On the Cooperation Strategies for Dense Sensor Networks

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Abstract—**In this paper we characterize the scaling laws of the generated traffic and scheduling delays associated with the broadcast problem in dense multi-hop sensor networks where sample measurements are highly correlated. More specifically, we assess the benefits, and possibly the trade-offs, of exploiting sample correlations via cooperatively compressing the data as it hops around the network. First, we determine, with the aid of basic information theory, the transport traffic and schedule length growth rates under the no cooperation and network-wide cooperation extremes. We observe that network-wide cooperation significantly improves the transport traffic growth rate, without any degradation in the linear schedule length growth rate. Second, we propose a novel two-phase cooperation strategy that localizes cooperation within regions of the network in an attempt to optimize the schedule length for a given network size. We demonstrate the role of the cooperation set size in trading transport traffic for schedule length, or vice versa, and how the two extreme strategies turn out to be special cases of the two-phase cooperation framework.**

Keywords— **Wireless sensor networks, source coding, spatial correlations, transport traffic, scheduling, scaling laws.**

I. Introduction

Future wireless networks are expected to accommodate large numbers of embedded devices that operate cooperatively to achieve a prespecified sensing/monitoring task. One of the main hurdles towards the realization of this objective is network scalability. It has been shown in [1] that the *peer-to-peer* (or one-to-one) transport capacity of wireless ad hoc networks scales as $O(\sqrt{N})$ where N is the number of nodes per unit area. This, in turn, implies that the per-node throughput scales as $O(\frac{1}{\sqrt{N}})$, and, hence, asymptotically vanishes as the node density grows to infinity. Therefore, it was concluded that designers should focus on wireless networks of small numbers of nodes. In [2], the authors studied the problem of broadcast communications (also known as *flooding* or *many-to-many communications*) in multi-hop sensor networks where samples of a random field are recorded at each node in the network and disseminated to all other nodes in order to obtain an estimate of the entire field within a prescribed distortion value. They observed that the scaling laws derived in [1] are based on the assumption that the traffic generated at different nodes in the network is generally independent. Furthermore, they argued that this conclusion may not be generally true for wireless sensor networks due to the fact that spatially close sensors experience correlations among their sample measurements. Thus, they proposed to use classical source codes and then re-encode the data as it hops around the network in order to remove correlations and, hence, reduce the traffic generated by each sensor. However, this may involve a trade-off between transport traffic and transmission scheduling delays that has been illustrated via a simple example in [2]. In this paper, we focus on this trade-off and potential avenues for solving it. In [3], a distributed algorithm for removing correlations among sensor data via computing wavelet transforms has been proposed. However, the scaling laws of the associated traffic and scheduling delays were left as open problems. On the other hand, [4], [5] fall within the scope of distributed source coding that utilizes Slepian-Wolf coding schemes [6] to remove correlations without any communications among sensors. Finally, the many-to-one capacity of dense sensor networks was characterized in [7] and [8] under different sets of assumptions.

Our contribution in this paper is two-fold: i) Characterize the scaling laws of the transport traffic and scheduling delays associated with two extreme cooperation strategies, namely no cooperation and network-wide cooperation and ii) Analyze a novel two-phase cooperation strategy that opens room for optimizing the transmission schedule length for a given network size. Thus, given a set of sensors whose sample measurements are correlated, our main objective is to quantify how the generated traffic and scheduling delays associated with the extreme strategies behave as the network size grows. Motivated by the scaling laws of those extremes, we propose a two-phase cooperation strategy, whereby sensors in the same cooperation set cooperatively encode their sample measurements according to a network-wide cooperation scheme in the first phase. In the second phase, respective cooperation sets exchange their samples without any compression (according to the no cooperation extreme). This, in turn, opens room for trading traffic for scheduling delays or vice versa via controlling the cooperation set size.

The paper is organized as follows: In section II, the network model underlying this study is introduced. Afterwards, the traffic-delay trade-off in cooperative sensor networks is investigated in section III. This is followed by a detailed description and analysis of the proposed two-phase cooperation strategy in section IV. Finally, conclusions are drawn in section V.

