A Computational Approach to the Joint Design of Distributed Data Compression and Data Dissemination in a Field-Gathering Wireless Sensor Network *

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Abstract

In this paper we present an approach to the joint design of distributed data compression and data dissemination for wireless sensor networks. We consider a wireless sensor network in which each sensor collects data (e.g., temperature) about the sensing field, transmits it back to a central collector/controller, which then combines the data from individual sensors to reconstruct and form a "snapshot" of the field, subsequently called a *field-gathering* wireless sensor network. Each sensor is constrained individually by the amount of energy that it possesses when it is deployed. Our goal is to prolong the functional lifetime of such a network and maximize the total number of snapshots the network can deliver (sample and transmit) to the collector via the proper selection of optimal routing pattern and optimal data rate allocation among all sensor nodes (using Slepian-Wolf type of encoding). We present a constrained maximization formulation for the joint optimization of routing and rate allocation. We solve this problem in the simple case of a linear network and explore via numerical experiments the properties of optimal rate allocation and its relationship with optimal routing under a variety of scenarios.

1 Introduction

In this paper we consider a *field-gathering* wireless sensor network, where each sensor collects certain data (e.g., temperature, pressure, wind speed, etc.) about the sensing field and transmits it back to a central collector/controller, via either a single hop direction transmission or multiple hops, using other sensor nodes as relays. The collector, upon

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receiving data from all sensors, will reconstruct a *snapshot* of the field, e.g, forming a temperature image/map, to some quality measure. This procedure can be repeated periodically to obtain a sequence of snapshots of the field over time. The concept of such a field-gathering wireless sensor network, along with its efficiency and performance measures, was first studied in [1], in which the asymptotic capacity and compressibility of the network were studied for a dense sensor deployment.

In this study we will focus on the capability of such a network in delivering snapshots given the energy constraint of each individual sensor. We will assume that each snapshot is independent from another. For a given reconstruction quality measure, it is desirable to have the network deliver as many snapshots as possible, or equivalently, last as long as possible. This objective depends on many factors, including the layout of the sensors, the size of sensing field, the energy reserve of individual sensor nodes, etc. In addition, this objective also relies heavily on two components of network design, namely *data dissemination* and *data compression*. The former refers to the routing strategy under which data is delivered from individual sensors to the collector. This includes the selection of transmission ranges and routes. The latter refers to the encoding schemes employed by individual sensors that determine the amount of data per snapshot required from each sensor, to meet a pre-defined quality measure. The design of these two components should lead to the energy-efficient operation of the network, so that the lifetime of the network is maximized while fulfilling the goal of delivering snapshots of the field to a prescribed quality measure. The design of these two components will be the focus of this paper.

There is an obvious coupling between data dissemination and data compression strategies. For example, nodes generating more data will need to conserve energy in communication by perhaps selecting nodes located close by as relays. Similarly, a node located at a bottleneck position may need to relay a lot of data for other sensors, and thus may need to generate less amount of data on its own. Consequently in this paper we will study the joint design and optimization of both to maximize the network lifetime and the number of snapshots the network can deliver. This joint design is done over all possible routing choices and all possible encoding rate allocation choices. In particular, we will consider an idealized scenario where sensor nodes can arbitrarily adjust their transmission power and be able to reach any other node in the network and establish arbitrary routes to the collector. We will also limit ourselves in this study to a distributed data compression scheme of the Slepian-Wolf type [2], which specifies a region within which all combinations of encoding rates of individual nodes lead to lossless data compression.

We present a mathematical programming framework that takes as input the layout of the network (i.e., the location of the collector and each sensor), the initial energy of the sensors, and a certain energy consumption model, and generates the maximum number of snapshots that can be produced by the network, along with the set of routing paths and encoding rates that achieve this maximum value. In doing so we first present a linear program formulation for maximizing the lifetime of such a field-gathering sensor network under fixed rate allocation over all routing choices. We then include the additional constraints on rate allocation imposed by the Slepian-Wolf encoding, which results in the joint optimization of routing and rate allocation. We show that this joint optimization formulation results in a non-linear program.

