequently provides the rate allocated to each node.

A. *Trellis Structure*

The trellis components are described below.

Stages: The total number of stages is equal to the total number of nodes. The stage *i* corresponds to the node, whose data is collected in the *i*'th order.

States: The state s in stage i is denoted by the pair (i,s) and indicates the nodes whose data have been collected so far. We split the set of these nodes to two, namely $B(i,s)$ or the ones whose data are stored in the buffer, and $A(i,s)$ as the rest of the nodes whose data are not considered as SI. We have:

- For $0\le i<\beta$, $A(i,s)=\{\}$ and each subset of nodes with i elements determines $B(i,s)$ and hence a state. Therefore, in stage i, there are a total of $\binom{N}{i}$ states.

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- For $\beta \le i \le N$, $A(i,s)$ contains $i-(\beta-1)$ nodes, and $B(i,s)$ contains $\beta-1$ nodes. The total number of states in stage i is then given by $\binom{N}{\beta-1}\binom{N-(\beta-1)}{i-(\beta-1)}$.

Branches: The branch b emanating from the state (i,s) is identified by (i,s,b) and corresponds to the node $n(i,s,b)$ that is to transmit in this stage. Of course, this node is not included in the set of nodes that identify the state (i,s).

Consider the branch (i,s,b) that enters the state $(i+1,s')$. For $i<\beta-1$, the node $n(i,s,b)$ is added to the set $B(i,s)$ to form $B(i+1,s')$. Similar to $A(i,s)$, the set $A(i,s')$ is empty. Corresponding to each specific node, there is only one branch emanating from the state (i,s). For $i \ge \beta-1$, the node $n(i,s,b)$ replaces one element of the set $B(i,s)$ to form $B(i+1,s')$ or it is added to $A(i,s)$ to form $A(i+1,s')$. In the former case, the set $A(i+1,s')$ is then the union of the replaced element of $B(i,s)$ and the set $A(i,s)$. In the latter case, the set $B(i+1,s')$ is equal to $B(i,s)$. Note that the number of branches going out of the state (i,s) that correspond to one specific node is equal to $|B(i,s)|+1, i \ge \beta-1$.

The number of branches that enter a state in stage i, for $i \le \beta$ is i and for $\beta < i \le \mathrm{N}$ is $\beta(i-(\beta-1))$.

B. Trellis Search Algorithm

Based on the described trellis structure, the search algorithm is set up by defining the branch metric and state cost as follows.

Metric: A specific SI and therefore a specific rate is assigned to the node $n(i,s,b)$ corresponding to the branch (i,s,b). According to the SW theorem and β-RAC structure, this rate is denoted by $R_{n(i,s,b)}$ and is given by,

$$R_{n(i,s,b)} = H(n(i,s,b)|\, B(i,s)), \tag{11}$$

where $H(.)$ is the entropy function. The metric of the branch (i,s,b) is defined as the cost of the node $n(i,s,b)$, i.e., $F_{n(i,s,b)}(R_{n(i,s,b)})$.

Remark: In case, there is a constraint on the maximum cost of a node, based on the computed metric of a branch, if the constraint is not satisfied then the branch is removed. This condition arises for example in the scenario with a maximum power constraint for the nodes.

State Cost: The cost of the state (i,s), denoted by $C(i,s)$, is defined as the minimum cost up to this state that is provided by the paths reaching this state. Considering the set of branches entering the state (i,s) as $L(i,s)$, we have

$$C(i,s) = \min_{(i-1,s_b,b)\in L(i,s)} \Big(C(i-1,s_b) + F_{n(i-1,s_b,b)}(R_{n(i-1,s_b,b)}) \Big), \tag{12}$$

in which index b in s_b emphasizes that branches entering the (i, s) are emanating of different states in stage $i-1$. The branch that results in the minimum cost at a given state, or alternatively its parent state is stored. Once the cost is computed for all the states up to the last stage, the optimal path resulting the smallest cost is traced back. This path indicates the optimal pair of node permutation (transmission order) and SI and hence the rate allocation for the nodes.

Note that the principle of optimality [10] for this dynamic programming solution is satisfied. Specifically, considering the definition of the trellis components, given the current state, the best branches reaching the states in subsequent stages do not depend on the previously reached states or previously chosen branches.