II. Network Model

In this paper we limit our attention to one-dimensional sensor networks consisting of N stationary nodes which communicate only via the wireless medium and are uniformly spaced along a horizontal straight line of unit length. We assume that nodes are indexed in an ascending order from left to right. Extending the results to two-dimensional grids lies out of the scope of this paper and is a subject of ongoing research. We assume that all nodes are equipped with omni-directional antennas that radiate energy according to an isotropic pattern. Moreover, nodes use fixed and equal transmission power, which translates to the same transmission range (r), where $\frac{1}{(N-1)} \leq r \leq \frac{2}{(N-1)}$, i.e. nodes $(m-1)$ and $(m+1)$ are one-hop neighbors of an arbitrary node m. All nodes are assumed to share the same frequency band, and time is divided into equal size slots and each transmission fits exactly into a single slot.

Each sensor is assumed to record periodic samples of the sensed field, scalar quantize, encode and transmit them such that the sensed field can be reconstructed at all nodes in the network up to certain level of distortion. We assume that successive samples taken by the same sensor are *temporally uncorrelated* and, hence, we focus on the set of samples recorded by all sensors at a given time instant and drop the time index. On the other hand, sensor measurements are assumed to be *spatially correlated* according to a stationary one-dimensional spatial random process $S(y)$, where $S(y)$ is a real-valued random variable representing the field value at location $0 \leq y \leq 1$. This is motivated by the fact that the vast majority of physical phenomena are analog such that sensors are better modeled as continuous rather than discrete sources. Moreover, we assume that the random process $S(y)$ has the property that the correlation between samples increases as the sensors get dense. We assume that the reading of sensor m, denoted S_m, is quantized by a fixed quantizer q(.) subject to a constraint on the average distortion per sample (i.e. $\frac{1}{N}\sum_{m=1}^{N} E(d(S_m, X_m)) \leq D$) where $q(S_m) = X_m$, $d(.,.)$ is a distortion measure and D is a prescribed constraint on distortion. Thus, the minimum number of bits needed to represent the output of the quantizer of node m is given by the entropy $H(X_m)$ of the associated discrete random variable X_m [11]. Finally, we focus on the sensor broadcast problem addressed in [2], [3], where each sensor wishes to disseminate an approximation of its sample to all other nodes in the network. This traffic pattern may arise under a wide variety of application scenarios ranging from collaborative video surveillance where individual cameras display images from other cameras in the area of interest to data gathering applications where the collector node (sink) is an unmanned aerial vehicle (UAV) that deploys a sensor network onto a geographical field and then intermittently covers that field for the purpose of receiving the aggregated data.

III. The Traffic-Delay Trade-off in Dense Sensor Networks

In this section, we derive the scaling laws for the transport traffic and scheduling delays associated with the sensor broadcast problem under extreme cooperation strategies, namely no cooperation and network-wide cooperation. Towards this objective, we employ the notion of transport traffic (measured in bit-meters), introduced in [1], to quantify the bandwidth requirements associated with the sensor broadcast problem under a variety of cooperation strategies. A network is said to transport one bit-meter when a single bit has been forwarded a distance of one meter towards its destination. On the other hand, the scheduling delays are measured in the number of slots needed to complete the sensor broadcast task.

A. No Cooperation Strategy

Under this strategy, each sensor transmits a quantized version of its sample to its neighbors. A node who receives a sample of a neighbor is supposed to rebroadcast it blindly without eliminating correlations with its own sample. Accordingly, node 1 generates $H(X_1)$ bits that pass through $(N-1)$ hops to reach all other nodes. Next, node 2 generates $H(X_2)$ bits which, also, go over $(N-1)$ hops. The algorithm proceeds until node N goes through the same procedure. This, in turn, explains the non-cooperative nature of this strategy, where the notion of cooperation in the context of this paper implies the role that each sensor plays in re-encoding the data of other sensors as it hops around the network.