We solve this problem in the simple case of a linear network topology and explore various properties of this joint design via numerical experiments. In particular, we will examine the relationship between the location of a sensor node and its optimal rate (defined really as the *number of bits per snapshot*), the optimal rate allocation under different auto-correlation functions of the field and the gain obtained via optimal rate allocation, the relationship between optimal rate allocation and optimal routing, and the effect of transmission range limit and relay nodes in the network. To the best of our knowledge, the study outlined in this paper is the first to jointly design distributed data compression and data dissemination to maximize the network's operational lifetime.

The rest of the paper is organized as follows. Section 2 presents the problem formulation. Section 3 gives the results of a range of numerical experiments. Section 4 provides a discussion on our formulation and results, along with a brief review of related work. Section 5 concludes the paper.

2 Problem Formulation

Consider a network of M sensor nodes randomly deployed over a certain region/field, which can be linear or higher dimension. Each node is indexed by $i, i = 1, 2, \cdots, M$. We will use M to denote both the total number of sensors and the set of sensors when there is no ambiguity. There is a collector denoted by C, located somewhere in or outside the field. We assume that the locations of these sensor nodes as well as the collector are known and fixed once deployed. $f_{i,j}$ denotes the total amount of data flow (in bits) directly transmitted from node i to node j. Similarly, $f_{i,C}$ denotes the total amount of data directly transmitted from node i to the collector. $\mathbf{f}$ denotes the vector of all these flows.

We assume that the energy consumption of a sensor node consists of transmit energy, receive energy, and sensing energy. We will ignore the amount of energy spent by a sensor while idling; thus our model describes an ideal scenario where nodes can turn the transceiver off when not used. We assume that nodes can adjust their transmission power arbitrarily to reach a destination. The energy consumed in transmitting data from node i to node j is denoted by $e_{tr}^{i,j}$ measured in joule per bit. This is clearly a function of the distance between nodes i and j, denoted by $d_{i,j}$. Similarly, e_{rx} denotes the energy consumed in receiving data, and e_s denotes the energy consumed in sensing and processing (quantization and compression), both measured in joule per bit. The initial energy node i has is E_i, measured in joule. Note that $e_{tr}^{i,j}$ and e_{rx} are assumed to be independent of the actual channel data rate used to transmit the bits; in practice, these would depend on the data rates and the associated modulation and error control coding schemes.

Below we first present a formulation for maximizing the network lifetime when nodes have fixed encoding rates, and then modify this formulation to include rate allocation.

2.1 Fixed Rate Allocation

Assuming that node i generates data at a rate r_i, we obtain the following optimization formulation (P1) as shown in Figure 1. Our objective is to maximize the lifetime of the network denoted by t, or alternatively to maximize the total amount of data delivered to the collector node C.

The constraints of P1 are as follows. (1) is the flow conservation constraint, which states that the total amount of data flowing into a node plus the total data generated at the node must equal the data flowing out of the node. This essentially implies that all data has to exit the network once generated. (2) is simply the energy constraint on

$$\max_{\mathbf{f}} \quad t \quad \sim \quad \max_{\mathbf{f}} \quad \sum_{i=1}^{M} f_{i,C}$$

$$\text{S.t.} \quad \sum_{j\in M} f_{i,j} + f_{i,C} = \sum_{j\in M} f_{j,i} + r_i \cdot t \qquad \forall\ i \in M \tag{1}$$

$$\sum_{j\in M} f_{i,j} \cdot e_{tx}^{i,j} + f_{i,C} \cdot e_{tx}^{i,C} + \sum_{j\in M} f_{j,i} \cdot e_{rx} + r_i \cdot t \cdot e_s \le E_i \qquad \forall\ i \in M, \tag{2}$$

$$f_{i,j} \ge 0, \qquad \forall i,j \in M \cup \{C\} \tag{3}$$

$$f_{i,i} = 0, \qquad \forall i \in M \tag{4}$$

$$f_{C,i} = 0, \qquad \forall i \in M \tag{5}$$

Figure 1: Formulation P1

each individual node. (3)-(5) ensure that all data flows are non-negative, nodes do not transmit to themselves, and data does not flow from the collector back into the network. In some scenarios there can be a feedback channel that allows the collector to transmit to the sensors. This can be easily incorporated in such a formulation. Here we will limit our discussion to the simpler case of one-way data transmission. It is implied that bits are infinitely divisible. This ensures that there is a non-trivial solution to P1 as long as $e_i > 0$ for all i. Any particular flow calculated by this formulation can be approximated in practice by an integer to within one bit.

