Data Dissemination in Wireless Broadcast Channels: Network Coding or Cooperation?

Ivana Stojanovic, Masoud Sharif, and David Starobinski
ECE Department, Boston University
Email: {*ivanas,sharif,staro*}@*bu.edu*

***Abstract*—Network coding and cooperative diversity have each extensively been explored in the literature as a means to substantially improve the performance of wireless networks. Yet, little work has been conducted to compare their performance under a common framework. Our goal in this paper is to fill in this gap. Specifically, we consider a single-hop wireless network consisting of a base station and N receivers. We perform an asymptotic analysis, as $N \to \infty$, of the expected delay associated with the broadcasting of a file consisting of K packets. We show that if K is fixed, cooperation outperforms network coding, in the sense that the expected delay is proportional to K (and thus within a constant factor of the optimal delay) in the former case while it grows logarithmically with N in the latter case. On the other hand, if K grows with N at a rate at least as fast as $(\log N)^r$, for $r > 1$, then we show that the average delay of network coding is within a factor less than two of the optimal delay, no worse than the average delay of cooperation. Our analytical findings are validated through extensive numerical simulations.**

I. Introduction

The significant breakthroughs in wireless technology over the past decade have enabled implementation of third generation cellular systems capable of offering services traditionally more applicable to wireline networks. In particular, the growing use of cellular systems has lead to demand for broadcasting services requiring simultaneous data transmission to multiple users. Notable examples of such services include podcasting and distributions of software updates [1].

It has been recently shown that network coding provides the maximum achievable throughput gains for multicast and broadcast wired networks [2], [4], [5]. In wireless networks, network coding has been proposed for disseminating information to all receivers [3] and has been shown to provide excellent delay performance compared to round-robin scheduling, in particular, for large file sizes. In this context, the delay is defined as the average number of packet transmissions to transmit a file consisting of K packets to all N receivers. Network coding relies on the transmission of algebraic combinations of K packets implying that the individual packets can be decoded only after the correct reception of at least K combinations [2].

In this paper, we propose a cooperative transmission scheme based on round robin scheduling that substantially reduces the error probability of the wireless link in re-transmissions of a packet and therefore improves the transmission delay. This is done by exploiting a relatively small number of receivers who have already successfully decoded the packet to cooperatively transmit the packet to the rest of network. This can therefore lead to a distributed multi-antenna system with substantial diversity gain benefit and reduction in the error probability [9] [10], [11]. The main goal of this paper is to compare the delay benefit of the cooperative-based scheduling schemes with the network coding.

Towards this end, we analyze and compare the delay performance of network coding and cooperation in a single-hop wireless network (i.e., downlink) composed of one base station and N nodes. We provide closed-form asymptotic expressions for the average delay of these two schemes, as $N \to \infty$. In particular, for network coding, we show that if the number of packets K of the file is fixed, then the average delay scales like $\log_{1/p_e} N$ where p_e[1] is the error probability of the link between the transmitter and any receiver. As the number of packets increases, even poly-logarithmically with N, it is shown that the delay achieved by network coding is less than or equal to $2K$. On the other hand, for cooperation, the average delay is proportional to K for any K, and thus achieves performance within a constant factor of the optimal delay. This result holds even if a relatively small receivers are allowed to cooperate, in fact as few as $(\log N)^r$ for $r > 1$, to achieve near-optimal delay performance.

Our results imply that when the number of packets K is much smaller than N, the cooperative scheme outperforms network coding. However, as K grows logarithmically with N or faster, the delay performance of both schemes are bounded by $2K$. Our analytical findings are validated through extensive numerical simulations.

The rest of the paper is organized as follows. In Section II, we introduce our network model and underlying statistical assumptions. In Section III, we provide delay bounds for the baseline, traditional round-robin scheduling. In Section IV and V, we respectively analyze the asymptotic performance of random linear coding and cooperation for large networks and different regimes of file sizes. In Section VI, we present numerical results comparing the performance of the two strategies. We conclude the paper in Section VII.