In the following, we determine the transport traffic (TT) generated under the no cooperation strategy. Towards this objective, we assume that each node sends only one sample per transmission, i.e. it does not include multiple samples from different sensors (generated and forwarded) in the same transmission[2]. Accordingly, the TT under this strategy would be given by,

$$\begin{aligned} TT(No\,Coop) &= \frac{1}{(N-1)}[(N-1)H(X_1) + (N-1)H(X_2) \\ &\quad + \ldots + (N-1)H(X_N)] \\ &= \sum_{j=1}^{N} H(X_j) \\ &= O(N)\ bit.meters \end{aligned} \tag{1}$$

In the remaining of this section, we determine the schedule length (SL) growth rate with the network size. To this end, we quantify the following two parameters: i) Total number of transmissions (NT) needed to complete the broadcast task and ii) Maximum number of non-conflicting transmissions per slot (NTPS). Accordingly, the minimum schedule length would be given by,

$$SL = \frac{NT}{NTPS}$$

As pointed out earlier, the sample of each node has to be forwarded over $(N-1)$ hops to reach all other nodes. Thus, NT would be given by $N(N-1)$, i.e. $O(N^2)$. On the other hand, the NTPS depends solely on the interference model. We adopt an interference model that is widely employed in the multi-hop packet radio networks literature [9], [10], whereby a collision arises whenever multiple transmissions are heard by a receiver in the same slot. Otherwise, a transmission is deemed successful if it is the only one heard by the receiver. Accordingly, the broadcast transmissions of nodes who are more than two-hops away are considered non-conflicting and may share the same time slot. This, in turn, guarantees that: i) No simultaneous transmission/reception could arise at a node and ii) No multiple transmissions to the same receiver could co-exist in the same slot. Thus, it is straightforward to notice that NTPS would be $\lceil \frac{2N}{3} \rceil$ when each node broadcasts its own sample to its left and right neighbors. On the other hand, when a node forwards a sample of another node received through one of its neighbors, its broadcast would yield one useful sample transfer to the other neighbor. Hence, NTPS would be given by $\lceil \frac{N}{3} \rceil$ under this scenario. Notice that the former scenario occurs only once for each node, whereas the latter one arises several times throughout the sample forwarding process. Accordingly, we argue that $\lceil \frac{N}{3} \rceil \leq NTPS \leq \lceil \frac{2N}{3} \rceil$ and, hence, SL(No Coop) would scale as $O(N)$. Thus, we conclude that both, transport traffic and schedule length of the non-cooperative broadcast strategy, grow *linearly* with the size of the network. In the next section, we explore candidate cooperation strategies for achieving sub-linear growth rate for the transport traffic. Moreover, we assess the price paid in terms of the schedule length growth rate.

[2]"Even if multiple samples are transmitted in a single slot via increasing the link data rate, it can be shown that the scaling laws determined in this section would still hold."

B. Network-wide Cooperation

We commence with a simple *sequential cooperation* strategy where each node takes a turn in a round-robin fashion to encode its sample given the samples of left nodes received through its left neighbor. Accordingly, node 1 generates $H(X_1)$ (since it has no left neighbors). Next, node 2 sends back $H(X_2|X_1)$ to 1 (denoted "2|1" in Figure 1) and sends a joint version of the two samples, i.e. $H(X_1, X_2)$ (denoted "1,2" in Figure 1), to node 3. The scheme proceeds in the same manner with node m sending $H(X_m|X_1, X_2, \ldots, X_{(m-1)})$ to node $(m-1)$ followed by $H(X_1, X_2, \ldots, X_m)$ to node $(m+1)$ until $m = N$ as shown in Figure 1 for $N = 4$. Notice that the encoded sample of node m sent to node $(m-1)$ should be propagated in the left direction until it reaches node 1. This is essential for each node to get the samples of all other nodes. Thus, the transport traffic generated by this cooperation strategy would be given by,

$$TT(Seq\ Coop) = \frac{1}{N-1}[H(X_1) + H(X_2|X_1) + H(X_1, X_2)$$

$$+2H(X_3|X_1, X_2) + \ldots + (N-1)H(X_N|X_1, \ldots, X_{(N-1)})]$$

$$= \frac{1}{N-1}[(N-1)H(X_1, X_2, \ldots, X_N)]$$

$$= O(H(X_1, X_2, \ldots, X_N)) \quad (2)$$

$$\leq O(N) \quad (3)$$

Notice that the second equality follows from the chain rule for entropies. Moreover, equality in (3) is satisfied when the sensors are sufficiently far to render their sample measurements independent. This, in turn, confirms that network-wide cooperation attempts to exploit correlations among sensor samples whenever they exist. For a given sensor density and spatial random process, if the sensor samples turn out to be uncorrelated, then no cooperation is needed. However, correlations may arise among sensor samples due to: i) Deploying dense sensor networks dictated by reliability and network connectivity constraints or ii) Measuring the random field with adaptive spatial resolution depending on the sensor activation strategy and the spatial process bandwidth which may be time varying.

