Queue Based Compression in a Two-Way Relay Network

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***Abstract*—We consider the problem of joint rate scheduling and lossy data compression in a two-way relay network with distortion-sensitive stochastic packet traffic. A relay node facilitates exchanging packets between the two sources. Network coding at the relay improves energy efficiency at the expense of additional packet delay. In addition, network coding couples the source queues through the distortion levels of their individual packet traffic. This fact motivates having each source adapt the transmission rate and the compression ratio jointly. We first formulate a centralized dynamic scheme for scheduling and compression with the objective of minimizing the energy consumption at the relay while satisfying stability and average distortion constraints. Lyapunov stability arguments are used to define a centralized policy based on the instantaneous queue backlogs and distortion levels. In addition, a decentralized algorithm is proposed where sources have limited (1-bit) information about each other's queue backlog and distortion levels. Numerical results demonstrate that the performance of the proposed decentralized algorithm approaches the energy-delay tradeoffs resulting from the centralized solution.**

***Index Terms*—Compression, Network Coding, Scheduling, Queue Stability, Distortion, Energy, Delay, Two-Way Relaying.**

I. Introduction

Data compression is fundamental for resource-efficient communications by reducing transmission rates for data traffic with redundancy. Rate-distortion theory focuses on quantifying the distortion incurred in the lossy compression of sources that produce a constant supply of bits. Though the classical setting did not take into account the effects of stochastic traffic and delay constraints, recently, there has been an increasing interest in performing compression paying attention to queueing aspects [1], [2], and stringent delay constraints [3], [4].

Lossy compression is considered in [3] for a single link carrying packets with delay deadlines. The objective in [3] is to minimize the total distortion while meeting the delay constraints. Again for a single link, [5] provides a two-step compression and rate scheduling algorithm for minimizing the compression and transmission power while satisfying queue stability for lossless compression. This work has been extended to the multi-hop scenario in [6]. On the other hand, [1] builds upon [5] to account for lossy compression as well with distortion constraints for a single link. Multiple description coding (MDC) is considered in [4], where it is shown that for delay-sensitive data, MDC reduces the end-to-end distortion compared with single description coding.

All of the work mentioned previously addresses queueing and delay aspects of compression for networks that operate under the traditional store-and-forward paradigm. In this paper, we consider such problems in a a two-way relay network, that may operate using network coding [7]. The fundamental rate limits of this model have been studied in [8], [9]. In particular, network coding can improve energy efficiency by simultaneously serving packets from both sources. However, for practical scenarios where packet traffic arrives at the sources randomly, energy efficiency through network coding may come at the price of higher delay, since the relay would have to match packets incoming from both sources. We investigated this energy-delay trade-off in [10] (without considering source compression), and provided centralized and decentralized rate allocation algorithms which operate with different levels of queue information available at the individual sources. There have been a number of works studying the interaction of network coding with stochastically varying traffic in both two-way relay networks [11], [12] and other network topologies [13]–[17]. Network coding has also been examined in [18] jointly with source coding such that compression is performed for correlated sources under the assumption of backlogged traffic.

More precisely, we consider a model in which packets of distortion sensitive data arrive at two sources. The sources compress their data packets and transmit them over a two-way relay network, where the relay can employ XOR network coding. The network coding operation at the relay couples the sources in terms of both energy consumption and distortion levels. The sources attempt to match the rates at which their compressed packets arrive at the relay in order to exploit the energy efficiency of network coding. For that purpose, they can adjust the service rates of the packet queues (subject to stability constraints) and the compression rates (subject to distortion constraints). Optimally, rate scheduling and compression decisions should be made jointly to balance energy, distortion and delay in stable operation. We use Lyapunov stability arguments to develop algorithms that attempt to strike such a balance. Our first algorithm requires a centralized scheduler with full information of instantaneous queue backlogs and distortion levels.

We next present a decentralized algorithm where sources individually adjust their transmission and compression rates depending on the availability of information on queue backlogs

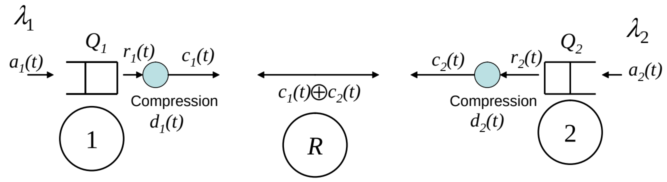

Fig. 1. Two-way relay network with data compression at sources.

and distortion levels. Numerical results demonstrate that one bit of information is sufficient to approach the energy-delay tradeoffs of our centralized solution.