II. System Model

We consider a cellular downlink consisting of a single antenna base station and N single antenna receivers. We are concerned with the case where a single file, consisting of K packets, is demanded by all the receivers in the network. We are interested in finding the average file transfer delay, defined

[1] In our analysis p_e is assumed to be fixed independent of N.

as the minimum number of time slots that guarantees complete download of the whole file by all nodes in the network.

Files are segmented into packets to be transmitted in time slotted manner, with a single packet transmission requiring one time slot. The transmission takes place over time varying broadcast channel. The assumed channel is Rayleigh block-fading that changes independently from one block to the other. One channel block corresponds to one time slot and, thus, one packet transmission.

In wireless channels, packets are usually dropped when the channel goes into deep fade resulting in an outage. In particular, the outage happens when instantaneous channel capacity falls below the amount of information carried in the packet [8]. Therefore, we can model the channel from the base station to the n-th receiver as a random on/off channel, with parameter p_e representing the probability of 'off' or outage state. Since fading is independent across time and users, the error events are similarly independent across time and users.

We assume that the network is homogeneous implying that the channels between any user and the base station have identical and independent distribution. In our set-up, we assume that each receiver has perfect knowledge of its own channel state, but the channel state information (CSI) is unknown to the transmitter. In this paper, we are interested in characterizing the average delay for the regime of large N and for various regime of K, i.e., K fixed or growing with N.

It is quite clear that the lower bounds on the minimum delay for sending the K packets to all users is K. In the next section, we show that the delay of a simple, plaintext round-robin transmission can be significantly worse than that of the lower bound.

III. Round Robin Scheduling

In this section, we consider a simple round robin transmission scheme in which the base station sends each packet sequentially until every user is able to decode all the K packets. In round-robin, the base station schedules packets cyclicly at regular time slots $mK+k$ for all $m = 1, 2 \dots$ until all receivers successfully receive the file. Here we assume that receivers feedback only successful file reception. To simplify the analysis, we ignore the overhead of the control channel.

Denote by D_n^k the number of slots needed for user n to receive packet k. The random variable D_n^k is geometrically distributed with mean $1/(1-p_e)$. A packet transmission is considered successful once it is received by all nodes in the network. Let D^k represent the number of transmissions of the packet k until its successful reception by all users. Therefore, the k-th packet delay is given by $D^k = \max_{n=1,\dots,N} D_n^k$. Since different packet transmissions are non-overlapping in the scheduling mode, the file completion delay is calculated as $D_{RR} = \sum_{k=1}^{K} D^k$.

Lower and upper bounds on the optimal expected completion delay for this policy are derived in [14], using properties of stochastic ordering. These result are reproduced here, for completeness.

Proposition 3.1: Consider the time slotted broadcasting of a single K-packet file to all N users. Under a round-robin scheduling, the expected delay, denoted by $\mathbb{E}[D_{RR}]$, is given by,

$$\mathbb{E}[D_{RR}] = K \log_{1/p_e}(N) + O(1). \tag{1}$$

for large N and any K.

This result shows, that for large N, the delay of a round robin scheme in a noisy channel can be substantially worse than in a noiseless channel. In the next section, we show that this large gap, i.e., $\log_{1/p_e} N$, can be reduced using random linear coding, but only for K growing fast enough with N.

IV. Random Linear Coding

In this section we analyze the scaling law of the expected delay achieved by a random linear coding (RLC) policy where the transmitted packet in a slot i is computed as a linear combination of all packets: $P[i] = \sum_{k=1}^{K} a_k[i] P_k$, such that $a_k[i] \in \mathbb{F}_q$ for each $k \in \{1, \dots, K\}$ and where q represents the size of the finite coefficient field $\mathbb{F}_q$ [6]. Coefficients $a_k[i]$ are chosen uniformly at random over the field $\mathbb{F}_q$ for each k.

