DeepNP: Deep Learning-Based Noise Prediction for Ultra-Reliable Low-Latency Communications

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Abstract—Closing the gap between high data rates and low delay in real-time streaming applications is a major challenge in advanced communication systems. While adaptive network coding schemes have the potential of balancing rate and delay in real-time, they often rely on prediction of the channel behavior. In practice, such prediction is based on delayed feedback, making it difficult to acquire causally, particularly when the underlying channel model is unknown. In this work, we propose a deep learning-based noise prediction (DeepNP) approach, which augments the recently proposed adaptive and causal random linear network coding scheme with a dedicated deep neural network, that learns to carry out noise prediction from data. This neural augmentation is utilized to maximize the throughput while minimizing in-order delivery delay of the network coding scheme, and operate in a channel-model-agnostic manner. We numerically show that performance can dramatically increase by the learned prediction of the channel noise rate. In particular, we demonstrate that DeepNP gains up to a factor of four in mean and maximum delay and a factor two in throughput compared with the AC-RLNC scheme, and operate in a channel-model-agnostic manner. We contrast the performance of the proposed approach with that of the channel-model-based AC-RLNC [11], where the a-posteriori decisions are made at the sender using average packets that contain new data information. Nonetheless, to date, existing solutions are not yet able to close this trade-off to obtain the desired performance.

A fundamental observation we exploit in this work is that losses of throughput rate and high in-order delays often occur due to differences between the amount of noise the code was designed for and the actual realizations of the noise. Although it is possible to estimate or calculate the average noise rate in some settings, e.g., as proposed using the delayed feedback in AC-RLNC, due to the variations in noise realizations, one may pay in throughput rate and high in-order delays. This performance degradation depends on the information missing when the adaptive coding scheme is designed, e.g., the noise realizations during a round-trip time (RTT) period for AC-RLNC. While AC-RLNC was shown to achieve over 90% of the communication capacity, it often yields high in-order delay which is far from the optimal lower bound of the communication, due to inaccurate predictions of the noise variations. In this work, we are interested in predicting the noise realizations to narrow this significant gap in reliable streaming communications, and do so without relying on knowledge of the underlying channel model, motivating a data-driven deep learning-based approach.

In this work, we propose a data-driven adaptive causal network coding for URLLC coined DeepNP. DeepNP augments the AC-RLNC scheme with deep learning-based noise prediction, which is designed to learn from data the pattern of the communication link and predict the realization of the noise during the delayed feedback. The resulting encoding scheme combines data-driven deep learning with the channel-model-based AC-RLNC algorithm, as a form of model-based deep learning [15], shown to empower and robustify various communications algorithms [16]–[20]. Noise prediction is achieved using a dedicated deep neural network (DNN), whose architecture is comprised of an interconnection of neural building blocks with interpretable internal features representing the predictions for each block in an RTT. While accurately predicting the instantaneous noise realization in each time slot is extremely challenging, our design builds upon the insight that adaptive coding does not require these realizations, and in fact relies on the noise rate, i.e., the rate of the errors induced by the channel during the delayed feedback period. Thus, we train the DNN in a manner which boosts it to predict the noise rate while adding penalizing terms to encourage its internal features to represent predictions of the instantaneous noise.

We contrast the performance of the proposed approach with the works [3]–[14]. In the presence of delayed feedback, the works [3]–[5] proposed codes to reduce the streaming delay over an erasure channel. For coded blocks, [6] proposed an adaptive solution, where the sender can choose the size of the next block and the number of packets information in the block for deadline-aware applications. The recently proposed adaptive and causal random linear network coding (AC-RLNC) scheme, applied to single-path, multi-path, and multi-hop networks [10]–[12], implements joint scheduling-coding in a manner that is both causal and adaptive. The former stems from its reactive operation which operates using sliding window applied to the delayed feedback acknowledgements, while the latter follows as its rate of retransmissions is adapted based on the estimated rate. According to this channel-model-based rate estimation, the sender first transmits, a priori, an adaptive amount of forward error correction (FEC) retransmissions periodically. Then, at each transmission, according to a posteriori retransmission criterion, the sender adaptively and causally decides if to send feedback FEC retransmissions or...
statistical information. We show that the proposed DeepNP can gain up to a factor of four in mean and maximum delay and a factor of two in throughput. Moreover, we show that this performance can be obtained even when the possible average prediction error per transmission is about 28%, demonstrating that despite the inherent challenges of noise prediction, a properly designed and trained DNN-based noise predictor can still notably contribute to adaptive network coding.