Example: For data gathering in a network with 4 nodes and $\beta = 3$, Fig. 1 depicts the corresponding trellis diagram. To avoid confusion, the diagram is only partially presented, i.e., some states in certain stages are not shown and therefore some of the branches are removed. The label of each branch illustrates the sensor node index. Each state is marked with its corresponding sets. Suppose that the highlighted path in the trellis is identified as the optimal path by the trellis search algorithm. This path corresponds to the transmission order $\boldsymbol{\pi} = [1,3,2,4]$ for the nodes, with the following SI: $\boldsymbol{SI} = (SI(1) = \emptyset, SI(3) = \{X_1\},\ SI(2) = \{X_1, X_3\}, SI(4) = \{X_2, X_3\})$. Therefore, the optimal rate allocation is then as follows:

$R_1 = H(X_1), R_3 = H(X_3|X_1), R_2 = H(X_2|X_1, X_3), R_4 = H(X_4|X_2, X_3)$.

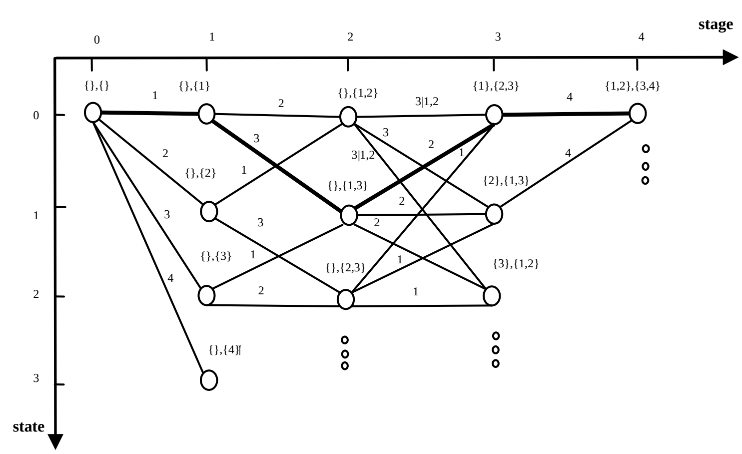

Figure 1. An example of a trellis to solve problem (10) for a network with 4 nodes, $\beta = 3$.

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IV. IMPLEMENTATION ISSUES

A. Solution Complexity

We compare the complexity of running full search algorithm with that of the proposed dynamic programming solution in terms of the number of operations and memory requirements. These quantities are measured in number of floating point operations or floating point values to be stored, simply referred to as floats [11]. The computational complexity for full search strategy can be obtained by considering the number of total pairs of permutation and SI for the nodes corresponding to β-RAC, the number of operations required to compute the total cost resulted by each pair and the number of operations to find the optimal pair. Hence, the number of operations (computational complexity) to find the solution of optimization problem (10) based on a full search strategy is:

$$CC_1 = (C+1)NN!\,\beta^{N-\beta}. \quad (13)$$

In (13), C is a constant that denotes the number of operations required to compute the cost function, e.g., based on equations (4) or (8), per node. The computational complexity for the proposed dynamic programming solution depends on the following parameters and elements: the number of states in each stage and the number of input branches to each state as provided in Section III-A, the number of operations required to compute the metric of each branch and the number of operations to find the optimal input branch to each state. Therefore, the computational complexity of the proposed dynamic programming solution is:

$$CC_2 = (C+2)\left[\sum_{i=1}^{\beta-1}\binom{N}{i} i + \beta\binom{N}{\beta-1} \times \sum_{i=\beta}^{N}\binom{N-(\beta-1)}{i-(\beta-1)}(i-\beta+1)\right]. \quad (14)$$

The memory required to run full search strategy is $M_1 = (N-\beta)\beta/2$ floats and to run the proposed dynamic programming solution is as follows:

$$M_2 = \frac{1}{2}\sum_{i=1}^{\beta-1}\binom{N}{i} + \frac{1}{2}\sum_{i=\beta}^{N-1}\binom{N}{\beta-1}\binom{N-(\beta-1)}{i-(\beta-1)} + \max\left\{\max_{i<\beta}\binom{N}{i}, \max_{i\geq\beta}\binom{N}{\beta-1}\binom{N-(\beta-1)}{i-(\beta-1)}\right\}. \quad (15)$$

Fig. 2 depicts the values of CC_1, CC_2, M_1, M_2 as a function of the number of network nodes N for $\beta = 5$. It is clear that the proposed solution substantially reduces the computational complexity compared to the full search at the cost of a much smaller increase in the memory requirement. Still, the presented optimal solution incurs a manageable complexity only for data gathering within a cluster of nodes with a small number of nodes. However, we present an alternative and more efficient solution.