Note that under such a formulation, the lifetime of the network t refers to the time until the first sensor runs out of energy. However, in maximizing the time to the first death sensors are forced to balance their energy consumption so that all sensors essentially die as the same time, as shown in [3]. The objectives of maximizing this lifetime and maximizing the total amount of data delivered by this lifetime are equivalent under this formulation. This is because given the data generation rate r_i *per snapshot*, we have $t = \frac{\sum_i f_{i,C}}{\sum_i r_i}$. As $\sum_i r_i$ is a given constant, maximizing one is the same as maximizing the other. It is also worth pointing out that in this formulation the notion of *time* has a rather unconventional meaning, in that we only consider time elapsed when a node is either actively transmitting, receiving or sensing. We do not take into account the time a node spends idling. Alternatively, it is *as if* transmissions and receptions can happen concurrently. In reality, they need to be properly scheduled, for example via certain MAC scheme, to avoid collision, and a node may have to wait from time to time for its scheduled transmission. Our model thus focuses only on the *operational lifetime* of the network. Consequently our model provides an upper bound for any practically realizable network.

It has to be mentioned that the fluid-flow model represented by P1 is not entirely new, as similar variations have been used by others, see for example [4], [5], and [6]. In particular, it has been shown in [4] and [5] that the solution to a formulation like P1 in terms of the optimal flows $f_{i,j}$ can always be realized in practice. In [3] we studied a continuous version of P1 to derive fast computation of network lifetime based on the distribution pattern of nodes rather than the precise locations of each node in the network.

2.2 Optimal Rate Allocation

P1 assumes that each node generates data at a pre-set fixed rate per snapshot. We now wish to jointly determine the rates of all nodes in an optimal fashion, based on certain assumed auto-correlation function of the field and conditions set forth by distributed data compression. We will assume that the sensing field is described by a Gaussian random process with mean zero and covariance matrix K. We assume that sensor nodes use identical scalar quantizers, and use a Slepian-Wolf type of distributed encoding. Thus the following constraint applies to the rate R_i of node $i, i = 1, 2, \cdots, M$.

$$\sum_i R_i \geq H_d\left(S|S^c\right), \quad \forall S \subseteq S_o\ , \tag{6}$$

where $H_d(\cdot)$ denotes the differential entropy, $S_o = X_1, ..., X_M$ and $X_i,\ i = 1, .., M$ is the sample taken by node i. Note that we are using the differential entropy because it only differs from entropy by a constant when identical scalar quantizers are used by sensors and thus can be used without having to assume a particular step size of the quantizer. The above constraints specify the region of all feasible combinations of rates. These rates are measured in bits per snapshot in our formulation.

The objective is to maximize the number of snapshots generated by the network, denoted by n, while each snapshot consists of data generated by nodes according to the rates specified by the above constraints. This is formulated in P2 shown in Figure 2. Constraints (7)-(8) and ((11)-(13) are same as before. In addition, (9) is the rate

$$\max_{n} \quad n$$

$$\text{S.t.} \quad \sum_{j\in M} f_{i,j} + f_{i,C} = \sum_{j\in M} f_{j,i} + n \cdot R_i \qquad \forall\ i \in M \tag{7}$$

$$\sum_{j\in M} f_{i,j} \cdot e_{tx}^{i,j} + f_{i,C} \cdot e_{tx}^{i,C} + \sum_{j\in M} f_{j,i} \cdot e_{rx} + n \cdot R_i \cdot e_s \leq E_i \qquad \forall\ i \in M \tag{8}$$

$$\sum_i R_i \geq H_d\left(S|S^c\right) \qquad \forall\ S \subseteq S_o \tag{9}$$

$$\sum_{i=1}^{M} f_{i,C} = n \cdot \sum_{i=1}^{M} R_i \tag{10}$$

$$f_{i,j} \geq 0, \quad \forall i, j \in M \cup \{C\} \tag{11}$$

$$f_{i,i} = 0, \quad \forall i \in M \tag{12}$$

$$f_{C,i} = 0, \quad \forall i \in M\ , \tag{13}$$

Figure 2: Formulation P2

allocation constraint, and (10) ensures that all data is destined for the collector.