The structure of this work is as follows. In Section II, we formally describe the system model and the metrics in use, and provide a background on adaptive causal network coding. In Section III we present DeepNP and how it augments AC-RLNC. In Section IV, we evaluate the performance of the proposed solution. Finally, we conclude the paper in Section V.

II. SYSTEM MODEL AND PRELIMINARIES

In this section, we present the system model and the problem formulation. Following that, we review relevant background in adaptive and causal network coding. Fig. 1 shows the system model and the encoding process of adaptive and causal network coding.

A. Problem Formulation

We consider a point-to-point real-time slotted communication system with delayed feedback. At each time slot the sender transmits a coded packet \( c_t \) to the receiver over a single-path forward channel with memory. The noisy forward channel may erase packets. The receiver may acknowledge the sender by sending an acknowledgment (ACK) for any received coded packet over the feedback channel, or send a negative acknowledgment (NACK) otherwise, and we assume that the feedback channel is noiseless. The delay between the a transmission time slot and the time the corresponding feedback is received is called RTT. The transmission delay of a coded packet in bits/seconds is denoted by \( t_d \), and maximum propagation delay is denoted by \( t_{\text{prop}} \). We assume that the size of the feedback acknowledgment is negligible, and fix the propagation delay for transmitted coded packets. The RTT for each coded packet is \( \text{RTT} = t_d + 2t_{\text{prop}} \). Hence, for each coded packet transmitted at time \( t \), the sender receives feedback at time instance \( t + \text{RTT} \). We use \( f_t \) to denote the binary feedback received at time \( t \), where

\[
    f_t \triangleq \begin{cases} 
        1 & \text{received ACK for } c_{t-}, \\
        0 & \text{received NACK at time } c_{t-}, 
    \end{cases}
    t^- \triangleq t - \text{RTT}.
\]

Our goal is to derive an adaptive coding scheme which forms \( c_t \) based on the past feedbacks \( \{f_j\}_{j<t} \). Here, unlike classical models and solutions considered in the literature [21], we assume the channel model and its statistics are unknown to the sender and the receiver. However, the sender may track the channel statistics by the delayed feedback acknowledgments and predict the next channel realizations. In particular, the sender has access to data comprised of past transmissions and their corresponding feedbacks taken from the channel.

Our main performance metrics are defined as follows:

1. **Throughput**, \( \eta \). This is defined as the total amount of information data, in units of bits per second, which are delivered to the receiver. In this paper, we focus on normalized throughput, which is the total amount of information data delivered to the receiver divided by the total amount of bits transmitted by the sender.

2. **In-order delivery delay of packets**, \( D \). This is the difference between the time slot in which an information packet is first transmitted by the sender and the time slot in which the packet is decoded in order by the receiver.

We thus aim in our design to maximize the throughput, \( \eta \), while minimizing the in-order delivery delay of packets, \( D \).

B. Adaptive and Causal Network Coding

Our design detailed in Section III builds upon the AC-RLNC scheme proposed in [10], which implements adaptive and causal network coding. In AC-RLNC, the sender decides at each time step whether to transmit a new coded linear combination or to repeat the last sent combination according to the feedback information. Here, “same” and “new” refer to the raw information packets of information contained in the linear combination. Sending the same linear combination thus means that the raw information packets are the same but with different random coefficients. For \( n \) transmissions, let \( \mu_i \) and \( p_i \), denotes the random coefficients drawn from a sufficiently large field and the raw information packets, respectively. Thus, using sliding window mechanism the coded linear combination transmitted, called a degree of freedom (DoF), given by

\[
    c_t = \sum_{i = w_{\min}}^{w_{\max}} \mu_i p_i.
\]

In (1), \( w_{\min} \) corresponds to the oldest raw information packet that is not yet decoded, and \( w_{\max} \) is incremented each time a new raw information packet is decided to be included in the linear combination by the sender.