The paper is organized as follows. Section II presents the system model, compression mechanism and queue dynamics. The problem of joint scheduling and compression is formulated in Section III and the centralized solution is presented. In Section IV, we introduce a distributed threshold-based algorithm. We demonstrate the energy-delay trade-offs for different distortion-sensitive scenarios in Section V. Final conclusions are drawn in Section VI.

II. System Model

We consider a two-way relay network with sources 1 and 2, and one relay R, as shown in Fig. 1. We assume a synchronous slotted system, in which each source $i = 1, 2$ buffers the incoming packets in queue Q_i with backlog $q_i(t)$ at time (slot) t.

Each source i chooses the service rate $r_i(t)$ at time t that corresponds to the amount of data removed from the buffer. Hence, the queue length at source $i = 1, 2$ evolves as

$$q_i(t+1) = \max\left(q_i(t) - r_i(t), 0\right) + a_i(t), \tag{1}$$

where $a_i(t)$ is the number of bits/packets arriving at source queue Q_i at time t. For each source i, we assume that $a_i(t)$ is generated via an ergodic process and let λ_i denote its long-term average rate.

For stochastic arrivals routed over a single link, [1] considers the case where all packet arrivals at a slot are compressed within that slot. Different than [1], here we assume that the incoming packets are buffered and the source chooses how many packets to compress before transmission at that slot. This provides the source with additional flexibility to adjust its transmission rate. At time slot t, $r_i(t)$ packets are served from the packet queue and only those packets are compressed by reducing the description length to $c_i(t)$ for $i = 1, 2$, where $c_i(t) \leq r_i(t)$. The length of compressed data, $c_i(t)$, is function $g(\cdot,\cdot)$ of the raw data served from queue, $r_i(t)$, and the compression rate, $k_i(t)$ given by:

$$c_i(t) = g(r_i(t), k_i(t)) := k_i(t) r_i(t), \tag{2}$$

where $0 \leq k_i(t) \leq 1$. We assume lossy compression such that packets from source i incur distortion

$$d_i(t) = h(r_i(t), c_i(t)), \tag{3}$$

$i = 1, 2$, for some function $h(\cdot,\cdot)$. We first note that a valid distortion function $d = h(r, c)$ should have the following properties:

- $h(r, c)$ should be decreasing with c for fixed r.
- $h(r, c)$ should be increasing with r for fixed c.
- $h(r, c) = 0$ should be satisfied for $r = c$, i.e. there should be no distortion without compression.

We will further characterize the function $h(\cdot,\cdot)$ in Section III. We assume that $r_i(t)$ is upper bounded by $r_i^{\max}$ to limit the maximum packet distortion. For each source $i = 1, 2$, we consider an average distortion constraint $d_{av,i}$ such that

$$\lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} \mathbb{E}[d_i(\tau)] \leq d_{av,i}. \tag{4}$$

Note that this is a constraint on the average distortion per unit-time. Another constraint that would be of interest is the average distortion per packet, which is given by the same expression scaled by λ (since the system is stable).

We assume that relay R does not buffer the incoming packets in queues and immediately forwards any received data over a single channel which is orthogonal to the channels used by each source. In particular, the relay uses network coding to transmit packets from both sources simultaneously at the common rate $\min_{j=1,2}(c_j(t))$. Any residual traffic is then routed in uncoded form at rate $c_i(t) - \min_{j=1,2}(c_j(t))$ only from the source with larger $c_i(t)$. Decoding is accomplished by combining the received network-coded packets with the individual packets previously transmitted by a source.

The relay communication consists of two phases: (*i*) multiple access from sources to the relay, and (*ii*) broadcast from the relay to sources. We assume that the achievable rates in the first phase are significantly larger than those in the second phase thereby making the rates in the second phase the only bottleneck that needs to be considered. Each use of the relay R is assumed to incur a cost, e.g., representing the energy expended by the relay. For simplicity, we do not consider here the energy cost of the sources, although our approach could readily extend to such a setting. If we assume additive white Gaussian noise channels with unit noise power and bandwidth in the broadcast phase, the individual min-cut capacities for each source i can be achieved via XOR-based network coding [19], [20], resulting in the end-to-end rate

$$\mu_i(t) \leq \log(1 + P(t)) \tag{5}$$

at time slot t for each source $i = 1, 2$, $i \neq j$, where μ_i is the rate (normalized to units of bits per time-slot) from source i forwarded by the relay, $P(t)$ is the common transmission power, and channel gains from the relay to sources are assumed to be normalized symmetric. The relay power is chosen such as to satisfy the signal-to-noise-ratio (SNR) requirement at both receivers. Accordingly, the power consumption at the relay node in this phase, $P_{rel}(t)$, depends on the maximum of the two rates $c_1(t)$ and $c_2(t)$ to be transmitted. More specifically, by (5), the relay power expended with network coding is given by

$$P_{rel}(t) = f(\max(c_1(t), c_2(t))) = (2^{2\max(c_1(t),c_2(t))} - 1), \tag{6}$$

for Gaussian channels.