An important difference between P2 and P1 is that P2 is no longer a linear program, since R_i is now to be optimized instead being fixed. It can be solved but various linear programming techniques cannot be directly applied. One way around this problem is to solve a sequence of linear programs by fixing n to a certain value and replacing the objective function in P2 by ($\min_{f,R} \quad n \sum_{i=1}^{M} R_i$), which results in a linear program. Then a semi-brute force approach can be use to solve this sequence of linear programs by enumerating n till the maximum value of n for which there is a feasible solution is found. While the above obviously is not the best way of solving this problem, our preliminary results presented in the next section are based on this approach.

3 Numerical Results

In this section we present the results obtained by solving the problem formulated in the previous section, under a variety of parameter settings. For simplicity and convenience of presentation, our experiments are based on a linear network topology, where M sensor nodes are deployed on a line segment of length D between $(0,0)$ and $(D,0)$. These nodes are spaced equal distance apart, to approximate the deployment pattern following a uniform distribution. The collector is located at $(D+\frac{D}{M},0)$, a distance D/M away from one end of the line segment.

The total energy in the network will be kept constant at $E=1$ joule. We adopt the following energy model. Total energy consumed by a sensor in transmission is $E_t(r) = (e_t + e_d r^\alpha)b$, where e_t and e_d are specifications of the transceivers, r is the transmission distance, b is the number of bits sent, and α depends on the characteristics of the channel and is assumed to be time invariant. Note that $e_{tx}^{i,j}$ used in the previous section is essentially $e_t + e_d r^\alpha$ when r is the distance between nodes i and j. Energy consumed in receiving is $E_r = e_{rx}b$. Finally $E_s = e_s b$ is the energy spent in sensing/processing data that is quantized and encoded into b bits. In this section we will use the following parameter values taken from [5]: $e_t = 45\text{x}10^{-9}$, $e_{rx} = 135\text{x}10^{-9}$, and $e_s = 50\text{x}10^{-9}$, all in J/bit, and $e_d = 10\text{x}10^{-12}$ in J/bit-meter$^\alpha$, and $\alpha = 2$. It should be mentioned that our results obviously depend on the energy model and its parameter values we use. However, our formulation is independent of the selection of these parameters.

3.1 Gain of Rate Allocation

We first examine the gain obtained via optimal rate allocation by comparing P2 with P1, where the same rate is allocated to all nodes (with total rate equal to $H_d(S_o)$), while keeping everything else the same. We will consider a relatively small network of $M=8$ nodes, and four cases between the choice of $D=200$ and $D=1000$ meters, and two different auto-correlation functions of distance $d_{i,j}$ between nodes i and j. These four cases and the corresponding results are summarized in Table 1.

Case	ρ	D	Optimal Rate	Equal Rate	% Gain
Case 1	$\exp(-\sqrt{d_{i,j}}/100)$	200	1,141,745	851,682	34 %
Case 2	$\exp(-\sqrt{d_{i,j}}/100)$	1000	56,294	51,572	9.16%
Case 3	$\exp(-d_{i,j}/100)$	200	307,147	294,054	4.45%
Case 4	$\exp(-d_{i,j}/100)$	1000	25,377	25,324	0.21%

Table 1: Four scenarios

We see the optimal rate allocation gain reduces significantly as the correlation between samples decreases (as a result of increased distance and reduced correlation). The optimal rate of each node in Cases 1 and 2 is shown in Figure 3 as a function of their distance to the collector. When we force rate to be equal for all nodes, the equal rate is 0.5035 for Case 1 and 0.9788 for Case 2. In both cases the equal rate is considered to be the joint entropy divided by M. As expected, nodes closer to the collector employs higher rates. However the rate of the node closest to the collector is not the maximum rate allowed by the rate allocation constraint $H_d(X_1)$ (which is 2.0471). This is because this node needs to spend energy relaying data for nodes that are further away from the collector. Interestingly, in both cases nodes furthest away from the collector employ roughly the same rate, approximately $H_d(X_1 \mid X_2)$, the conditional entropy of one sensor's data given its neighbor's data. As nodes are placed closer to the collector their rate increases rapidly. This creates a knee in the rate allocation curve in both cases, but more prominent in the second case. As the correlation between nodes is reduced, the position of the knee moves closer to the collector.

