# A Memory-less Proof Calculus for Queuing Timing Channels

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Use Point Process Entropy + Algebraic  
Approach on Counting Functions  
A Converse for Tandem Queue Capacity  

$$X \xrightarrow{(M/1 \text{ queue})} (\mu_1) \xrightarrow{(M/1 \text{ queue})} (\mu_2)$$
  
 $Y \xrightarrow{(\mu_1)} (\mu_1) \xrightarrow{(\mu_2)} (\mu_2)$   
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 $H(s_1) = H(s_2) = 0$ How it works: Two-stage coding scheme.

- 1.Encode **counts** (*s*) at 0 rate.
- 2. Conditioned on s: a memoryless channel

# Key insight.

H(Z|X,S) **independent** of X for the tandem queue! Simple max-entropy argument (just like AWGN): Poisson inputs!

# Assumptions and limitations:

•Packet losses due to congestion heterogeneity not modeled



Queuing Timing Channels Afford New Degrees of Freedom in MANETs and are Analogous to AWGN Channels



Fig. 1. Conveying information through packet timings in a queueing system.

#### Single Server Queue:

$$C(\lambda,\mu) = \lambda \log \frac{\mu}{\lambda}, \ \lambda < \mu \text{ nats/s.}$$
 (1)

$$C(\mu) = e^{-1}\mu \text{ nats/s}, \qquad (2)$$

a) Related Work on Proving  $C(\lambda, \mu)$ :

- Original Anantharam & Verdu '96: "Bits through Queues": proved closed-form structure of C(λ, μ) by considering the probabilistic dynamics relating n packet arrivals to n packet departures of an ESTC. Required information density arguments
- Bedekar & Azizoglu '98: "The information-theoretic capacity of discrete-time queues": analogous proof technique (requiring information density arguments) as in CT case.
- Prabhakar & Gallager '03: focused on information rates but never explicitly showed achievability of these rates
- Sundarasen & Verdu '06: took a point process approach but still require information densities to illustrate achievability.

#### A. Methodology of Our Approach

We illustrate that one can reason about this channel coding problem completely from a traditional memoryless channel perspective, by exploiting a few key properties:

- 1) The numerical entropy rate of any finite-rate point process tending to 0 (Lemma 0.2),
- 2) The memoryless nature of the channel departure likelihood, when conditioned upon a process whose entropy rate tends to 0 (equation (12)).
- 3) The maximum-entropy nature of the Poisson process (Lemma 0.1).

The reasoning of this paper is completely dual to that of the two-stage lossy compression scheme developed in [7]. Such two-stage compression schemes for non-stationary independent-increments processes date back to Rubin [8] (for Poisson processes) and [9], [10] (for Wiener processes).

#### **B.** Notation on Point Processes

• Define  $\Gamma_T$  to be the set of all counting functions on [0,T]:

$$\Gamma_T \triangleq \{y : [0,T] \to \mathbb{Z}_+, y \text{ is nondecreasing, and right-continuous }\}.$$
 (3)

• Point process  $\mathcal{Y}$  with occurrence times  $\{\mathcal{Y}_1, \mathcal{Y}_2, \ldots\}$ . Counting function  $(Y_t : t \ge 0)$ :

$$Y_t = \sup \left\{ n \in \mathbb{N} : \mathcal{Y}_n \le t \right\}.$$

• The *entropy* on [0,T] of a point process  $\mathcal{Y}$  with arrival times  $\{\mathcal{Y}_1, \mathcal{Y}_2, \ldots\}$  is defined [11] as the sum of its *numerical entropy* and its *positional entropy*:

$$h_T(\mathcal{Y}) := H(Y_T) + h\left(\mathcal{Y}_1, \dots, \mathcal{Y}_{Y_T} | Y_T\right),$$

where  $H(\cdot)$  is discrete entropy,  $h(\cdot)$  is differential entropy, and  $\{\mathcal{Y}_1, \ldots, \mathcal{Y}_{Y_T}\}$  are the locations (in time) of the arrivals on [0, T].