Based on the above assumptions, in this paper, we focus on a simple achievable rate region $C(t) = \{(c_1(t), c_2(t)) :$

$0 \leq c_i(t) \leq \mu_i^{\max}(t), i = 1,2\}$ for the relay R, where $\mu_i^{\max}(t) < r_i^{\max}$. This represents the case of orthogonal channels from sources to the relay and provides a simple example that highlights the coupling of the transmission scheduling decisions between the sources. Note that this coupling would further increase for more general rate regions.

III. Joint Rate Scheduling and Data Compression

We start with the case where a centralized controller makes transmission decisions for both sources based on complete knowledge of the system parameters and the history of queue backlogs and received distortions. The objective is to minimize the total energy consumption at the relay while ensuring that the average delay does not exceed a given threshold D and average distortion constraint (4) is satisfied. This leads to the following optimization problem:

$$\min_{(r_1(t),r_2(t),c_1(t),c_2(t))} \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}\left[P_{rel}(c_1(\tau), c_2(\tau))\right] \qquad \textbf{(PD)}$$

$$\text{s.t.} \quad \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i=1}^{2} \frac{\mathbb{E}[q_i(\tau)]}{\lambda_1+\lambda_2} < D,$$

$$\lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}[d_i(\tau)] \leq d_{av,i}, \;\; i=1,2,$$

$$(c_1(t), c_2(t)) \in C(t), \;\; t \geq 0,$$

$$c_i(t) \leq r_i(t) \leq \min(q_i(t), r_i^{\max}), \;\; t\geq 0, \;\; i=1,2.$$

Here, the average delay constraint follows from the ratio of the average queue length to the total arrival rate according to Little's theorem [21]. Note that the objective in **(PD)** is equivalent to minimizing the average power per packet by normalizing by the total long-term arrival rate $\lambda_1 + \lambda_2$. Let $\mathcal{P}^*(D)$ denote the solution to **(PD)** as a function of the delay constraint D. This solution represents the energy-delay tradeoff. In general, this will be a decreasing function of D and as $D \to \infty$, it will yield the minimum cost solution subject to the condition that the queues are stable.

In principle, for a given delay constraint, **(PD)** can be solved via dynamic programming. However, such a solution quickly becomes intractable except for very simple arrival processes and requires *a priori* knowledge of arrival statistics. Instead, we will follow the approach in [22], [1], and use Lyapunov stability arguments to yield an approximate solution to **(PD)**. This approach is based on generalizing the classical back-pressure algorithm, which is guaranteed to stabilize the packet queues, if this is possible under capacity constraints [23].

A. Centralized Solution

We propose a joint rate scheduling and compression algorithm **(CA)** which chooses the service rate of the packet queue and the compression rate for each source to approximate the solution to **(PD)**.

To track the average distortion constraint over time, we use the idea of a *virtual distortion queue* introduced in [1]. Define $x_i(t)$ as the distortion queue for source i with constant service rate $d_{av,i}$ and arrival rate $d_i(t)$. If this distortion queue is stable, then (4) is satisfied. Then, the virtual distortion queue dynamics are given by:

$$x_i(t+1) = \max\left(x_i(t) - d_{av,i}, 0\right) + d_i(t). \tag{7}$$

We note that since $d_i(t)$ is bounded by assumption, it has a finite second moment.