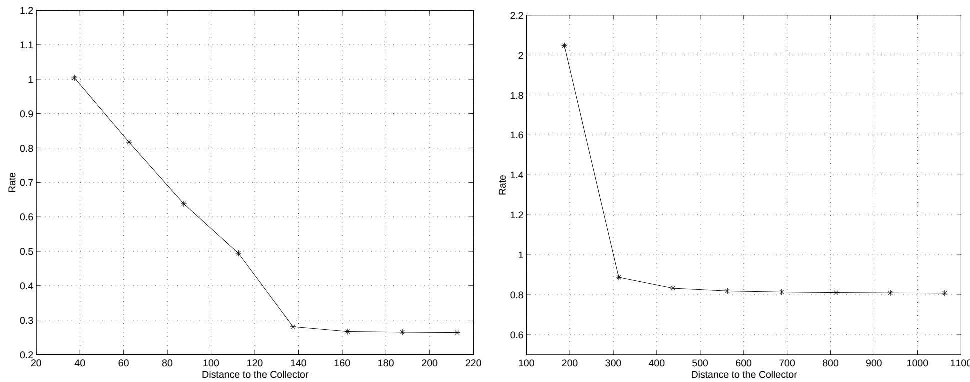

Figure 3: Optimal rate allocation in Cases 1 (left) and 2 (right)

3.2 Effect of Limited Transmission Range

So far we have assumed that nodes have an unlimited range of transmission. This enables the nodes to use the optimal path by selecting the best relay (or direct transmission to the collector). In practice nodes have a maximum range of transmission, thus the choice of routes may be limited to sub-optimal ones. We consider Case 1, but limit the maximum transmission range to 150, 100, and 50 meters, respectively. The resulting number of snapshots is reduced form 1,141,745 (unlimited) to 874,781, 586,078 and 205,689, respectively. The noticeable decrease in the number of snapshots is clearly caused by the use of sub-optimal routes, which has a significant effect on energy efficiency.

Figure 4 shows the optimal rate allocation under each range of transmission. Note that the optimal rates vary with path selections, revealing a complicated interaction between rate allocation and route optimization. In particular, when there is no transmission range limit, more nodes can afford a higher rate as they spend less energy on communication due to optimal routing. On the other hand as the transmission range decreases, almost all nodes (except for those closet to the collector) employ a minimum rate, since they consume more energy on communication.

Figure 5 further examines the change in optimal routing when the transmission range is limited. We compare the fraction of data transmitted over a given distance in the case of equal rate assignment and the case of optimal rate allocation, both with unlimited transmission range. We see from the graph on the left that in the case of equal rate allocation, the bulk of data transmission is done over a range between 100 and 150 meters. However, in the case of optimal rate allocation data transmission is not concentrated at a particular distance. Indeed all distances are used equally frequently. The graph

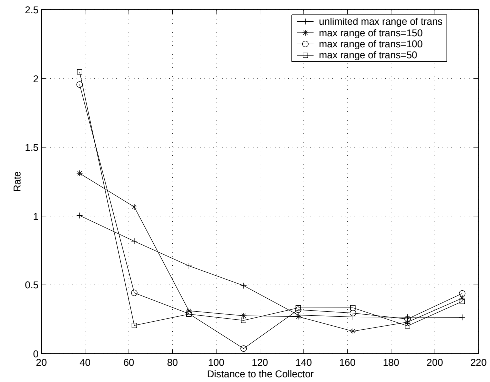

Figure 4: Optimal rate allocation under different transmission ranges

on the right shows the mean transmission distance of nodes at different locations using optimal routing when optimal rate allocation and equal rate are used, both with unlimited transmission range. We see that nodes further away from the collector have larger mean transmission distance in the case the optimal rate allocation.

There are two implications of these results. Firstly, optimal rate allocation results in very different routing pattern. In particular, there seems to be an incentive for node to transmit over longer distances to achieve better energy efficiency. Since nodes further away from the collector generate less data, they can afford to transmit over longer distances. Secondly, as a result of longer transmission ranges employed by optimal routing, any limitation on the maximum range of transmission has a significant effect on the number of snapshots delivered in the case of optimal rate allocation.