Each receiver stores all correctly received packets up until a time it collects K linearly independent combinations. The expected number of transmissions before a user receives K linearly independent combinations is upper bounded by $Kq/(q-1)$. In this paper we assume that the upper bound is made close to K by choosing field size q sufficiently large. Then, by standard linear coding arguments, the mean completion time of the K packet file is equal to $\mathbb{E}[\max_{n=1,\dots N} T_n]$, where T_n is the minimum number of channel uses before K transmissions can be successfully decoded. The random variable T_n is the sum of K independent geometric random variables and thus, T_n has a negative binomial distribution with parameters $1-p_e$ and K. The average transmission delay is given by [3]:

$$\begin{aligned}\mathbb{E}[D_{RLC}] &= K \\ &+ \sum_{t=K}^{\infty} \left[1 - \prod_{i=1}^{N} \left(\sum_{\tau=K}^{t} \binom{\tau-1}{K-1} p_e^{\tau-K} (1-p_e)^K \right) \right]\end{aligned} \tag{2}$$

To gain more insight into behavior of the expected delay for large networks, we provide an asymptotic analysis of the delay in the regime of large N and for different cases of the file length K where K is fixed, K grows logarithmically with N, and finally K grows faster than logarithmically with N.

Theorem 4.1: Consider the setting of Proposition 3.1. Under randomized linear coding strategy and for large N, the scaling law of the average delay in sending the file of size K packets to all N users is given by,

1) For fixed K,

$$\begin{aligned}\mathbb{E}[D_{RLC}] = &\log_{1/p_e} N \\ &+ (K-1) \log_{1/p_e} \log N + o(\log \log N).\end{aligned}$$

2) For K growing logarithmically with N, i.e., $K = \log N$,

$$\mathbb{E}[D_{RLC}] = \beta_1 K + o(\log N),$$

where $3.146 \leq \beta_1 \leq 4.146$.

3) For K growing faster than $(\log N)^r$, where $r > 1$,

$$\mathbb{E}[D_{RLC}] = \beta_2 K + o\left((\log N)^r\right),$$

where $1 \leq \beta_2 \leq 2$.

Proof: We first obtain lower and upper bounds on the expected delay using the properties of stochastic ordering as in [14]. Next, given the upper and lower bounds on the expected delay we derive the asymptotic result for the first moment of D_{RLC} for different regions of K and N.

As mentioned $D_{RLC} = \max_{n=1,\dots N} T_n$ where T_n is the sum of K independent geometric variables T_n^k, i.e., $T_n = \sum_{k=1}^{K} T_n^k$. Here T_n^k has a geometric distribution with parameter p_e. An equivalent continuous random variable X_n^k with the same mean has the pdf $f(x) = \sum_{i=1}^{\infty} p_e^{i-1}(1-p_e)\delta(x-i)$ where $\delta(x)$ is the Dirac's delta function. The ccdf of this variable is $\bar{F}(x) = p_e^{\lceil x \rceil - 1}$, for $x > 0$.

Now we consider an exponential random variable Y_n^k with parameter $\lambda = \log \frac{1}{p_e}$ that has the ccdf of $\bar{F}_{Y_n^k}(x) = p_e^x$. We further define $Z_n^k = Y_n^k + 1$ with ccdf of $\bar{F}_{Z_n^k}(x) = \min(1, p_e^{x-1})$. The ccdfs of X_n^k, Y_n^k, Z_n^k clearly satisfy $\bar{F}_{Y_n^k}(x) \leq \bar{F}_{X_n^k}(x) \leq \bar{F}_{Z_n^k}(x)$ implying the desired stochastic ordering of $Y_n^k \leq_{st} X_n^k \leq_{st} Z_n^k$. Note that the notation $X \leq_{st} Z$ denotes that the random variable X is stochastically dominated by the random variable Z.