• We define the *rate*  $r(\mathcal{Y})$  of a point process  $\mathcal{Y}$  to be  $\lambda$  if

$$\lim_{T \to \infty} \frac{E[Y_T]}{T} = \lambda.$$

*Poisson* processes are known to have desirable *extremal entropic* properties [11]:
 *Lemma 0.1:* The Poisson process of rate λ is maximum-entropy over all rate-λ point processes, and has entropy on [0, T] given in closed form by

$$h_T(\mathcal{Y}) = T\lambda(1 - \log \lambda).$$

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Lemma 0.2: For any point process  $\mathcal{Y}$  such that  $r(\mathcal{Y}) < \infty$ ,

$$\lim_{T \to \infty} \frac{1}{T} H\left(Y_T\right) = 0.$$

#### C. The Likelihood of a Point Process

Point process  $\mathcal{Y}$ :  $H_t \triangleq \sigma$ -algebra generated by  $\{Y_\tau : \tau \in [0, t)\}$ .

$$\lambda_t \triangleq \lim_{\Delta \to 0} \frac{P\left(Y_{t+\Delta} - Y_t = 1 | H_t\right)}{\Delta}.$$
(4)

$$p_T(y) = \exp\left\{\int_0^T \log \lambda_t dy_t - \lambda_t dt\right\}$$
(5)

#### D. Queuing Timing Channels: the ESTC

• service times are i.i.d. and exponentially distributed:

$$\lambda_t = \mu \mathbb{1}_{\{Q_t > 0\}},\tag{6}$$

$$Q_t \triangleq X_t + Q_0 - Y_t \tag{7}$$

where  $Q_0$  is the initial condition, i.e. the state of the queue at time 0.

For specific realizations of  $y \in \Gamma_T$  and  $x \in \Gamma_T$ :

$$p_T(y|x,q_0) = \exp\left\{\int_0^T \log\left(\mu \mathbf{1}_{\{q_t>0\}}\right) dy_t - \mu \mathbf{1}_{\{q_t>0\}} dt\right\}$$
$$= \begin{cases} \mu^{y_T - y_0} \exp\left\{\int_0^T -\mu \mathbf{1}_{\{x_t+q_0-y_t>0\}} dt\right\} & \text{if } x_t + q_0 - y_t \ge 0 \ \forall \ t \in [0,T] \\ 0 & \text{otherwise} \end{cases}$$

Note that this can be expressed as

$$p_T(y|x,q_0) = Z_T(y) \exp\left\{\int_0^T -\mu\rho \left(x_t + q_0 - y_t\right) dt\right\}$$
(8a)

$$Z_T(y) \triangleq \mu^{y_T - y_0} \tag{8b}$$

$$\rho(u) \triangleq \begin{cases} 0, & u = 0, \\ 1, & u > 0, \\ \infty, & u < 0 \end{cases}$$
(8c)

## E. Memoryless Nature of Channel Dynamics Given Queue States

Succinct explanation of ESTC:  $\mathcal{X} - Q - \mathcal{Y}$ . Specifically, for  $x \in \Gamma_{nT}$  and  $y \in \Gamma_{nT}$ , associate

$$x \Leftrightarrow \tilde{x}^n = (\tilde{x}_1, \dots, \tilde{x}_n), \quad \tilde{x}_i \triangleq (x_{t+(i-1)T} : t \in [0, T])$$
(9)

$$y \Leftrightarrow \tilde{y}^n = (\tilde{y}_1, \dots, \tilde{y}_n), \quad \tilde{y}_i \triangleq (y_{t+(i-1)T} : t \in [0, T])$$
 (10)

$$\tilde{q}^n = (\tilde{q}_1, \dots, \tilde{q}_n), \quad \tilde{q}_i \triangleq q_{(i-1)T} - q_0 \tag{11}$$

where  $\tilde{x}_i \in \Gamma_T$  and  $\tilde{y}_i \in \Gamma_T$ .

It follows directly from (8) that given knowledge of  $\{\tilde{q}_i\}_{i=1}^n$ , this induces a memoryless channel:

$$p_{nT}(\tilde{y}^n | \tilde{x}^n, \tilde{q}^n) = \prod_{i=1}^n p_T(\tilde{y}_i | \tilde{x}_i, \tilde{q}_i)$$
(12)