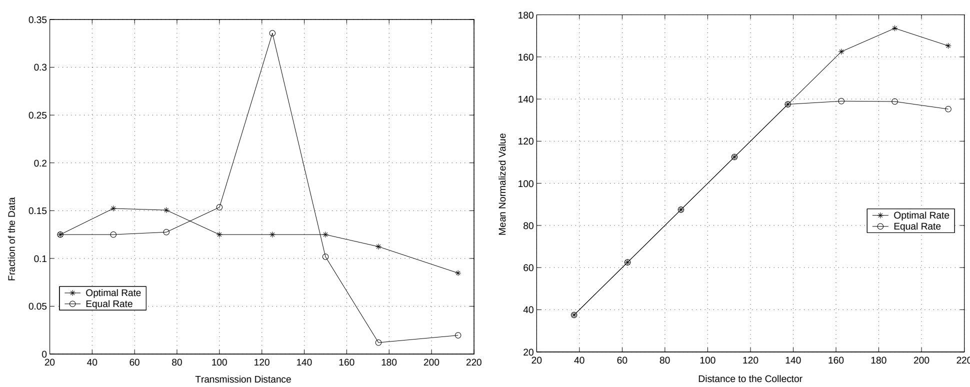

Figure 5: Fraction of data transmitted at given distance (left) and mean transmission distances (right)

3.3 Effect of Relay Nodes

In this subsection we consider the effect of using relay nodes. These are nodes deployed for the purpose of serving as data relays but do not generate data themselves. We again fix the total energy in the network as well as the number of sensor nodes to $M = 8$, but vary the percentage of energy allocated to relay nodes. The sensors are deployed evenly as before. We would like to determine if there is an advantage in using relays, and if so how they should be deployed.

We will consider the relays deployed following a class of probability density distribution of the following form: $f_X(x) = cx^a, \quad a \geq 0$, where c is a normalizing constant, and x denotes the location along the line between 0 and D. Different values of a represents different distribution of relay nodes. We found that there is no advantage in using relays in this Case 1 with $D = 200$. However, if we increase D to 500, then without relays the network can transmit up to 213,717 snapshots. If we use 30% sensors and 70% relays we can transmit up to 232,948 snapshots, a gain of about 9%, achieved when $a = 2.08$. In general, when D is sufficiently large, then adding relay nodes (optimally distributed) can help improve the energy efficiency of the network as the optimal rate allocation is not sufficient in adapting to the longer distance D. The value of a in the distribution of the relays that maximizes the number of snapshots is 2.08.

4 Discussion and Related Work

One concern regarding the joint optimization problem is its computational complexity. Note that P1 is a linear program and its number of constraints grows linearly with the number of nodes in the network. On the other hand P2 is not a linear program, and the additional constraint introduced by the rate allocation region contains $2^M - 1$ linear constraints, which is exponential in the number of nodes in the network. This sets a severe limit on our ability of using P2 to handle large networks. In [3] we showed that the *average* lifetime of networks (not considering optimal rate allocation) of a given node distribution (uniform or non-uniform) can be very well approximated by a grid network constructed based on the original node distribution, and this accuracy holds for a wide range of granularities of the grid network. This greatly reduces the computational effort in solving P1 for a large network. It would be interesting to see if similar properties hold for P2, which would then allow us to partition the network into grids and solve a problem with much fewer number of constraints.

Our joint design of distributed data compression and data dissemination seeks to maximize the amount of information that is delivered by the sensor network. As mentioned before, the fluid-flow based model represented by P1 has been used before, e.g., [5, 4, 3]. In a related problem, a similar linear program is used in [6] in designing energy efficient routing protocols. More recently, similar models have been used to study the maximum throughput achievable in a network, see for example [7, 8]. Alternatively, the lifetime of specific sensor network topologies has also been studied using hybrid automata modeling [9]. The issue of lifetime is directly related to the power consumption in the network, which has been very extensively studied both within the context of wireless sensor networks and within the context of generic ad hoc networks, see for example [10, 11].

5 Conclusion

We presented an approach to the joint design of distributed data compression and data dissemination for wireless sensor networks. We first presented a linear program formulation for maximizing the lifetime of a wireless sensor network under fixed rate allocation over all routing choices. We then included the additional constraints on rate allocation imposed by the Slepian-Wolf encoding, which results in the joint optimization of routing and rate allocation. We solved this problem in the simple case of a linear network and explored via numerical experiments the properties of optimal rate allocation under different auto-correlation function of the field, the relationship between optimal rate allocation and optimal routing, and the effect of transmission range limit and relay nodes in the network.

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