The next step towards quantifying the TT under the sequential cooperation strategy is to determine the scaling law of the joint entropy of N quantized random variables given in (2). This problem has been addressed by Marco et al. in [7] for a stationary Gaussian random process and a scalar quantizer with uniform step size and infinite number of levels. Furthermore, it was assumed that the distortion measure is mean square error (MSE) and the autocorrelation function of the spatial process $S(y)$ is exponential and is given by $R_s(y) = e^{-y^2}$. For this setup, they showed that $H(X_1, X_2, \ldots, X_N)$ scales as $O(log\ N)$ as $N \rightarrow \infty$. Thus, we conclude that the TT for the sequential cooperation strategy grows only *logarithmically* with the network size, that is well below the linear scaling law achieved by the no cooperation strategy.

Next, we quantify the schedule length using the same procedure followed in the previous section. According to Figure 1, it is evident that node 1 participates in 1 transmission and $(N-1)$ receptions,

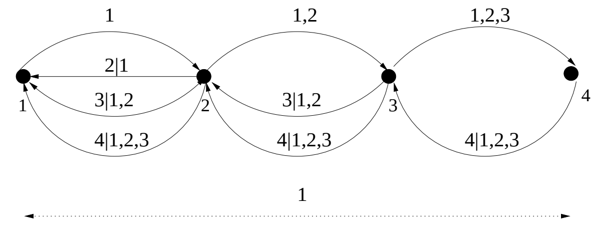

Fig. 1. Sequential cooperation over a 4 node sensor network

node 2 participates in 1 transmission and $(N-2)$ receptions, and node $(N-1)$ participates in 1 transmission and 1 reception. Hence, NT would be given by $\frac{(N-1)(N+2)}{2}$, i.e. $O(N^2)$.

Notice that sequential cooperation enforces certain order on nodes' communication since node m has to wait for the joint samples of nodes 1,2, ... , $(m-1)$, in order to generate its own conditional and joint samples. This significantly limits spatial slot reuse which causes NTPS to be one and SL(Seq Coop) to scale as $O(N^2)$. This considerable degradation, compared to the no cooperation extreme, may suggest that sequential cooperation reduces the transport traffic growth rate at the expense of longer schedule lengths. However, we show next that this is not generally the case since sequential cooperation discussed so far is highly inefficient. The key observation that led to this conclusion is two-fold. First, there is no need to have dedicated transmissions for individual conditional samples to send them back to left nodes as shown in Figure 1. This is attributed to the fact that conditional samples could be sent collectively in a more efficient way. Second, slot reuse plays an important role in minimizing the schedule length. Next, we illustrate these observations with the aid of two examples. In the first example, we eliminate the dedicated intermediate conditional sample transmissions propagated to left nodes. Instead, we gather the joint samples of all nodes at node N, through cooperation in the forward direction, and then start sending collective conditional samples in the reverse direction at higher data rates, compared to the transmission rate of individual conditional samples, in order for each transmission to fit in a single slot. We refer to this strategy as *forward/reverse cooperation* since nodes cooperate in the forward direction first and then in the reverse direction as shown in Figure 2. It is straightforward to show that this strategy entertains a logarithmic growth rate for the transport traffic as the sequential cooperation strategy. Furthermore, it consumes $(N-1)$ transmissions in the forward direction and $(N-1)$ transmissions in the reverse direction, i.e. NT scales as $O(N)$. On the other hand, NTPS turns out to be one since, again, this policy does not exploit spatial reuse of slots. Accordingly, we conclude that SL(Forward/Reverse Coop) scales as $O(N)$, well below the quadratic growth rate associated with sequential cooperation. In the second example, we investigate the impact of slot reuse on the scaling laws of the forward/reverse cooperation strategy. Notice that the transmissions of nodes $m + 3j$, where j takes integer values, can share the same slot and, hence, cooperation in the forward direction consumes $\sum_{j=1}^{\lceil \frac{N}{3} \rceil} 3j$ slots in this case. This is attributed to the fact that cooperation is limited to reuse clusters (of size 3 nodes)[3] and is repeated over those clusters in order to achieve network-wide cooperation. On the other hand, cooperation in the reverse direction will remain unchanged (i.e. $O(N)$) since it involves propagating condi-

[3]"A reuse cluster is defined as a group of nodes where no slots are reused within this group."

tional samples throughout the entire the network. Accordingly, NT scales as $O(N^2)$ for the forward/reverse cooperation strategy with slot reuse. Moreover, NTPS scales as $O(N)$ based on arguments similar to those used in the previous section. Therefore, we notice that SL still scales as $O(N)$, even when slot reuse is exploited. This result stems from the fact that slot reuse does not only increase NTPS from one to $O(N)$, but it also increases NT from $O(N)$ to $O(N^2)$ in order to achieve network-wide cooperation in the forward direction.

