

# On the tail decay of M/G/1-type Markov renewal processes

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## Abstract

The tail decay of M/G/1-type Markov renewal processes is studied. The Markov renewal process is transformed into a Markov chain so that the problem of tail decay is reformulated in terms of the decay of the coefficients of a suitable power series. The latter problem is reduced to analyze the analyticity domain of the power series.

## 1 Introduction

Consider a Markov Renewal Process (MRP)  $(X_n, \tau_n)_n$  of M/G/1-type on the state space  $E = \{(i, j, x) : i \geq 0, 1 \leq j \leq m, x \geq 0\}$  defined by the kernel

$$K(x) = \begin{bmatrix} \tilde{B}_0(x) & \tilde{B}_1(x) & \tilde{B}_2(x) & \tilde{B}_3(x) & \dots \\ \tilde{A}_{-1}(x) & \tilde{A}_0(x) & \tilde{A}_1(x) & \tilde{A}_2(x) & \dots \\ & \tilde{A}_{-1}(x) & \tilde{A}_0(x) & \tilde{A}_1(x) & \ddots \\ & & \tilde{A}_{-1}(x) & \tilde{A}_0(x) & \ddots \\ 0 & & & & \ddots & \ddots \end{bmatrix}, \quad x \geq 0,$$

where the  $m \times m$  matrices  $\tilde{A}_k(x)$  and  $\tilde{B}_k(x)$  are defined as follows:

$$\tilde{A}_k(x) = P\{X_{n+1} \in \ell_{i+k}, \tau_{n+1} - \tau_n \leq x | X_0, \dots, X_n, \tau_0, \dots, \tau_n, X_n \in \ell_i, i \geq 1\}, \quad k \geq -1,$$

$$\tilde{B}_k(x) = P\{X_{n+1} \in \ell_k, \tau_{n+1} - \tau_n \leq x | X_0, \dots, X_n, \tau_0, \dots, \tau_n, X_n \in \ell_0\}, \quad k \geq 0.$$

Here  $\ell_i$ , for  $i = 0, 1, \dots$ , denotes the  $i$ -th *level*, i.e., the set of pairs  $\{(i, j), j = 1, \dots, m\}$ .

For  $n \geq 0$  let  $\tilde{G}(n, x)$  be the probability that in  $n$  steps and in time at most  $x$  the system goes from level  $\ell_1$  to level  $\ell_0$ .

An important issue arising in the applications is the analysis of the speed of convergence to zero of the sequence  $\{\tilde{G}(n, x)\}_n$ , as  $n$  tends to infinity, or in

other words, the analysis of the tail decay of the sequence  $\{\tilde{G}(n, x)\}_n$ . In order to simplify the problem, one may apply the Laplace-Stiltjes transform to  $\tilde{A}_k(x)$  and to  $\tilde{G}(n, x)$ , by defining

$$\begin{aligned} A_n(s) &= \int_0^\infty e^{-sx} \tilde{A}_n(dx), \quad n \geq -1, \\ G(w, s) &= \sum_{n=1}^\infty w^n \int_0^\infty e^{-sx} \tilde{G}(n, dx), \quad s \in \mathbb{C}^+0. \end{aligned}$$

In this way, one finds that

$$G(w, s) = w \sum_{n=-1}^\infty A_n(s) G(w, s)^{n+1}, \quad |w| \leq 1, s \in \mathbb{C}^+.$$

Now, let us define

$$\begin{aligned} G(w) &= \lim_{s \rightarrow 0^+} G(w, s), \quad |w| \leq 1, \\ A_n &= \lim_{s \rightarrow 0^+} A_n(s), \quad n \geq -1. \end{aligned}$$

It is proved in [4] that the matrices  $A_n$  for  $n \geq -1$  are nonnegative, and that  $\sum_{n=-1}^\infty A_n$  is a stochastic matrix. Therefore, the matrices  $A_n$  define the homogeneous part of the transition matrix of an M/G/1-type Markov chain. Moreover, the matrix  $G(w)$  solves the matrix equation

$$G(w) = w \sum_{n=-1}^\infty A_n G(w)^{n+1}$$

and  $|G(w, s)| \leq |G(w)|$  for any  $s \in \mathbb{C}^+$ . It is known (see [4]) that, if  $0 \leq w \leq 1$ , the matrix  $G(w)$  is the minimal nonnegative solution of the matrix equation

$$X = w \sum_{n=-1}^\infty A_n X^{n+1}.$$

Moreover, the function  $G(w)$  is analytic for  $|w| < 1$  and its power series expansion  $G(w) = \sum_{n=0}^\infty w^n G_n$ , is such that  $G_n \geq 0$  for any  $n \geq 0$ , and is convergent for  $|w| = 1$ . The coefficients  $G_n$  have the following probabilistic interpretation:  $G_n$  is the probability that in  $n$  steps the system goes from level  $\ell_1$  to level  $\ell_0$ .