#### I. A CONVERSE FOR THE SINGLE-SERVER ESTC

For the single-server ESTC, we first compute the information capacity over all input processes that satisfy the constraint that  $r(\mathcal{X}) = \lambda$ . Note that for the converse, we can simply use a genieaided decoder, that has  $\tilde{Q}^n$  at the decoder. As a consequence, from (12), it follows that this is a memoryless channel, and thus for any T, from Fano's inequality [14] it must be that

$$R < \frac{1}{nT} I_T(\tilde{X}^n; \tilde{Y}^n | \tilde{Q}^n)$$
  
$$\leq \sup_{\substack{p(\tilde{X}): E[X_T] = \lambda T \\ p(\tilde{Q}): E[\tilde{Q}] < \infty}} \frac{1}{T} I_T(\tilde{X}; \tilde{Y} | \tilde{Q})$$

Now allowing  $T \to \infty$  so that we are conditioning on less and less genie-adided information  $(\tilde{Q}^n)$ , we have:

$$R < C(\lambda, \mu),$$

$$C(\lambda, \mu) = \sup_{\substack{p(\mathcal{X}): r(\mathcal{X}) = \lambda \\ p(\tilde{Q}): E[Q_0] < \infty}} \liminf_{T \to \infty} \frac{1}{T} I_T(X; Y | Q_0)$$

$$I_T(X; Y | Q_0) \triangleq E\left\{\log \frac{p_T(Y | X, Q_0)}{p_T(Y | Q_0) p_T(X | Q_0)}\right\}.$$

Note that because

$$I_T(X;Y|Q_0) - I_T(X;Y) = I(Q_0;X|Y) - I(Q_0;X)$$
(13)

and  $\lim_{T\to\infty} \frac{H(Q_0)}{T} = 0$  because  $E[Q_0] < \infty$  and Lemma 0.2 below, the probability distribution of the initial state  $Q_0$  will not affect  $C(\lambda, \mu)$ . So we now assume  $Q_0 = 0$  to calculate  $C(\lambda, \mu)$ :

$$C(\lambda,\mu) = \sup_{p(\mathcal{X}): r(\mathcal{X})=\lambda} \liminf_{T \to \infty} \frac{1}{T} I_T(X;Y).$$
(14)

It will be shown in Section III that  $C(\lambda, \mu) = \lambda \log(\frac{\mu}{\lambda})$  and it is achieved with  $p(\mathcal{X})$  corresponding to a Poisson process of rate  $\lambda$ .

#### II. ACHIEVABILITY FOR THE SINGLE-SERVER ESTC: A TWO-STAGE CODING APPROACH

We now show that we can achieve the rate  $C(\lambda, \mu)$ . We use a simple two-stage coding scheme, using a Poisson process of rate  $\lambda$  as the input.

• For  $i \in \{1, ..., n\}$ : define

$$\tilde{W}_i \triangleq X_{iT} - X_{(i-1)T}.$$
(15)

$$C_i \triangleq X_{iT} = \sum_{k=1}^{i} \tilde{W}_i.$$
(16)

First communicate  $\tilde{W}^n = {\tilde{W}_1, \dots, \tilde{W}_n} \Leftrightarrow C^n = {C_1, \dots, C_n}$ . Note that

$$p(\tilde{y}^n | \tilde{w}^n) = \prod_{i=1}^n p(\tilde{y}_i | \tilde{y}_{i-1}, \tilde{w}_i)$$

and so the capacity of this channel is defined in terms of its information rate.

Since  $r(\mathcal{X}) = \lambda$ , for sufficiently large T, each  $\tilde{W}_i$  is a non-negative random variable of mean approximately  $\lambda T$ . Since we are constraining the process  $\mathcal{X}$  such that  $r(\mathcal{X}) = \lambda$ , Lemma 0.2, it follows directly that

Corollary 2.1: For each  $i \in \{1, \ldots, n\}$ ,  $\lim_{T \to \infty} \frac{H(\tilde{W}_i)}{T} = 0$ .

Thus it follows that we can communicate  $\{\tilde{W}_i\}$  with 0 rate using a Poisson- $\lambda$  input.

• Note that given the information  $\tilde{W}^n$  at the decoder, since

$$Q_{iT} = Q_0 + X_{iT} - Y_{iT},$$

the decoder now has  $\tilde{Q}^n$  at its disposal. Constructing X to be a Poisson process, it follows that we can achieve  $C(\lambda, \mu)$  as discussed in Section III.