In this adaptive setting, the sender uses \( f_t \) to track the channel erasure probability \( \epsilon_t \), and the number of erased and repeated DoFs, denoted \( \text{md} \) and \( \text{ad} \), respectively. These tracked quantities are used by two suggested forward error correction (FEC) mechanisms, a priori and a posterior, to counteract the channel erasures. The a priori mechanism transmits \( \lceil \epsilon_t \cdot k \rceil \) repeated DoFs, with \( \lceil \cdot \rceil \) denoting rounding.
to the nearest integer, periodically after \( k \) transmissions of new packets of information. In the a posteriori mechanism, a retransmission criterion is used by the sender. As demonstrated in [10], [11], when the actual channel rate denoted \( r_t \triangleq 1 - \epsilon_t \) is higher than the rate of the DoFs \( d \triangleq \text{md}/\text{ad}, \) the decoder has sufficient DoFs to immediately decode the delivered packets. However, these quantities cannot be computed exactly at the sender due to the RTT delay. At time step \( t, \) the sender can only compute these quantities for time step \( t' = t - \text{RTT}, \) using the delayed feedback. Hence, with a tunable parameter \( th, \) the DoF rate gap is given by

\[
\Delta_t \triangleq \frac{md_{\text{nack}} + \epsilon_t \cdot c_{\text{new}}}{ad_{\text{ack}} + r_{t'} \cdot c_{\text{same}}} - 1 - th,
\]

(2)

where \( md_{\text{nack}} \) and \( ad_{\text{ack}} \) denote the DoFs with feedback acknowledges, and \( \epsilon_t \) and \( c_{\text{same}} \) denote the number of new information packets and same retransmission packets in the actual coded linear packet transmitted, respectively. As such, retransmission is suggested at each time step for which

\[
\Delta_t > 0.
\]

(3)

The statistic-based estimation of the erasure probability \( \epsilon_t \) can be calculated for example as,

\[
\epsilon_t = 1 - \frac{\sum_{j=1}^{t'} f_j}{t'} + \frac{\sqrt{V}}{\text{RTT}},
\]

(4)

where \( V \) is the variance of the channel during the period of RTT. We refer the readers to [10], [11] for details examples of how the tracked quantities and estimation presented above is computed based on channel modelling.

To manage the maximum delay, a maximum sliding window of size \( w \) is defined, such that \( w_{\text{max}} - w_{\text{min}} \leq w. \) When the limit is reached, the sender transmits the same packet until all the information packets in the linear combination transmitted are decoded. We again refer the readers to [10], [11] for further details on the operation of AC-RLNC.

AC-RLNC aims at mitigating the throughput-delay trade-off by adapting the required retransmissions using its a posteriori mechanism. This adaptation relies on tracking the channel, e.g., the erasure probability \( \epsilon_t. \) However, when the channel exhibits high variations in its conditions, the statistic-based estimation is likely to be inaccurate, which in turn results in too few or too many retransmissions. Statistic-based estimations, as in (4), are not sufficient to represent the current channel behavior. This gap between the statistic-based estimations and the actual channel realizations reduces the performance of the streaming solutions, as reflected in the throughput-delay trade-off. To close this gap we propose a data-driven approach which augments AC-RLNC with a dedicated DNN, as described in the following section.

III. DeepNP

In this section, we propose DeepNP, which augments AC-RLNC with a DNN designed to predict the noise realizations during the RTT period. Specifically, we are interested in improving the statistical estimation of \( \epsilon_t \), i.e., the erasure rate during RTT channel realizations, as defined in Section II-B. In order to set the rate at time instance \( t, \) AC-RLNC needs an estimate of \( s_t, \) where

\[
s_t \triangleq \sum_{j=t-\text{RTT}+1}^{t} f_j.
\]

(5)

This prediction should be carried out based on the available feedback at time index \( t, \) which is \( \{f_j\}_{j \leq t-\text{RTT}}. \) Assuming that the channel has memory, we demonstrate such an estimate is meaningful, and its error is expected to be smaller than that of the naive mean estimate \( \tilde{s}_t = E\{s_t\}. \) The fact that the underlying statistical relationship is complex motivates a data-driven approach, i.e., the use of deep learning method, which are known for their ability to disentangle semantic information in complex environments [22].