Our goal is to estimate the decay rate of the coefficients  $G_n$  of the power series  $G(w)$ . From a classical result in complex analysis [3, Theorem 2.2f], if  $r > 1$  is the convergence radius of  $G(w)$ , then for any matrix norm, one has  $\|G_n\| = O(\theta^n)$  for any  $\theta$  such that  $1/r < \theta < 1$ . Therefore, our problem is reduced to estimating the convergence radius of  $G(w)$ .

We prove that, under suitable mild assumptions, the matrix power series  $G(w)$  is analytic for  $|w| < R$  and convergent for  $|w| \leq R$ . Here  $R = \sigma/\theta(\sigma)$ , where  $\sigma$  is the unique solution of the equation  $\theta'(z)z = \theta(z)$  in the interval  $(0, r_a)$ , where  $r_a > 1$  is the convergence radius of  $A(z) = \sum_{n=-1}^{+\infty} z^{n+1} A_n$  and  $\theta(z)$  is the spectral radius of  $A(z)$ .

The numerical value of  $R$  can be computed by relying on any effective iterative algorithm for solving a nonlinear scalar equation where at each step of the iteration the spectral radius of  $A(z)$  must be computed together with its derivative.

## 2 Tail decay analysis

In this section we study the tail decay of the matrix power series  $G(w) = \sum_{n=0}^{\infty} w^n G_n$ . We recall that  $G(w)$ , for  $|w| \leq 1$ , solves the matrix equation

$$X = w \sum_{n=-1}^{\infty} A_n X^{n+1}. \quad (1)$$

Moreover,  $G_0 = 0$ ,  $G_n \geq 0$  for any  $n \geq 1$  and, if  $0 < w \leq 1$ ,  $G(w)$  is the minimal nonnegative solution of (1).

We denote by  $r_a$  the convergence radius of the matrix power series  $A(z) = \sum_{n=-1}^{+\infty} z^{n+1} A_n$ , and we assume that the matrix  $A(1)$  is irreducible and stochastic. We will denote by  $\theta(z)$  the spectral radius of  $A(z)$ . It is proved in [2, Lemma 1] that, since  $A(1)$  is irreducible,  $\theta(z)$  is a real analytic function for  $0 < z < r_a$ . Moreover,  $\theta(z)$  is strictly increasing for  $0 < z < r_a$ .

The tail decay analysis of  $G(w)$  is performed by estimating the speed of convergence to zero of  $G_n$  as  $n \rightarrow \infty$ . To do this, we determine the analyticity domain of  $G(w)$  on the complex plane. Indeed, from a classical result on analytic functions (see [3, Theorem 2.2f]), if  $G(w)$  is analytic for  $|w| < R$ , where  $R > 1$ , then  $\|G_n\| = O(\sigma^n)$  for any  $1/R < \sigma < 1$  and for any matrix norm.

Define the scalar function

$$\phi_w(z) = w\theta(z), \quad w \in \mathbb{C},$$

and recall that the drift of an M/G/1-type Markov chain is defined by  $\mu = \boldsymbol{\alpha}^T \mathbf{a}$ , where  $\boldsymbol{\alpha}^T$  is the stationary probability vector of  $A(1)$ ,  $\mathbf{a} = \sum_{n=-1}^{+\infty} n A_n \mathbf{e}$ , and  $\mathbf{e}$  is the vector of all ones.

We assume throughout that one of the following two conditions holds:

1.  $\mu \geq 0$
2.  $\mu < 0$ ,  $r_a > 1$  and  $\det(A(z) - zI)$  has a zero outside the closed unit disk.