### III. CALCULATION OF $C(\lambda, \mu)$ ANALOGOUSLY TO THE AWGN CHANNEL

Define S as the sequence of induced service times  $\{S_1, S_2, \ldots\}$  of a an ESTC queuing system with X as the input and Y as the output. Specifically,

$$S_i = \mathcal{Y}_i - \max(\mathcal{Y}_{i-1}, \mathcal{X}_i) \tag{17}$$

For any  $\tilde{\mathcal{X}} \in \Gamma_T$  and  $\tilde{\mathcal{Y}} \in \Gamma_T$ , note that

$$I_{T}(\tilde{\mathcal{X}};\tilde{\mathcal{Y}}) = h_{T}(\tilde{\mathcal{Y}}) - h_{T}(\tilde{\mathcal{Y}}|\tilde{\mathcal{X}})$$
  
$$= h_{T}(\tilde{\mathcal{Y}}) - H\left(\tilde{Y}_{T}|\tilde{\mathcal{X}}\right) - h_{T}\left(\tilde{\mathcal{Y}}_{1},\ldots,\tilde{\mathcal{Y}}_{\tilde{Y}_{T}}|\tilde{Y}_{T},\tilde{\mathcal{X}}\right).$$
(18)

Define  $\widehat{I}_T(\tilde{\mathcal{X}}; \tilde{\mathcal{Y}})$  and  $\tilde{C}(\lambda, \mu)$  as

$$\widehat{I}_{T}(\mathcal{X};\mathcal{Y}) \triangleq h_{T}(\widetilde{\mathcal{Y}}) - h_{T}\left(\widetilde{\mathcal{Y}}_{1},\ldots,\widetilde{\mathcal{Y}}_{\widetilde{Y}_{T}}|\widetilde{Y}_{T},\widetilde{\mathcal{X}}\right),$$
(19)

$$\tilde{C}(\lambda,\mu) \triangleq \sup_{P_{\tilde{\mathcal{X}}}:r(\tilde{\mathcal{X}})=\lambda} \liminf_{T \to \infty} \frac{1}{T} \widehat{I}_{T}(\tilde{\mathcal{X}};\tilde{\mathcal{Y}})$$
(20)

Note that by Lemma 0.2, we have that

Corollary 3.1:

$$C(\lambda,\mu) = \tilde{C}(\lambda,\mu).$$

Now note that for any  $\mathcal{X}$  such that  $r(\mathcal{X}) = \lambda$ , we have:

$$\widehat{I}_{T}(\mathcal{X}; \mathcal{Y}) = h_{T}(\mathcal{Y}) - h_{T}(\mathcal{Y}_{1}, \dots, \mathcal{Y}_{Y_{T}} | Y_{T}, \mathcal{X})$$
$$= h_{T}(\mathcal{Y}) - h_{T}(\mathcal{S}_{1}, \dots, \mathcal{S}_{Y_{T}} | Y_{T}, \mathcal{X})$$
$$= h_{T}(\mathcal{Y}) - h_{T}(\mathcal{S}_{1}, \dots, \mathcal{S}_{Y_{T}} | Y_{T})$$
(21)

$$= h_T(\mathcal{Y}) - E[Y_T](1 - \log \mu) \tag{22}$$

$$\Rightarrow \liminf_{T \to \infty} \frac{\widehat{I}_T(\mathcal{X}; \mathcal{Y})}{T} = \liminf_{T \to \infty} \frac{h_T(\mathcal{Y})}{T} - \lambda(1 - \log \mu)$$
(23)

$$\leq \lambda (1 - \log \lambda) - \lambda (1 - \log \mu) \tag{24}$$

$$=\lambda\log\left(\frac{\mu}{\lambda}\right).$$

(21) follows because the service times are independent of the arrival process in an ESTC; (22) follows because the service times in an ESTC are exponentially distributed of rate  $\mu$ ; (23) follows because for any stable queue,  $r(\mathcal{Y}) = r(\mathcal{X}) = \lambda$ ; and (24) follows from Lemma 0.1; This bound is tight because of Burkes' theorem [15], [16]: a Poisson ( $\lambda$ ) arrival process to an ESTC results in a Poisson ( $\lambda$ ) departure process.