A. Noise Prediction DNN

DeepNP uses a dedicated DNN to predict the noise. Since the noise is assumed to have memory, e.g. a bursty noise channel, we propose an architecture that is based on long short-term memory (LSTM) [23]. The architecture attempts to identify in which time slots erasures occurred. It does so in a soft manner, that is, the architecture estimates the probability of erasure in each time slot in an RTT. While in general noise prediction is statistically related to all past feedbacks, here we fix the number of past feedbacks used for noise prediction to be \( m, \) i.e., the input to the DNN is the \( m \times 1 \) binary vector \( f_t \triangleq [f_{t-m+1}, \ldots, f_t], \) while the internal memory of the LSTM units is exploited to learn longer-term correlations.

Architecture: The DNN used by DeepNP is comprised of RTT neural building blocks. Each building block consists of an LSTM layer, followed by a fully connected layer with sigmoid as the activation function. The input of each estimation block is the \( m \) last available feedbacks, i.e., \( f_t, \) and the output of the previous estimation block. The latter relies on the fact that adjacent channel realizations are likely to be more correlated, hence the prediction at time instance \( t \) is affected by the prediction at time \( t - 1. \) A schematic of the architecture is depicted in Fig. 2, where \( \hat{p}_t \) represents the estimate of probability that \( c_t \) is correctly delivered at the receiver.
Data: The data used for training is a sequence of past feedbacks, e.g., \( \{f_j\}_{j=1}^t \). The DNN is trained to map \( f_t \) into a prediction of \( \{f_{t-1}, \ldots, f_t\} \) for each \( t \in [t + m + \text{RTT}, t_2] \).

Training: While the DNN is designed to predict the noise at each instance, the metric required by AC-RLNC is an estimate of how many erasures occurred in each RTT interval. Consequently, we train the DNN to minimize the squared error between the predicted erasures and the actual ones, while also boosting successful individual predictions. To help the architecture learn the correct estimations of each time slot, we assign larger weights to earlier time slots, using logarithmic weight decay as in [24]. This encourages the DNN to be more confident in learning them. As a result, the loss function we use is:

\[
\mathcal{L} \left( \{\hat{p}_j\}_{j=t-1}^t, \{f_j\}_{j=t-1}^t \right) = \left( \sum_{j=t-1}^t (\hat{p}_j - f_j)^2 \right)^{1/2} + \lambda \sum_{j=t-1}^t \log (\text{RTT} - i + 1) H_b(\hat{p}_j, f_j),
\]

for some \( \lambda > 0 \), where \( H_b(\cdot, \cdot) \) is the binary cross entropy.

B. Neural Augmented Adaptive Causal Network Coding

DeepNP uses the DNN detailed in the previous subsection to implement AC-RLNC in a learned fashion. On each incoming feedback \( f_t \), DeepNP stacks the last \( m \) observed feedbacks to form the vector \( f_t \), which is fed to the DNN in Fig. 2. Then, the outputs of the DNN, \( \{\hat{p}_j\}_{j=t-1}^t \), are used to estimate the erasure rate as

\[
\hat{e}_{t-1} = 1 - \left( \frac{1}{\text{RTT}} \sum_{j=t-1}^t \hat{p}_j \right).
\]

Note that the rounding of \( \hat{p}_j \) to the nearest integer in (7) represents hard decision as to whether or an erasure occurred or not. Finally, the estimated \( \hat{e}_{t-1} \) is used to determine the retransmission criteria \( \Delta \) via

\[
\Delta_t = \frac{md_{\text{ack}} + \hat{e}_{t-1} \cdot c_{\text{ew}}}{ad_{\text{ack}} + (1 - \hat{e}_{t-1}) \cdot c_{\text{same}}} - 1 - th.
\]

The resulting adaptive network coding scheme is summarized as Algorithm 1.

Algorithm 1: DeepNP

\begin{enumerate}
\item \textbf{Init:} Trained DNN, AC-RLNC parameter \( th \),
\item \textbf{Input:} Feedback \( f_t \) \[ \text{Stack } f_t = [f_{t-m+1}, \ldots, f_t]; \]
\item \textbf{Noise prediction:} Feed \( f_t \) to DNN to obtain \( \{\hat{p}_j\} \);
\item \textbf{Adaptive threshold:} Set \( \Delta_t \) using (8);
\item \textbf{if} \( \Delta_t \leq 0 \) \textbf{then}
\item \textbf{end}
\item \textbf{Output:} Next coded packet \( c_t \)
\end{enumerate}