Finally, we consider $X_n = \sum_{k=1}^{K} X_n^k$, $Y_n = \sum_{k=1}^{K} Y_n^k$ and $Z_n = \sum_{k=1}^{K} Z_n^k$. These variables have the same stochastic ordering $Y_n \leq_{st} X_n \leq_{st} Z_n$ leading to

$$\mathbb{E}[\max_{n=1,\dots N} Y_n] \leq \mathbb{E}[D_{RLC}] \leq \mathbb{E}[\max_{n=1,\dots N} Z_n] \tag{3}$$

where we used the fact that $\mathbb{E}[D_{RLC}] = \mathbb{E}[\max_{n=1,\dots N} X_n]$.

Now, we evaluate the asymptotic behavior of the bounds. In fact, the distribution of Y_n can be written as

$$\bar{F}_{Y_n}(x) = \sum_{i=1}^{K-1} \frac{(\lambda x)^i}{i!} \exp^{-\lambda x}.$$

as Y_n is the sum of K exponentially distributed random variables. Therefore,

$$\mathbb{E}[\max_{n=1,\dots N} Y_n] = \frac{1}{\lambda} \int_0^{\infty} (1 - (1 - S_m(x) e^{-x})^N) dx \tag{4}$$

where $S_m(x) = \sum_{i=1}^{K-1} \frac{x^i}{i!}$ and $\lambda = \log 1/p_e$. The asymptotic behavior of the integral in (4) is studied in [13] in a different context for large N. When K is fixed, it is shown that the right hand side of (4) scales like,

$$\frac{1}{\lambda}(\log N + (K-1)\log\log N + o(\log\log N)), \tag{5}$$

which leads to a lower bound on the expected delay. We can also find an upper bound by evaluating $\mathbb{E}[\max_{n=1,\dots N} Z_n]$ and noting that $\bar{F}_{Z_n}(x) = \bar{F}_{Y_n}(x-K)$ and $\mathbb{E}[\max_{n=1,\dots N} Z_n] = K + \mathbb{E}[\max_{n=1,\dots N} Y_n]$. Therefore, we get

$$\mathbb{E}[\max_{n=1,\dots N} Z_n] = K + \frac{1}{\lambda}(\log N + (K-1)\log\log N + o(\log\log N)). \tag{6}$$

Substituting (5) and (6) into (3), we obtain the first part of the theorem.

The proofs of the second and third parts follow the same line as the proof of the first part, appealing arguments similar to those developed in [13]. We omit the proof for the sake of brevity. ■

Theorem 4.1 implies that when K is fixed, the delay performance of RLC in a noisy channel can be much worse than that of the noiseless channels, even though the performance is K times better than that of the round robin scheduling obtained in Section 3. As K grows slowly with N, i.e., only logarithmically with N, the delay scales linearly with K and the performance gap is at most 4.14. Finally, if K grows faster than logarithmically with N, the expected delay of RLC is at most twice worse than in a noiseless channel.

In the next section, we show that for fixed or slowly growing K the performance gap between noisy and noiseless channels can be further reduced using cooperative transmissions.

V. Cooperative Scheduling

In this section we describe and analyze a cooperative scheduling strategy. The idea behind the cooperative round-robin lies on the simple observation that a successful file download by all users in the scheduling mode requires repeated transmissions of the same packet. Therefore at the beginning of the second transmission of a packet, there exist additional M spatially dispersed nodes that can decode the packet successfully with high probability. Therefore, these M nodes can collaborate in transmitting the packet to the rest of the users. In particular, it is well known that by using space time coding, significant improvement on the error probability can be obtained using M collaborative nodes [15]. The gain is due to the fact that the fading channels corresponding to the different transmitters, i.e., the base station and M cooperative nodes, are independent leading to better error probability via space diversity.

The packet loss probability in point-to-point MIMO channels is commonly characterized through a diversity gain d and a coding gain α as $p_e = \alpha\rho^{-d}$, where ρ is the signal to noise ratio [15]. The diversity gain of multi-antenna transmitters have been well studied in the literature. In particular, for the case where $M+1$ transmitters and one antenna receiver, it is straightforward to show that the packet error probability $p_e = \alpha\rho^{-1}$ can be reduced to $p_e(M) = \beta\rho^{-(M+1)}$ with proper space time coding where α and β are constants independent of the SNR[2]. This shows the significant reduction in the error probability in the second transmission by exploiting the receivers that have decoded the packet in the first transmission of a packet.