Let $S(t) = [q_1(t), q_2(t), x_1(t), x_2(t)]$ denote the combined state of the system. We define the corresponding Lyapunov function as

$$L(t) = L(S(t)) = \frac{1}{2}(q_1(t)^2 + q_2(t)^2 + x_1(t)^2 + x_2(t)^2). \tag{8}$$

Since

$$X^2 \leq Y^2 + Z^2 + W^2 - 2Y(Z-W) \tag{9}$$

for $X \leq \max(Y - Z, 0) + W$, the Lyapunov drift can be written as

$$\begin{aligned} &\Delta(S(t)) = \mathbb{E}\{L(S(t+1)) - L(S(t)) | S(t)\} = B \qquad (10)\\ &-q_1(t)\mathbb{E}\{r_1(t) - a_1(t)|S(t)\} - q_2(t)\mathbb{E}\{r_2(t) - a_2(t)|S(t)\}\\ &-x_1(t)\mathbb{E}\{d_{av,1} - d_1(t)|S(t)\} - x_2(t)\mathbb{E}\{d_{av,2} - d_2(t)|S(t)\}, \end{aligned}$$

where B is a term that can be bounded by the sum of second moments of the arrival rates, and distortion values. Here, the expectations are taken over the arrival and control decision statistics. If we add the weighted expected power as a penalty term to (10), we have

$$\begin{aligned} &\Delta(S(t)) + V\mathbb{E}\{P_{rel}(t)|S(t)\} = B\\ &-q_1(t)\mathbb{E}\{r_1(t) - a_1(t)|S(t)\} - q_2(t)\mathbb{E}\{r_2(t) - a_2(t)|S(t)\}\\ &-x_1(t)\mathbb{E}\{d_{av,1} - d_1(t)|S(t)\} - x_2(t)\mathbb{E}\{d_{av,2} - d_2(t)|S(t)\}\\ &+V\mathbb{E}\{P_{rel}(t)|S(t)\}, \qquad (11) \end{aligned}$$

where the weight V is a control parameter to tune the trade-off between the upper bound to the average queue backlog and the distance from the minimum achievable cost. The algorithm (**CA**) aims at minimizing the sum of Lyapunov drift and penalty by solving the following optimization problem for the given system state $S(t)$:

$$\begin{aligned} \max_{(r_i(t),c_i(t)),i=1,2} \quad & q_1(t)r_1(t) + q_2(t)r_2(t) \qquad (12)\\ & -x_1(t)d_1(t) - x_2(t)d_2(t)\\ & -V[P_{rel}(\max(c_1(t), c_2(t)))].\\ \text{s.t.} \quad & (c_1(t), c_2(t)) \in C(t), c_i(t) \leq r_i(t), \; i=1,2 \end{aligned}$$

***Remark** 1:* The first two terms in (12) are maximized by maximizing the rate $r_i(t)$ for each source i and the last term is maximized by minimizing the compressed rate $c_i(t)$. However, the other terms are optimized by minimizing the distortion, which in turn minimizes $r_i(t)$ and maximizes $c_i(t)$. Hence, the optimal solution to (12) balances $r_i(t)$ and $c_i(t)$ objectives. We also note that in contrast to [10], the optimal network coding rates are not necessarily equal, i.e., $c_1(t)$ is not necessarily equal to $c_2(t)$ and the optimal solution depends on the particular instances of $d_1(t)$ and $d_2(t)$ at any time slot t.

Next, we discuss this joint rate scheduling-compression algorithm for a specific distortion-rate function and energy cost. Note that all constraints in (12) are linear. Therefore, choosing $d_i(t)$ as a strictly convex function of $(r_i(t), c_i(t))$ would result in standard convex optimization with unique optimal transmission and compression rates. The choice of $h(r, c)$ depends on the underlying application for data transmission, and it is outside the scope of this paper. For simplicity, we assume the distortion function $h(r, c) = r - c$, which represents the number of bits discarded in the compression operation. Furthermore, for bounded r and c, the second moment of distortion is also bounded, which is necessary to show the stability of the distortion queues.

The energy consumption depends on the underlying channel model. Again, for simplicity, we assume that there exists a linear relationship between the energy expended and the amount of data transmitted, which corresponds to the low SNR regime. Also, without loss of generality let $r_i^{\max} = r^{\max}$ and $\mu_i^{\max} = \mu^{\max}$, $i = 1, 2$.

Accordingly, (12) can be rewritten as

$$\begin{array}{ll} \max & (q_1(t) - x_1(t))r_1(t) + (q_2(t) - x_2(t))r_2(t) \\ & +x_1(t)c_1(t) + x_2(t)c_2(t) - V\max(c_1(t), c_2(t)) \\ \text{s.t.} & 0 \le r_i(t) \le \min(q_i(t), r^{\max}), \\ & 0 \le c_i(t) \le \min(r_i(t), \mu^{\max}). \end{array} \tag{13}$$

Note that (13) is a standard linear program. The explicit solution depends on the particular instances of $q_i(t)$ and $x_i(t)$, $i = 1, 2$. For illustration purposes, we point out at the following special cases:

- $q_i(t) > x_i(t)$, $x_i(t) > V$, $i = 1, 2$:
  $r_i(t) = \min(q_i(t), r^{max})$, $c_i(t) = \min(r_i(t), \mu^{\max})$
  (Maximum rate scheduling with compression)

- $q_i(t) < x_i(t)$, $i = 1, 2$,
  $q_1(t) + q_2(t) > V > \max(q_1(t), q_2(t))$:
  $r_1(t) = r_2(t) = c_1(t) = c_2(t) = \min(q_1(t), q_2(t), \mu^{\max})$
  (No compression with perfect rate match at the relay for network coding)

- $q_i(t) < x_i(t)$, $i = 1, 2$, $q_1(t) + q_2(t) < V$:
  $r_1(t) = r_2(t) = c_1(t) = c_2(t) = 0$,
  (No rate scheduling)

A particular case of interest is the symmetric queue backlog and distortion level at both sources:

- $q_1(t) = q_2(t) = q$, $x_1(t) = x_2(t) = x$:
  If $q > x$ and $x > V$, $r_i(t)$ and $c_i(t)$ are maximized for $i = 1, 2$, with possible lossy compression.
  If $\frac{V}{2} < q < \min(x, V)$, then $r_1(t) = r_2(t) = c_1(t) = c_2(t) = \min(q, \mu^{\max})$, i.e., no compression with perfect network coding applied at the relay.
  If $q < x$ and $q + x < V$, then $r_1(t) = r_2(t) = c_1(t) = c_2(t) = 0$.

Note that the queue service rate increases with increasing buffer size and decreasing distortion state, while the lengths of compressed representations increase with larger virtual distortion queues and lower trade-off parameter V, reflecting the priorities at the current time slot among the different objectives of stability, distortion sensitivity, and relay power consumption.

IV. Decentralized Algorithm with 1-Bit Information

Next, we consider a decentralized algorithm where each source has only limited information about the queue backlogs and distortion levels of each other. From the solutions to (13), it is seen that the source i tends to serve the packet queue if $q_i(t) > x_i(t)$ (with possible compression) or $q_i(t) > V$ (without compression), and tends to transmit data if $x_i(t) > V$ or $q_i(t) > V$.

To exploit the energy efficiency through network coding, it is necessary to synchronize both source transmissions as much as possible with limited queue backlog and distortion information. We consider a decentralized algorithm in which each source i has 1-bit information on whether $\min(q_j(t), x_j(t))$ exceeds V or not. We are motivated by the fact that in the centralized algorithm source j is likely to transmit, if $\min(q_j(t), x_j(t)) \ge V$. If so, instead of V each user focuses on its own queue states and energy consumption with parameter V replaced with $\mu^{\max}$, which would increase the likelihood of transmission for the source, provided that the other source is likely to transmit as well.

The resulting algorithm **(DA)** is given by:

$$(r_i(t), c_i(t)) = \begin{cases} (0,0), & \text{if } q_i(t) < \mu^{\max}, \\ (u_i(t), u_i(t)), & \text{if } \mu^{\max} \le q_i(t) < x_i(t), \\ & \quad \min(q_j(t), x_j(t)) > V, \\ (v_i(t), u_i(t)), & \text{if } \mu^{\max} \le x_i(t) < q_i(t), \\ & \quad \min(q_j(t), x_j(t)) > V, \\ (v_i(t), 0), & \text{if } x_i(t) < \mu^{\max} \le q_i(t), \\ & \quad V < \min(q_j(t), x_j(t)), \\ (v_i(t), u_i(t)), & \text{if } V < x_i(t) < q_i(t), \\ & \quad V > \max(q_j(t), \mu^{\max}), \\ (u_i(t), u_i(t)), & \text{if } V < q_i(t) < x_i(t), \\ & \quad V > \max(q_j(t), \mu^{\max}), \\ (v_i(t), 0), & \text{if } x_i(t) < \min(q_i(t), V), \\ & \quad V > \max(q_j(t), \mu^{\max}), \end{cases} \tag{DA}$$

where $u_i(t) = \min(q_i(t), \mu^{\max})$, $v_i(t) = \min(q_i(t), r^{\max})$ and $j \neq i$.

We will show in Section V that the cost performance of **(DA)** is very close to the centralized algorithm, especially as we increase the parameter V.