C. Discussion

DeepNP implements adaptive network coding in a learned fashion. It carries out the principled AC-RLNC scheme, while relaxing its reliance on modelling of the channel to predict the erasure rate. It is emphasized that even when one has knowledge of the underlying channel model, predicting \( \epsilon_{t-1} \) is typically challenging, and approximations based on first and second-order statistical moments as in (4) are utilized. Consequently, the gains of augmenting AC-RLNC with a DNN are twofold: First, it allows it to operate without channel knowledge, requiring only the RTT to be known; Further, even when channel knowledge is available, DeepNP learns to achieve improved performance, as demonstrated in Section IV.

The DNN in DeepNP is assigned with the challenging task of noise prediction. To successfully carry this out, we carefully designed both the architecture and the training objective to facilitate the learning process. In particular, we observed that conventional architectures for processing time sequences based on recurrent neural networks were not able to provide accurate results. Therefore, we propose the architecture in Fig. 2, which unrolls the noise prediction procedure over a single RTT as a form of deep unfolding [25], while allowing to assign different weights for different time instances and preserving the ability of LSTMs in tracking correlations that are longer than the input length \( m \). Our training objective accounts for the fact that some of the internal features of the interpretable architecture are in fact individual noise predictions, boosting their correct
Fig. 4: AC-RLNC simulation with and without noise prediction for a high bursty channel. The top results are for normalized throughput (left), and mean in order delay (right), while the bottom result is for the deep learning-based noise prediction approach. The noise predictor’s MAE, for the case presented at the bottom with RTT = 20, is 0.887. This represents, on average possible prediction error per RTT period of about 4.5%.

detection and further encouraging early decisions, which affect future decisions. Moreover, we also account in the loss (6) to the fact that while the DNN predicts the noise, AC-RLNC requires the erasure rate rather than the individual predictions. As a result, while the DNN may at some time instances provide inaccurate estimates of the individual erasures, its estimated erasure rate notably contributes to the performance of AC-RLNC, as observed in Section IV. Finally, our DNN predicts future feedbacks based on past feedbacks, and is thus trained in a self-supervised manner, i.e., it does not require dedicated labelling. This allows to train DeepNP on-site, with possible pre-training using offline simulated data.

The proposed DeepNP gives rise to a multitude of possible extensions. The internal DNN currently provides soft estimates \( \{ \hat{p}_j \} \), which are converted during inference into hard decisions (7). However, since we are interested in the erasure rate rather than the actual erasures, one can consider computing \( \epsilon_t \) by averaging the soft estimates, possibly combining with techniques such Bayesian DNNs to better relate \( \{ \hat{p}_j \} \) to uncertainty [26]. Furthermore, DeepNP currently trains its DNN separately from the adaptive coding procedure. One can thus train the overall algorithm end-to-end, by backpropagating the loss gradient through the AC-RLNC steps, which is likely to further improve performance. Additional possible extensions include the combination of deep noise prediction with adaptive network coding algorithms other than AC-RLNC, as well as extension to multi-link centralized setups.

IV. Performance Evaluation

In this section, we describe how simulation was conducted. We first present the simulation environment in Subsection IV-A, then show the results in Subsection IV-B.

A. Experimental setup

The simulation represents multiple scenarios of burst channels with memory, which we modeled by a Gilbert-Elliott (GE) channel with erasures [27]. The GE channel is a Markovian channel with two states: a good state and a bad state. In the good (bad) state, packets are erased with probability \( e_G \) (\( e_B \)). The good (bad) state represents a channel with good (bad) signal to noise ratio (SNR), hence erasures are rare (common), and thus \( e_G \ll e_B \). The transition probability from a good (bad) state to a bad (good) state is denoted by \( q \) (\( s \)). As a result, the stationary distribution satisfies \( \pi_G = s/(s+q), \pi_B = q/(s+q) \), where \( \pi_G \) (\( \pi_B \)) denotes the stationary probability to be in a good (bad) state. The erasure probability in the steady state is therefore given by

\[
e = \pi_G e_G + \pi_B e_B. \tag{9}
\]

We implement DeepNP where each block is comprised of an LSTM with four output neurons followed by a \( 4 \times 1 \) dense layer. A time series of length \( 10^5 \) was generated in each simulation, where 60% of it was used for training with hyperparameter \( \lambda = 1 \), and the rest for testing. Adam optimizer was used for training [28] with learning rate 0.0001 and batch size 100. It is important to note that DeepNP is unaware of the underlying GE model, but rather learns it.