In particular, the gain G_M in error probability by using M cooperative nodes can be defined as the ratio of the logarithm of the corresponding error probability expressed as,

[2]Here α and β only depend on the space time code and the geometry of the channel, i.e., the distances between the transmitters and the receiver.

$$G_M = \frac{-\log p_e(M)}{-\log p_e(M=0)} = \frac{(M+1)\log\rho + \log\beta}{\log\rho + \log\alpha} = M+1+O(\frac{1}{M+1})$$

for large M (or large ρ). Therefore if M tends to infinity, G_M tends to $M+1$ when α and β are fixed. Here is a formal description of the cooperative round robin scheduling.

Definition 5.1: Cooperative Scheduling (CS) Policy is the strategy in which K packets of a file F are transmitted in two stages. For every packet, in the first stage, the base station transmits the packet until at least M nodes can decode the packet. In the second stage, the packet is re-transmitted cooperatively by the base station and the M nodes who have successfully decoded the packet.

It turns out that by letting M grow only logarithmically with N, or even faster like $(\log N)^r$ for $r > 1$, we can achieve most of the gain offered by cooperation and can reduce the delay to within a factor two of the delay in a noiseless channel for any K.

The next theorem provides the scaling law of the expected delay using a cooperative scheduling.

Theorem 5.1: Consider the setting of Proposition 3.1. The average delay $\mathbb{E}[D_{CS}]$ in sending K packets of a file to all N users achieved by a cooperative round robin scheduling is given by:

$$\mathbb{E}[D_{CS}] = 2K(1+o(1)),$$

for large N and any K where M grows at least as fast as $(\log N)^r$ for any $r > 1$ independent of N.

Proof: We show the result by proving that the expected number of transmission in each of the two stages is equal to $K(1+o(1))$. In the first stage, we obtain the expected number of transmission $\mathbb{E}[D^k_{step1}]$ in order to have at least $M = (\log N)^r$ users successfully decode the k'th packet for $r > 1$. Letting N^k_s be the number of users that have successfully received packet k after its first transmission, we get,

$$\mathbb{E}[D^k_{step1}] \leq \mathbb{P}\{N^k_s \geq M\} + \log_{1/p_e} N \times \mathbb{P}\{N^k_s < M\} \leq 1 + \log_{1/p_e} N \times \mathbb{P}\{N^k_s < M\}$$

where we used the fact that $\mathbb{E}[D_{step1}]$ is bounded by $\log_{1/p_e} N$ using the result of Proposition 3.1. We can further easily prove that for $M = (\log N)^r$,

$$\mathbb{P}\{N^k_s < M\} = \sum_{i=0}^{M-1} \binom{N}{i} p_e^{N-i}(1-p_e)^i = O(e^{-N\log 1/p_e + r(\log N)^{r+1}}),$$

leading to the proof of $\mathbb{E}[D^k_{step1}] = 1 + o(1)$.

In the second stage the cooperation of the base station and M nodes reduces the probability of error from p_e to p_e^{M+1}. The minimum second stage delay is K, which is easily justified by noting that the probability of having to transmit each packet to at least one user in the second stage becomes one for fixed p_e and $N \to \infty$. Furthermore, the delay for the transmission of the k'th packet D^k_{step2} in the second step has an exponential distribution leading to,

$$\begin{aligned}
\mathbb{E}[D_{step2}] &= \mathbb{E}\left[\sum_{k=1}^{K} D^k(M)\right] \\
&= K\sum_{i=1}^{\infty}\left(1-(1-p_e^{(M+1)(i-1)})^N\right) \\
&= \frac{K}{M}\sum_{i=1}^{\infty} M\mathbb{P}\{D^k \geq (M+1)(i-1)+1\} \\
&\leq K\frac{M-1}{M} + \frac{K}{M}\sum_{i=1}^{\infty}\mathbb{P}\{D^k \geq i\} \\
&= K\frac{M-1}{M} + \frac{1}{M}\mathbb{E}[D_{RR}] \\
&= K + O\left(\frac{K}{M}\log N\right),
\end{aligned}$$