V. Comparison of Cost-Delay Trade-offs

We compare the cost and delay performance of the **(CA)** and **(DA)** algorithms for scenarios with different distortion requirements and traffic loads. We consider Poisson traffic with symmetric arrival rates $\lambda_i = \lambda$ and assume $c_i^{\max}(t) = \mu^{\max}$, and $r_i^{\max} = 5\mu_{\max}$, $i = 1, 2$.

Figures 2 and 3 depict the average delay as function of the average cost per packet (by varying the parameter V). The two figures differ in the choice of the distortion constraint $d_{av,i} = d_{av}$, $i = 1, 2$. As expected, the average energy cost increases with more stringent distortion constraints. However, there is no significant effect on the average delay.

For both algorithms **(CA)** and **(DA)**, the usual energy-delay trade-off is observed such that the energy cost decreases, as delay increases.

For comparison purposes, we also consider the case where each source only knows its own queue and distortion state. Then, each source optimizes its individual transmission rate and compression rate assuming the other source makes the worst-case decision at each time slot (i.e. source i assumes $c_j(t) = 0$, $j \neq i$). The cost-delay trade-off for this decentralized algorithm **(DWC)** cannot approach the behavior of the centralized solution because sources make blind decisions without any information on each other's queue backlogs.

Note that the average cost per packet achieved by **(DA)** is very close to the centralized algorithm **(CA)**, which also provides low delay. When transmission decisions are adapted depending on whether the other user is expected to transmit, the cost and delay performance can be significantly improved compared to the case without any knowledge about the other source queue.

VI. Conclusion

In this paper, we considered the problem of minimizing an energy cost subject to distortion and stability constraints in a two-way relay network. The relay exchanges distortion sensitive data from two sources with stochastically varying packet traffic. The sources apply lossy compression before transmitting to the relay node for more efficient use of the relay under rate constraints. Either network coding or routing is used at the relay depending on the availability of packets incoming from both sources. We considered different levels of source cooperation and availability of queue state information at the sources. First, we derived a centralized control scheme to jointly optimize the cost and stable throughput rates. For distributed operation, we assumed that each source has limited information of one bit on the queue and distortion state of the other source. We showed that with only one bit queue information, the threshold-based scheduling and compression algorithms approach the performance of the centralized solution.

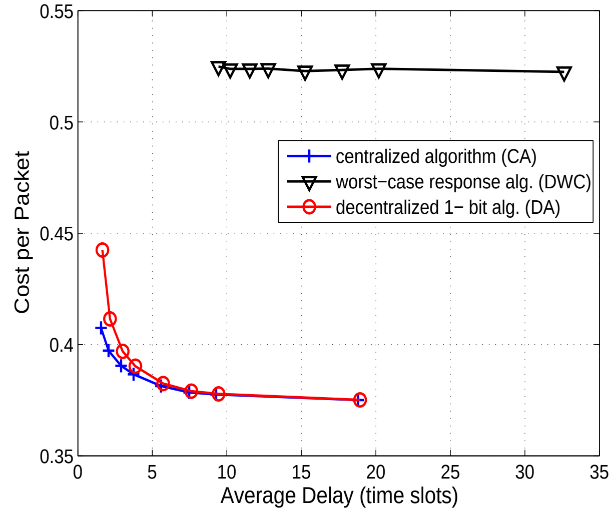

Fig. 2. Cost per packet as function of packet delay, $\lambda = 4$, $\mu^{\max} = 5$, $d_{av} = 1$.

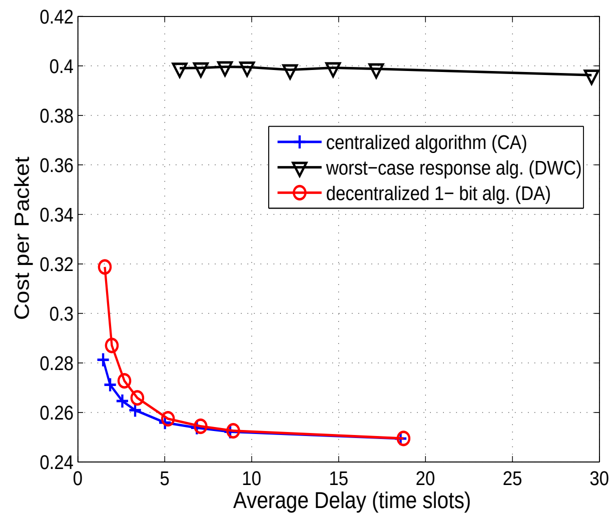

Fig. 3. Cost per packet as function of packet delay, $\lambda = 4$, $\mu^{\max} = 5$, $d_{av} = 2$.

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