B. Suboptimum Solution

In this subsection, a suboptimum, yet high performance algorithm to solve the optimization problem (10) is proposed that have polynomial complexity. The solution is also based on a trellis structure, however with a different definition for the states of stages $\beta \le i \le N$. In this scheme, a state is uniquely identified by the set $B(i,s)$. Therefore, the number of states in stage $i, \beta \le i \le N$ is $\binom{N}{\beta-1}$. The set $A(i,s)$ for each state may be determined by the path with minimum cost reaching that state.

Consider the branch (i,s,b) that enters the state $(i+1,s')$. For $i < \beta - 1$, the node $n(i,s,b)$ is added to the set $B(i,s)$ to form $B(i+1,s')$. Similar to $A(i,s)$, the set $A(i+1,s')$ is still empty. For $i < \beta - 1$, note that corresponding to one specific node only one branch exits the state (i,s). For $i \ge \beta - 1$, the node $n(i,s,b)$ replaces one element of the set $B(i,s)$ to form $B(i+1,s')$ or it is added to $A(i,s)$ in which case, the set $B(\mathrm{i}+1,s')$ is equal to $B(i,s)$. Note that the number of branches going out of the state (i,s) that correspond to one specific node is equal to $|B(i,s)|+1, i \ge \beta - 1$. Once the costs due to all the branches entering the state $(i+1,s')$ are computed, the one with the least cost is selected and the corresponding set $A(i+1,s')$ is determined and stored. The path with minimum cost may be consequently traced back as discussed in Section III-B.

For the presented suboptimal solution, the number of branches entering each state at stage i, $i \ge \beta$, is smaller than $N+\beta-i$. Therefore, the worst case computational complexity of the suboptimal solution is determined as follows:

$$CC_3 = (C+2)\left[\sum_{i=1}^{\beta-1}\binom{N}{i}i + \sum_{i=\beta}^{N}\binom{N}{\beta-1}(N+\beta-i)\right]. \quad (16)$$

The memory required to run the suboptimum solution is then given by:

$$M_3 = \frac{1}{2}\sum_{i=1}^{\beta-1}\binom{N}{i} + \frac{1}{2}(N-\beta)\binom{N}{\beta-1} + \max_{i<\beta}\binom{N}{i}. \quad (17)$$

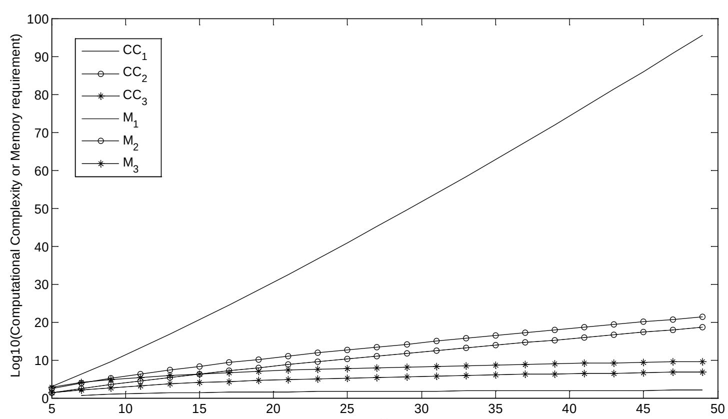

Figure 2. Comparison of complexity to run full search, proposed optimal and suboptimum solutions to solve optimization problem (10) for $\beta = 5$ and $C = 1$.

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For large N and a limited β, the analysis of CC_3 and M_3 in (16) and (17) indicate a polynomial complexity in terms of N as $O(N^{\beta+1})$ and $O(N^{\beta})$, respectively. Fig. 2 also depicts CC_3 and M_3 as a function of the number of network nodes for comparison.

V. Numerical Results

We consider a network with N nodes uniformly distributed in a unit square and a CH located at the center of the square. A sample network is depicted in Fig.3. The data of the nodes are generated based on an N-dimensional jointly Gaussian distribution with covariance matrix K and mean vector μ. The covariance between the nodes i and j with a distance of d_{ij} is $k_{ij} = \sigma^2 e^{-\alpha d_{ij}^2}$, and the variance of the sensed data at each node is $k_{ii} = \sigma^2, 1 \leq i \leq N$. The correlation between the observed data of pairs of nodes increases as the parameter α is reduced [6].