We prove the following

**Proposition 1.** *The following properties hold:*

1. *the equation  $z\theta'(z) = \theta(z)$  has a unique solution  $\sigma$  in  $(0, r_a)$ ;*
2. *the equation  $\phi_w(z) = z$  has:*
  - *a solution of multiplicity two in  $(0, r_a)$  if  $w = \sigma/\theta(\sigma)$ ,*
  - *two distinct solutions in  $(0, r_a)$  for any  $0 < w < \sigma/\theta(\sigma)$ .*

*Proof.* Define the function  $f_w(t) = \log \phi_w(e^t) - t$ , for  $-\infty < t < \log r_a$ . In [2] it is shown that the function  $\log \theta(e^t)$ , for  $-\infty < t < \log r_a$  is a convex increasing function of  $t$ . Moreover, according to the results of [2], the equation  $f_1(t) = 0$  has in  $(-\infty, \log r_a)$ : two distinct solutions  $t_1 < 0$  and  $t_2 = 0$  if  $\mu > 0$ , a solution of multiplicity two in  $t = 0$  if  $\mu = 0$ , two distinct solutions  $t_1 = 0$  and  $t_2 > 0$

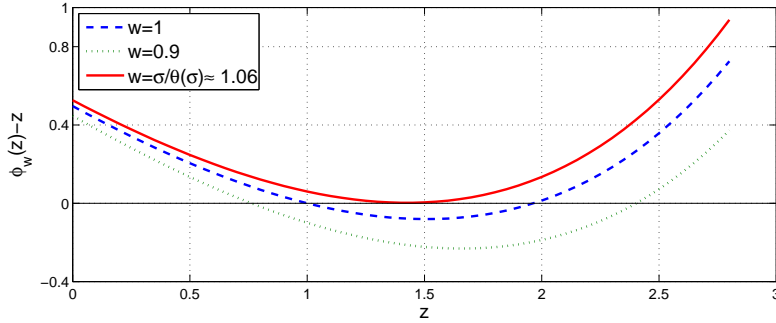


Figure 1: Plot of the function  $\phi_w(z) - z$  for different values of  $w$ , case  $\mu < 0$

if  $\mu < 0$ . In all the cases, for convexity, the function  $f_1(t) = \log(\theta(e^t)) - t$  has a unique global minimum  $t_1 \leq t^* \leq t_2$  in  $-\infty < t < \log r_a$ . Moreover,  $t^*$  is the unique solution to the equation  $f_1'(t) = 0$  in  $(-\infty, \log r_a)$ . By computing the derivative, we find that  $t^*$  is the unique solution to  $e^t \theta'(e^t) = \theta(e^t)$  in  $(-\infty, \log r_a)$ . By setting  $\sigma = e^{t^*}$ , we conclude that  $\sigma$  is the unique solution to  $z\theta'(z) = \theta(z)$  in the interval  $(0, r_a)$ . Concerning the second part, observe that  $\phi_w(z) = z$  has a solution in  $0 < z < r_a$  if and only if the equation  $f_w(t) = 0$  has a solution in  $-\infty < t < \log r_a$ . Since  $f_w(t) = f_1(t) + \log w$ , the equation  $f_w(t) = 0$  has a solution of multiplicity two if  $f_w(t^*) = 0$ , two distinct solutions if  $f_w(t^*) < 0$ . Since  $\sigma = e^{t^*}$ , one finds that  $f_w(t^*) = 1/\theta'(\sigma) = \sigma/\theta(\sigma)$ .  $\square$

Figure 1 shows the behaviour of the function  $\phi_w(z) - z$  for different values of  $w$ .

By Proposition 1, if  $0 < w \leq R$ , the equation  $\phi_w(z) = z$  has at least a solution in  $(0, r_a)$ . Let us denote by  $\xi(w)$  the smallest  $\xi(w) \in (0, r_a)$  such that  $\phi_w(\xi(w)) = \xi(w)$ . Since  $A(1)$  is irreducible, also  $A(\xi(w))$  is irreducible and by the Perron-Frobenius theorem [1], there exists a positive vector  $\mathbf{v}(w)$  such that  $wA(\xi(w))\mathbf{v}(w) = \xi(w)\mathbf{v}(w)$ .

**Proposition 2.** Consider the matrix sequence  $X^{(k)}(w)$  defined by

$$X^{(k+1)}(w) = w \sum_{n \geq -1} A_n (X^{(k)}(w))^{n+1}, \quad k \geq 0, \quad (2)$$

with  $X^{(0)}(w) = 0$ . Then:

1.  $X^{(k)}(w)$  is analytic for  $|w| < R$  and convergent for  $|w| = R$ , where  $R = \sigma/\theta(\sigma)$ ;
2.  $X^{(k)}(w) = \sum_{n=0}^k w^n G_n + \sum_{n=k+1}^{\infty} w^n E_n^{(k)}$ ;
3. if  $0 < w \leq R$ , then  $0 \leq X^{(k)}(w) \leq X^{(k+1)}(w)$  and  $X^{(k)}(w)\mathbf{v}(w) \leq \xi(w)\mathbf{v}(w)$  for any  $k \geq 0$ ;

4. the sequence  $\{X^{(k)}(w)\}_k$  converges uniformly to  $G(w)$  in any closed disk  $\{|w| \leq r\}$ , with  $0 < r \leq R$ .