#### IV. A CONVERSE FOR THE TANDEM QUEUE

Very difficult timing channel problem... We still enforce the arrival process  $\mathcal{X}$  to satisfy  $r(\mathcal{X}) = \lambda$ . Define

$$Q_{1,t} = Q_{1,0} + X_t - Y_t$$
$$Q_{2,t} = Q_{2,0} + Y_t - Z_t$$



Fig. 2. The tandem queue

We note that analogous to above, the following relationship holds:

$$\mathcal{X} - Q_1 - \mathcal{Y} - Q_2 - \mathcal{Z}.$$

Thus it follows that

$$p_T(z|x, q_{1,0}, q_{2,0}) = \int_{y \in \Gamma_T} p_T(z|y, q_{2,0}) p_T(y|x, q_{1,0}).$$

Note that it must be the case that  $x_t \ge y_t$  for all  $t \in [0, T]$ , and also that  $y_t \ge z_t$  for all  $t \in [0, T]$ . Thus we can re-write this in terms of a convolution:

$$p_T(z|x, q_{1,0}, q_{2,0}) = \int_{y \in \Gamma_T : 0 \le x - y \le x - z} p_T(z|y, q_{2,0}) p_T(y|x, q_{1,0}).$$
(25)

$$= \int_{x-y=0}^{x-z} p_T(z|y, q_{2,0}) p_T(y|x, q_{1,0}).$$
(26)

where (26) follows by denoting, for  $x \in \Gamma_T$  and  $y \in \Gamma_T$ ,  $x \leq y$  if  $x_t \leq y_t$  for all  $t \in [0, T]$ .

Continuing on, we have:

$$\log p_{T}(z|x, q_{1,0}, q_{2,0})$$

$$= \log \left[ \int_{x-y=0}^{x-z} p_{T}(z|y, q_{2,0}) p_{T}(y|x, q_{1,0}) \right]$$

$$= \log \left[ \int_{x-y=0}^{x-} \mu_{2}^{z_{T}} \mu_{1}^{y_{T}} \exp \left\{ \int_{0}^{T} -\rho_{1} \left( x_{t} + q_{1,0} - y_{t} \right) - \rho_{2} \left( y_{t} + q_{2,0} - z_{t} \right) dt \right\} \right]$$

$$= \log \left[ \left( \mu_{1} \mu_{2} \right)^{x_{T}} \int_{x-y=0}^{x-z} \mu_{1}^{y_{T}-x_{T}} \mu_{2}^{z_{T}-x_{T}} \exp \left\{ \int_{0}^{T} -\rho_{1} \left( x_{t} + q_{1,0} - y_{t} \right) - \rho_{2} \left( y_{t} + q_{2,0} - z_{t} \right) dt \right\} \right]$$

$$= x_{T} \log(\mu_{1} \mu_{2})$$

$$+ \log \left[ \int_{x-y=0}^{x-z} \mu_{1}^{y_{T}-x_{T}} \mu_{2}^{z_{T}-x_{T}} \exp \left\{ \int_{0}^{T} -\rho_{1} \left( x_{t} + q_{1,0} - y_{t} \right) - \rho_{2} \left( y_{t} + q_{2,0} - z_{t} \right) dt \right\} \right]$$

$$= x_{T} \log(\mu_{1} \mu_{2}) + \log \left[ \int_{u=0}^{x-z} f_{1}(u) f_{2}(x - z - u) \right]$$

$$= x_{T} \log(\mu_{1} \mu_{2}) + \log \left[ f_{1} * f_{2}(x - z) \right]$$

$$(27)$$

for appropriately defined functions  $f_1$  and  $f_2$  in (27) and (28).

Now it follows as a consequence that

$$\lim_{T \to \infty} \frac{1}{T} h_T(\mathcal{Z}|\mathcal{X}, Q_{1,0}, Q_{2,0}) = -\lambda \log(\mu_1 \mu_2) - E \{ \log f_1 * f_2(X - Z) \}$$
  

$$\Rightarrow \lim_{T \to \infty} \frac{1}{T} h_T(\mathcal{Z}|\mathcal{X}, Q_{1,0}, Q_{2,0}) \qquad \text{does not depend on } P_X$$
  

$$\Rightarrow \text{max-entropy argument:} \qquad \text{Poisson inputs optimal}$$
  

$$\Rightarrow \text{precise converse:} \qquad \text{with genie info of zero entropy}$$

#### V. DISCUSSION

- Conceptually simple, memoryless calculus to view the "Bits Through Queues" problem and solve it
- Calculus enables first known non-trivial converse for tandem queue

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