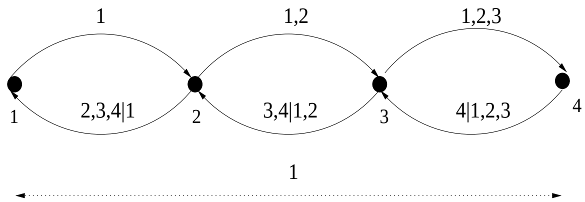

Fig. 2. Forward/Reverse cooperation over a 4 node sensor network

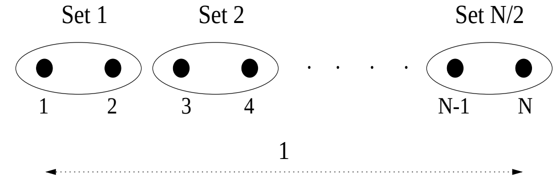

Fig. 3. Example of a sensor network with cooperation set size $i = 2$

Finally, we conclude that forward/reverse cooperation reduces the transport traffic growth rate from linear to logarithmic, while maintaining the linear growth rate for the schedule length. Motivated by the scaling laws of the extreme cooperation strategies, we need to investigate the trends of TT and SL over the space of strategies bounded by the two extremes. This is achieved with the aid of the two-phase cooperation framework introduced in the next section.

IV. Two-Phase Cooperation

In this section, we propose a novel cooperation strategy that opens room for optimizing the schedule length associated with the sensor broadcast problem. The essence of this strategy is to ”localize” cooperation within regions of the network, where nodes cooperate in compressing each others' samples, and beyond those regions no cooperation is performed. This constitutes a simple approach for trading traffic for scheduling delays, or vice versa, via controlling the size of the cooperation set. Under this strategy a one dimensional network of N nodes is partitioned into $\frac{N}{i}$ cooperation sets, each accommodating i nodes as shown in Figure 3 for $i = 2$. As the name indicates, this strategy proceeds through two phases. In the first phase, members of each set cooperatively compress their sample data according to the forward/reverse cooperation strategy described in the previous section. Once this is done, any node in an arbitrary set would have the sample measurements of all other nodes in its set, however, it would lack the sample measurements of nodes in other sets. Hence, the role of the second phase is to exchange the sample measurements among various cooperation sets. This is achieved via inter-set exchange among representative nodes in respective cooperation sets (e.g. nodes 1,$(i+1)$,$(2i+1)$, $\ldots$,$(N-i+1)$) in a non-cooperative manner as described in section $III.A$[4]. This non-cooperative exchange should be followed by data distribution within each set in order to disseminate the sample measurements gathered at the representative nodes to the other members in their respective sets.

Next, we determine the scaling laws for the transport traffic under the two-phase cooperation strategy. In the first phase, cooperation takes place within $\frac{N}{i}$ sets in parallel. This could be achieved assuming that neighboring nodes at the edges of two neighboring sets (e.g. nodes i and $(i+1)$) do not interfere throughout their communication tasks (possibly using directional antennas). Accordingly, the transport traffic generated in phase 1 would be,

$$TT(Phase\ 1) = [\frac{(i-1)}{(N-1)}\ H(X_1, X_2, \ldots, X_i)]\ \frac{N}{i}$$

$$= O(H(X_1, X_2, \ldots, X_i)) \quad (4)$$

On the other hand, the transport traffic generated in phase 2 would be given by,

$$TT(Phase\ 2) = O(\frac{N}{i}\ H(X_1, X_2, \ldots, X_i))$$

$$+ O(\frac{i}{N}\ H(X_{i+1}, X_{i+2}, \ldots, X_N | X_1, X_2, \ldots, X_i)\ \frac{N}{i}) \quad (5)$$