*Proof.* The analyticity of  $X^{(k)}(w)$  is proved by induction on  $k$ . More specifically, we prove that, for any  $k \geq 0$ ,  $X^{(k)}(w)$  is a matrix power series in  $w$  with nonnegative matrix coefficients, and that  $X^{(k)}(R)\mathbf{v}(R) \leq \xi(R)\mathbf{v}(R)$ . For the nonnegativity of the matrix coefficients and for the positivity of  $\mathbf{v}(R)$ , this latter property implies that  $X^{(k)}(w)$  is analytic for  $|w| < R$  and convergent for  $|w| = R$ . For  $k = 0$  then  $X^{(k)}(w) = 0$  and therefore the property trivially holds. Assume that  $X^{(k)}(w)$  is a power series with nonnegative matrix coefficients such that  $X^{(k)}(R)\mathbf{v}(R) \leq \xi(R)\mathbf{v}(R)$ . Then  $X^{(k+1)}(w)$  is a formal matrix power series, since  $X^{(k+1)}(w) = wA(X^{(k)}(w))$ , where  $A(z) = \sum_{n \geq -1} A_n z^{n+1}$ ; moreover the matrix coefficients of  $X^{(k+1)}(w)$  are an infinite sum of nonnegative matrices since  $A_n \geq 0$  for any  $n \geq -1$ . Observe that, by inductive hypothesis, one has

$$\begin{aligned} X^{(k+1)}(R)\mathbf{v}(R) &= R \sum_{n \geq -1} A_n (X^{(k)}(R))^{n+1} \mathbf{v}(R) \leq \\ &R \sum_{n \geq -1} \xi(R)^{n+1} A_n \mathbf{v}(R) = \xi(R)\mathbf{v}(R), \end{aligned}$$

hence  $X^{(k+1)}(R)\mathbf{v}(R) \leq \xi(R)\mathbf{v}(R)$ .

Let us prove Part 2. For  $|w| \leq 1$  let  $E^{(k)}(w) = X^{(k)}(w) - G(w)$ . We prove by induction on  $k$  that  $E^{(k)}(w) = \sum_{n=k+1}^{\infty} w^n E_n^{(k)}$ . If  $k = 0$  one has  $E^{(0)}(w) = X^{(0)}(w) - G(w) = \sum_{n=1}^{\infty} w^n G_n$ , since  $G_0 = X^{(0)}(w) = 0$ , therefore the property holds. Assume that  $E^{(k)}(w) = \sum_{n=k+1}^{\infty} w^n E_n^{(k)}$ . One has

$$E^{(k+1)}(w) = w \sum_{n \geq -1} A_n ((X^{(k)}(w))^{n+1} - G(w)^{n+1}).$$

By using the identity  $X^n - Y^n = \sum_{i=0}^{n-1} X^i (X - Y) Y^{n-i-1}$ ,  $n \geq 1$ , from the latter equation we obtain

$$E^{(k+1)}(w) = w \sum_{n \geq -1} A_n \sum_{i=0}^n (X^{(k)}(w))^i E^{(k)}(w) G(w)^{n-i}.$$

Therefore  $E^{(k+1)}(w) = \sum_{n=k+2}^{\infty} w^n E_n^{(k+1)}$  for suitable matrix coefficients  $E_n^{(k+1)}$ .

Part 3 can be easily proved by induction on  $k$ .