Figures 4 and 5 depict the performance of the proposed optimal scheme for this network as a function of parameter β and for different values of α. Following the description in section II-B, Figure 4 examines case 2 for data gathering over noisy channels, where the network cost is the total energy consumption. Figure 5 examines case 1, where the network cost is considered as the sum of the nodes rates. In both Figures, it is observed that for a given α and values of β beyond a threshold, the resulting minimum network cost is only negligibly different with the setting $\beta = N$. Note that $\beta = N$ corresponds to the SW coding (corner points) with no buffer constraints, where the dependency with all prior nodes are exploited. Hence, the results verify that a limited value of β larger the threshold can capture most of the available dependency and achievable compression gain. It is also evident that a smaller α (stronger dependency between the nodes) results in a larger threshold.

Figure 5 also provides a comparison between the costs obtained by the proposed optimal and suboptimal algorithms. The gap in the performance of the two is rather small, and it diminishes for $\beta \geq 5$.

VI. Conclusions

In this paper, a rate allocation structure in data gathering wireless sensor networks with a complexity constrained data gathering node was proposed. Based on this structure, we considered the problem of rate allocation for the nodes to minimize the network cost. To solve this problem an optimal dynamic programming solution and an alternative suboptimal solution with polynomial complexity order in terms of number of nodes was presented. Numerical results indicate that although a limited buffer size limits the dependency that may be exploited for compression, if effectively utilized, it still allows for capturing most of the available compression gain.

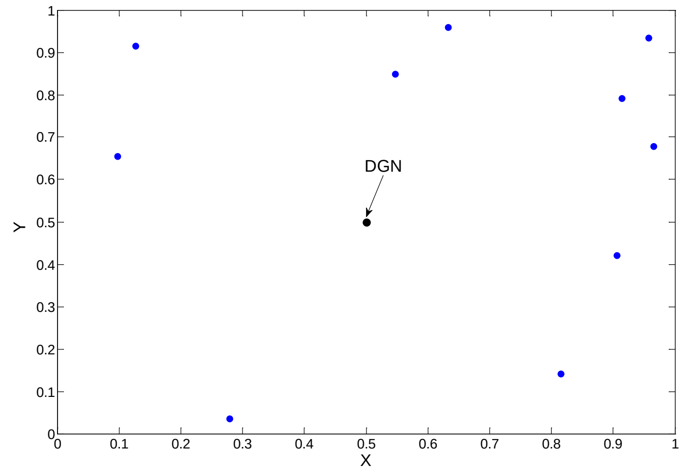

Figure 3. Position of the nodes in the investigated network.

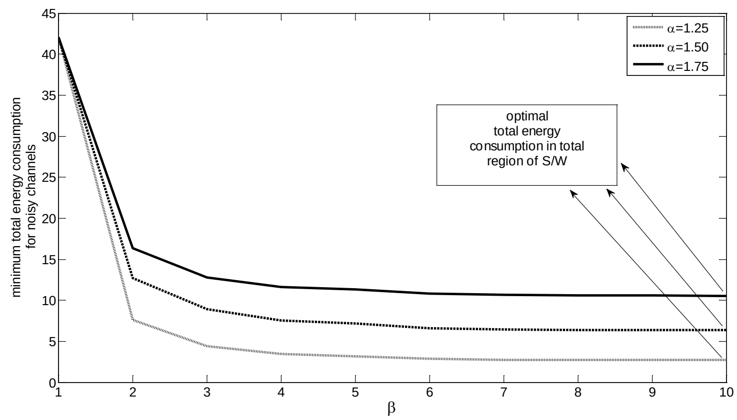

Figure 4. Minimum total energy consumption vs. β for data gathering over orthogonal noisy channels. Results of the proposed optimal solution.

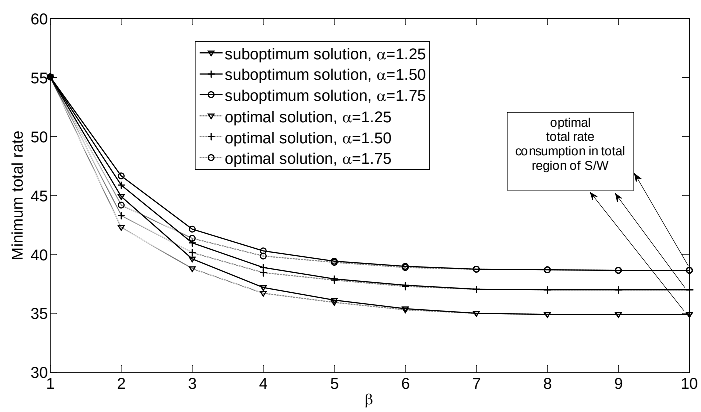

Figure 5. Minimum total rate vs. β. Results of the proposed optimal and suboptimal algorithms for a network with $N = 10$ nodes.

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