which shows that the expected delay for the second step is also equal to $K(1+o(1))$ for the case where M grows like $(\log N)^r$ for $r > 1$. Therefore,

$$\mathbb{E}[D_{CS}] = \mathbb{E}[D_{step1}] + \mathbb{E}[D_{step2}] = 2K(1+o(1)),$$

which completes the proof. ■

This Theorem shows that the expected delay in a noisy channel achieved by cooperative transmission is at most worse than that of noiseless channels by a factor of two in the regime of large N and for any K. It is worth mentioning that this result is achieved using a relatively small number of cooperative nodes proportional to $(\log N)^r$ for $r > 1$. Using more cooperative nodes, we can not further improve the expected delay beyond $2K$. However, it does improve the convergence rate of the expected delay to $2K$.

As mentioned, the diversity gain promised in the second round of transmission can be obtained via space time codes. In this scheme, the transmitters do not have the knowledge of the channel state of the users, however, every node expecting the packet in the second step needs to estimate its own channel to the base station and the M other cooperative transmitters. It is also worth mentioning that since M is relatively small and the channel estimation can be done in parallel for all receiving users, the corresponding overhead of each packet may be made negligible. Furthermore, since the cooperative nodes are spatially dispersed, some sort of control messages has to be exchanged among all cooperating nodes in order to ensure proper space-time encoding. In our analysis we did not take into account the delay cost associated with these overheads.

VI. Comparison and Numerical Results

In this section we present simulation results comparing the performance of the various schemes discussed in the paper,

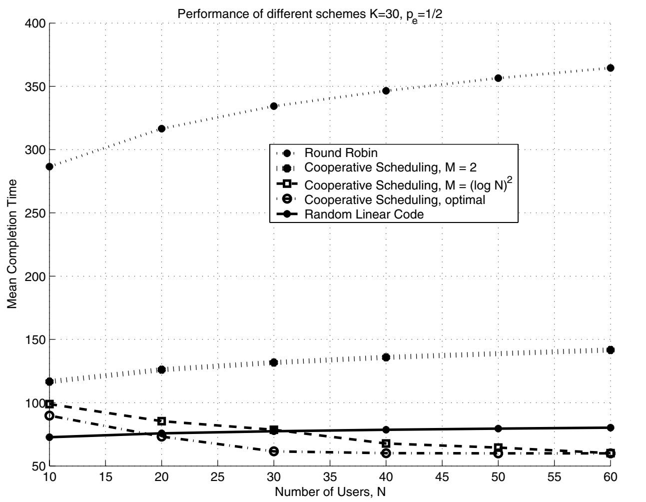

Fig. 1. *Expected delay of different transmission strategies for* $p_e = 1/2, K = 30$

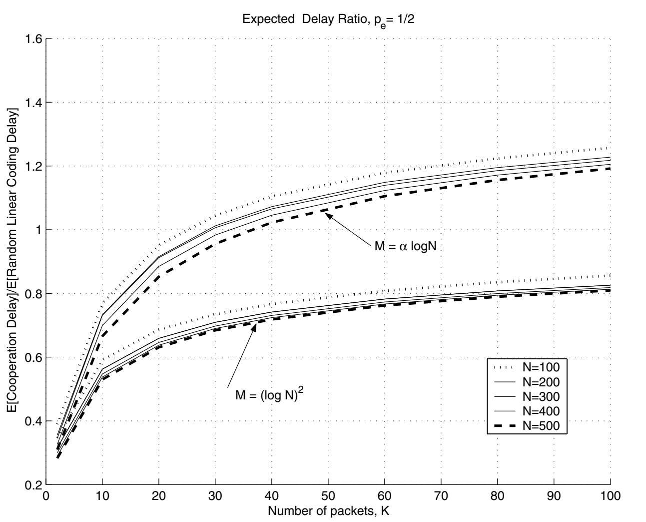

Fig. 2. *Ratio of the expected file completion delay of the cooperative scheduling to the random linear coding at* $p_e = 1/2$ *for different sizes of cooperation set* M, *and* $\alpha = (\log \frac{1}{p_e})^{-1}$.