Concerning Part 4, let  $0 < r \leq R$  and let  $\|\cdot\|_1$  be the 1-norm. Since the matrix coefficients of  $E^{(k)}(w)$  are nonnegative, one has

$$\sup_{|w| \leq r} \|E^{(k)}(w)\|_1 = \sup_{|w| \leq r} \left\| \sum_{n=k+1}^{\infty} w^n E_n^{(k)} \right\|_1 = \left\| \sum_{n=k+1}^{\infty} r^n E_n^{(k)} \right\|_1$$

and the latter quantity converges to zero as  $k \rightarrow \infty$ .  $\square$

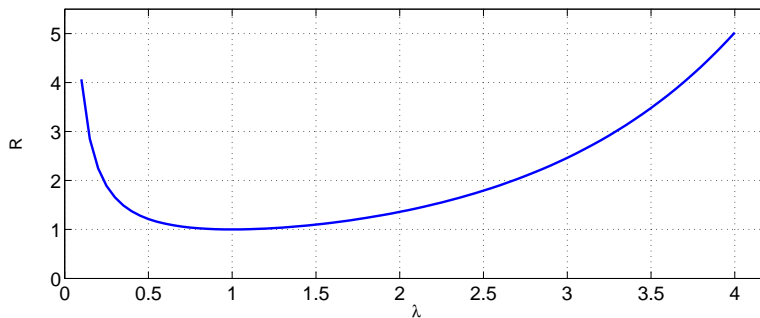


Figure 2: Convergence radius of  $G(w)$  for Example 1, as a function of  $\lambda$

**Theorem 3.** *The matrix function  $G(w)$  is analytic for  $|w| < R$  and convergent for  $|w| \leq R$ , where  $R = \sigma/\theta(\sigma)$  and  $\sigma$  is defined in Proposition 1. Moreover, if  $0 < w \leq R$ , then the spectral radius of  $G(w)$  is  $\xi(w)$ .*

*Proof.*  $G(w)$  is a power series with nonnegative matrix coefficients, therefore it is sufficient to prove that  $G(R)$  is bounded. This latter fact follows from Proposition 2, since the sequence  $\{X^{(k)}(R)\}_k$  is bounded and convergent to  $G(R)$ . In order to prove that  $\rho(G(w)) = \xi(w)$ , we consider the matrix  $B(w) = D^{-1}G(w)D$ , where  $D = \text{Diag}(\mathbf{v}(w))$  and  $\mathbf{v}(w)$  is a positive vector such that  $G(w)\mathbf{v}(w) = \xi(w)\mathbf{v}(w)$ . It easily follows that  $B(w)\mathbf{e} = \xi(w)\mathbf{e}$ , this implies that  $\|B(w)\|_\infty = \xi(w)$ . Since  $\rho(B(w)) \leq \|B(w)\|_\infty = \xi(w)$ , and since  $\xi(w)$  is an eigenvalue of  $B(w)$  one has  $\rho(G(w)) = \rho(B(w)) = \xi(w)$ .  $\square$

From the proof of Proposition 1, the unique solution  $\sigma$  in  $(0, r_a)$  of the equation  $z\theta'(z) = \theta(z)$  is  $\sigma = e^{t^*}$ , where  $t^*$  is the global minimum of the function  $f_1(t) = \log(\theta(e^t)) - t$  in  $(-\infty, \log r_a)$ . Moreover  $t_1 < t^* < t_2$  if  $\mu \neq 0$ , and  $t^* = t_1 = t_2$  if  $\mu = 0$ , where  $t_1$  and  $t_2$  are the solutions to the equation  $f_1(t) = 0$  in  $(-\infty, \log r_a)$ .

**Example 1.** Consider the simple scalar case of a Poisson distribution of parameter  $\lambda > 0$ , where  $A_n = e^{-\lambda} \frac{\lambda^{n+1}}{(n+1)!}$ , for  $n \geq -1$ . We may verify that  $G(w) = \sum_{i=1}^{\infty} w^i e^{i(1-\lambda)} \lambda^{i-1}$ , therefore the convergence radius of  $G(w)$  is  $R_G = \frac{e^{\lambda-1}}{\lambda}$ . Since  $A(z)$  is a scalar function,  $\theta(z) = A(z) = e^{\lambda(z-1)}$ , and the equation  $z\theta'(z) = \theta(z)$  becomes  $\lambda z e^{\lambda(z-1)} = e^{\lambda(z-1)}$ , therefore  $\sigma = \lambda^{-1}$ . According to Theorem 3  $R = \sigma/\theta(\sigma) = \lambda^{-1}/A(\lambda^{-1})$ , which coincides with  $R_G$ . Figure 2 illustrates the convergence radius of  $G(w)$  as a function of  $\lambda$ : we observe that for  $\lambda = 1$  (the null recurrent case) the radius is minimum, and equal to 1, while it diverges as  $\lambda \rightarrow 0$  and  $\lambda \rightarrow +\infty$ .

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