B. Results

We show simulations results for two channel conditions. One, for the case where there is more variation in channel noise realizations. The second, when the channel is with more bursts, namely low variations in the noise.

In the first simulation, we evaluate AC-RLNC with and without DeepNP as a function of the RTT. Fig. 3 show the performance in terms of normalized throughput, mean, and maximum in-order delivery delay as defined in Subsection II-A. The parameters used to simulate a low bursty channel, i.e., channel with high variation during the time, are the following: \( e_G = 0.1, e_B = 0.9, s = 0.1, q = 0.1, m = 5 \). With these parameters the average erasure probability of the channel is 0.5, according to (9). In Fig. 3, the top results are for normalized throughput (left), mean in order delay (middle), and maximum in order delay (right), while the bottom result is for the deep learning-based noise prediction approach. The noise predictor’s mean absolute error (MAE), for the case presented at the bottom with RTT = 10, is 2.855. This represents, on average possible prediction error per RTT period of about 28%. We note that in practical wireless and wired communication systems, the weaver of the channel observation at the receiver transport layer is controlled by redundancy in the FEC codes at the physical layer. The parameters selected to create the weaver presented at the bottom of Fig. 3, i.e., a low bursty channel, represent the case where the designer system includes low redundancy at the physical layer coded...
correction. In this case, using DeepNP with AC-RLNC at the higher layers, one can increase the performance dramatically. As presented in Fig. 3, the proposed method in this case can gain up to a factor of four in mean and maximum delay and a factor two in throughput. This performance improvement is obtained by using adaptive coded solution, despite the low accuracy of the predictor, whose average error is approximately 28%. The proposed coded solution mitigates the requirement to predicate the noise correctly at each particular channel realization. Moreover, AC-RLNC adjusts the retransmission rate by using the posteriori mechanism to maximize the performance. We emphasize that in this case, by using the proposed approach, the obtained throughput can almost reach the optimal capacity of the channel where the sender knows all the channel realizations non-causally, while the mean in-order delay almost reaches the optimal lower bound.

In the second simulation, we explore how the erasure probability $\epsilon$ in (9) affects the performance of AC-RLNC, with and without DeepNP. The simulations are for point-to-point communication system with RTT of 10 and 20 time slots. The parameters used to simulate a high bursty channel, i.e., channel with low variation during the time, are the following: $e_G = 0$, $e_B = 1$, $s = 0.01$, $m = 5$, and $q$ varies to control the overall erasure probability $\epsilon$, according to (9). The results are depicted which are shown in Fig. 4. The parameters selected to create the channel weaver, presented at the bottom of Fig. 4, represent high bursty channel, where the designer system includes high redundancy at the physical layer via FEC coding. The top results in Fig. 4 are for normalized throughput (left) and mean in order delay (right). In this simulation the maximum in-order delay is dominated in both of the solutions by the burst duration’s. As presented in Fig. 3, by using the proposed approach in a communication system with RTT = 20, the obtained throughput can almost reach the optimal capacity of the channel where the sender knows all the channel realizations non-causally, while the mean in-order delay almost reaches the optimal lower bound. This performance is obtained by using adaptive coded solution with predictor accuracy, whose average error is approximately 4.5%.

As noticed comparing both simulated channel weavers, the predictor accuracy increases when the channel is more bursty. As we elaborated above, the channel weaver can be, at some level, managed by the designer system, changing the redundancy in the physical layer error correction code. Further, using conventional adaptive network coding, performance typically degrades as the channel is more bursty. The results presented here are very encouraging, as the principled incorporates of DeepNP allows to avoid this behavior, allowing to dramatically increase the performance in bursty channels.

V. CONCLUSIONS

In this work we presented DeepNP, which learns from data to implement adaptive network coding without relying on channel modelling. DeepNP augments the recently proposed AC-RLNC scheme with a dedicated DNN architecture designed to predict the instantaneous channel noise and estimate the erasure rate. DeepNP is numerically demonstrated to notably improve the performance of AC-RLNC in terms of both throughput and delay for different bursty channels.

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