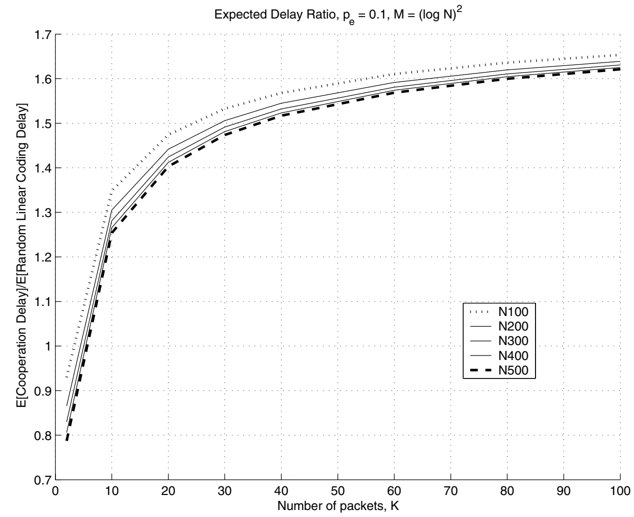

Fig. 3. *Ratio of the expected file completion delay of the cooperative scheduling to the random linear coding policy at* $p_e = 0.1$ *and* $M = (\log N)^2$.

for various settings of the parameters N, K, M, and p_e.

Figure 1 shows that both network coding and cooperative scheduling offer significant average delay gains as compared to the baseline round-robin scheduling. The figure also shows that cooperation can achieve significant reduction in the expected delay by using as few as two cooperating nodes. Increasing the number of cooperating nodes to $M = (\log N)^2$, brings in the average cooperation delay below the delay of random linear coding and close to the delay of optimal cooperative scheduling as N increases. Furthermore, cooperative scheduling with an unlimited number of cooperating nodes almost consistently outperforms random linear coding as it quickly approaches the minimum of $2K$.

Figure 2 depicts the ratio of the average delay of cooperation to that of coding for highly lossy links with packet error probability $p_e = 1/2$. For $M = \alpha \log N$, where $\alpha = (\log \frac{1}{p_e})^{-1}$, cooperation outperforms RLC for files roughly smaller then 30 packets and a network size in the range of $100-500$ receivers. Increasing M to $(\log N)^2$, we see that cooperation approaches its best possible delay of $2K$ and consistently outperforms RLC over the packet range of interest. The ratio is growing rather slowly with the number of packets, so there must be a rather large file size to make random linear code eventually do better. By our analysis this ratio can approach at most two.

Figure 3 has the same setting as Figure 2, except that performance is compared for higher quality links with $p_e = 0.1$. Even though cooperation is at its optimal mean delay of $2K$, RLC better utilizes the higher quality channel and performs better in this regime. As noted before the maximum ratio between the performance of the two schemes is at most two.

VII. Conclusion

In this paper we analyzed and compared delay performance of network coding and cooperative diversity under the common framework. Specifically, we analyzed the expected file completion delay of a K-packet file broadcast to N users in a single hop wireless network as $N \to \infty$. The results show that no technique is superior to the other in all regimes of different file lengths K.

In the regime of large file transmissions where K grows at least as fast as $(\log N)^r, r > 1$, random linear coding achieves better performance. Its delay is within a factor less or equal than two of the optimal delay K, whereas the average cooperation delay scales asymptotically as $2K$. On the other hand, in the fixed K regime, cooperation outperforms network coding. In this regime, network coding delay grows logarithmically with network size N, while cooperation retains its near-optimal delay of $2K$.

In summary, the results indicate that in order to achieve near-optimal expected delay in both file length regimes one should choose network coding when broadcasting large files and cooperative scheduling for transmission of smaller files.

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