Notice that the first term corresponds to the non-cooperative data exchange among the representative nodes of various cooperation sets, whereas the second term represents the transport traffic associated with distributing the sample measurements to other members within each set. The summation of (4) and (5) yields the transport traffic associated with the two-phase cooperation strategy as follows,

$$TT(Two\ Phase\ Coop) = O(H(X_1, X_2, \ldots, X_i)$$

$$+\frac{N}{i}\ H(X_1, X_2, \ldots, X_i)$$

$$+H(X_{i+1}, X_{i+2}, \ldots, X_N | X_1, X_2, \ldots, X_i))$$

$$= O(H(X_1, X_2, \ldots, X_N) + \frac{N}{i}\ H(X_1, X_2, \ldots, X_i)) \quad (6)$$

It is straightforward to verify the scaling law in (6) via observing that the special cases of $i = 1$ and $i = N$ simply reduce to the no cooperation and network-wide cooperation extremes described in the previous section. Moreover, it is evident that the transport traffic monotonically increases as the cooperation set size (i) decreases. This is attributed to the fact that the first term in (6) does not depend on i and constitutes the minimum amount of transport traffic when $i = N$. For $1 < i < N$, the two terms in (6) persist and hence the transport traffic would be greater than the first term. Finally, it is easy to show that as i decreases the second term increases.

In the remaining of this section, we determine the behavior of the schedule length under the two-phase cooperation strategy. It is evident that phase 1 consumes $O(i)$ slots to be completed. In addition, phase 2 consumes $O(\frac{N}{i})$ throughout the non-cooperative sample exchange task and $O(i)$ for distributing the gathered sample measurements throughout each set. Therefore, the schedule length for this

[4]”We assume that the transmission power of the representative nodes could be raised in order to reach each other directly over a single-hop.”

policy, SL(Two-phase Coop), scales as $O(i + \frac{N}{i})$ slots. Although the linear growth rate with N still persists, the parameter i provides a degree of freedom for optimizing the schedule length for a given network size. The question that remains unanswered is: How does SL vary with i? For a given N, the non-linear dependence of SL on i suggests that this function has an extremum which turns out to be a minimum at $i^* = c\sqrt{N}$, where c is a constant. For $i < i^*$, SL decreases as i increases until it reaches the minimum at i^*. For $i > i^*$, SL increases with i until the two-phase cooperation scheme reduces to network-wide cooperation at $i = N$. Accordingly, with proper choice of the parameter i, we can control the relative importance of TT and SL. For instance, the best operating point for SL is around its minimum. However, if the associated TT is excessive, then we should start increasing i in order to reduce the generated traffic. Thus, we conclude that two-phase cooperation attempts to strike a balance between minimizing traffic and minimizing scheduling delays. Moreover, extending two-phase cooperation to hierarchical $log_i N$-phase cooperation constitutes a potential approach for achieving sub-linear SL growth rate. Quantifying the scaling laws for hierarchical cooperation lies out of the scope of this paper and is the subject matter of [12].

V. Conclusions

In this paper, we studied the trade-off between generated traffic and scheduling delays associated with the broadcast problem in dense multi-hop sensor networks where sample measurements are correlated. First, we determined the transport traffic and schedule length scaling laws under the no cooperation and network-wide cooperation extremes. We observed that the no cooperation extreme experiences the worst (linear) scaling laws among all strategies. At the other extreme, we analyzed two examples of network-wide cooperation, namely sequential and forward/reverse cooperation. We showed that the former reduces the transport traffic scaling law from $O(N)$ to $O(log\ N)$ at the expense of a quadratic schedule length growth rate. On the other hand, the latter achieves a logarithmic scaling law for the transport traffic while preserving the linear schedule length growth rate. Second, we introduced a novel two-phase cooperation framework that localizes cooperation within regions of the network in an attempt to investigate the trends over the space of strategies bounded by the aforementioned extremes. This strategy introduces the cooperation set size as a degree of freedom to trade-off between transport traffic and scheduling delays for a given network size. Extending the results of this paper to two-dimensional grids is a potential avenue for future work. Furthermore, it is imperative to employ more realistic interference models where the signal-to-interference-and-noise-ratio (SINR) at the receiver serves as the main criteria for successfully receiving a signal.

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