

TRANSIENT ANALYSIS OF A MARKOV MODULATED FLUID QUEUE WITH LINEAR SERVICE RATE

L. RABEHASAINA, B. SERICOLA

IRISA-INRIA

Campus universitaire de Beaulieu

35042 Rennes cedex, France

Email : {landy, sericola}@irisa.fr,

Abstract: We consider an infinite capacity fluid queue governed by a continuous time Markov chain and with linear service rate. The transient behavior of this fluid flow model is described by a linear differential equation. We study the transient distribution of the fluid level in the queue and we derive a partial differential equation satisfied by the cumulative distribution function of the fluid level. Using this partial differential equation, we obtain a simple expression of the moments of this transient distribution, as well as its Laplace transform.

Keywords: Stochastic Models, Fluid Queue, Markov Models, Queueing Systems.

1 INTRODUCTION

We consider in this paper an infinite capacity fluid queue of which level at time t is denoted by $Q(t)$. Fluid arrives in this queue according to a non decreasing process $A(t)$ and leaves the buffer at a rate $\tau(X(t), Q(t))$, where $X(t)$ is a continuous time Markov chain and τ is a non negative function. This is a generalization of standard fluid queues driven by a superposition of On-Off sources (see [Anick et al, 1982]), since here the service rate depends on the queue level, in addition to the state of the underlying Markov chain.

The fluid level in the queue $Q(t)$ then satisfies the following differential equation reflected at 0

$$dQ(t) = dA(t) - \tau(X(t), Q(t))dt + dL_t$$

where L_t is a non decreasing process, (called the *regulator*), interfering only when $Q(t) = 0$ and preventing it from being negative.

We consider in this paper the *linear* model which corresponds to the case where $\tau(X(t), Q(t))$ is linear in $Q(t)$, that is $\tau(X(t), Q(t)) = \mu(X(t))Q(t)$, where μ is a positive function which depends only on the Markov chain X . This model has been studied in [Asmussen and Kella, 1996], [Kella and Stadje, 2002] and [Kella and Whitt, 1999], where $A(t)$ is a Lévy process or a Markov modulated Lévy process. These papers mainly focus on the limiting distribution of

$Q(t)$. The authors identify a functional equation satisfied by the Laplace-Stieltjes transform of the limiting distribution, which can be used to evaluate the two first moments of the buffer level distribution.

We consider in this paper the case where $dA(t) = \lambda(X(t))dt$, where λ is a non negative function of the Markov chain. The evolution of $Q(t)$ is then described by the following equation.

$$dQ(t) = \lambda(X(t))dt - \mu(X(t))Q(t)dt, \quad (1)$$

the term L_t having disappeared because 0 is an impenetrable barrier for $Q(t)$ (see [Asmussen and Kella, 1996]). Note that $(X(t), Q(t))$ is then a Markov process. In the literature, the differential equations governing this process are generally obtained from backward analysis. In this paper we use a forward argument to obtain them, this yields an easier study of the moments of $Q(t)$.

Throughout this paper, X denotes a stationary ergodic Markov chain evolving on a finite state space $S = \{1, \dots, N\}$. We denote by $A = (a_{i,j})_{(i,j) \in S \times S}$ its infinitesimal generator and by $\pi = (\pi_1, \dots, \pi_N)$ its stationary distribution. We also suppose that X is a two sided process, i.e. indexed by \mathbb{R} .

The paper is organized as follows. In Section 2, we give an explicit expression of the fluid level $Q(t)$ and we describe the jumps of its distribution. In Section 3, we derive a partial differential equation satisfied by the cumulative distribution function of $Q(t)$

and we obtain in Section 4 an expression of the moments of $Q(t)$, as well as its Laplace transform.

2 PRELIMINARIES

Let us denote by $Q^y(t)$ the fluid level in the queue at time t with the initial condition $Q^y(0) = y$. For $t \geq 0$, $Q^y(t)$ satisfies the equation (1) and it can be easily checked that $Q^y(t)$ is given by

$$\begin{aligned} Q^y(t) &= y \exp \left(- \int_0^t \mu(X(s)) ds \right) \\ &+ \int_0^t \exp \left(- \int_s^t \mu(X(v)) dv \right) \lambda(X(s)) ds. \end{aligned}$$

We also have the following relation between $Q^y(t)$ and $Q^y(t')$ for $t \geq t' \geq 0$,

$$\begin{aligned} Q^y(t) &= Q^y(t') \exp \left(- \int_{t'}^t \mu(X(s)) ds \right) \\ &+ \int_{t'}^t \exp \left(- \int_s^t \mu(X(v)) dv \right) \lambda(X(s)) ds. \end{aligned}$$

Using the stationarity of X , we have that $Q^y(t)$ and $\tilde{Q}^y(t)$ have the same distribution, where $\tilde{Q}^y(t)$ is given by

$$\begin{aligned} \tilde{Q}^y(t) &= y \exp \left(- \int_{-t}^0 \mu(X(s)) ds \right) \\ &+ \int_{-t}^0 \exp \left(- \int_s^0 \mu(X(v)) dv \right) \lambda(X(s)) ds. \quad (2) \end{aligned}$$

Let us denote by X^* the reversed process of X defined by $X^*(s) = X(-s)$. It is standard that X^* is a continuous time Markov chain with infinitesimal generator $A^* = \Pi^{-1} A^T \Pi$, where T denotes the transpose operator and Π is the diagonal matrix containing the vector π , which is also the stationary distribution of X^* . The variable changes $s := -s$ and $v := -v$ in Relation (2) leads to the following expression for $\tilde{Q}^y(t)$

$$\begin{aligned} \tilde{Q}^y(t) &= y \exp \left(- \int_0^t \mu(X^*(s)) ds \right) \\ &+ \int_0^t \exp \left(- \int_0^s \mu(X^*(v)) dv \right) \lambda(X^*(s)) ds. \quad (3) \end{aligned}$$

Because the initial buffer level y is fixed throughout this paper, and for readability purpose, we simply use the notation $Q(t)$ instead of $\tilde{Q}^y(t)$.

It is easy to check that for a fixed $t > 0$, the distribution of $Q(t)$ has jumps which correspond to the fact that the Markov chain X^* stays during the whole interval $[0, t]$ in a subset of states having the same values for $\lambda(i)$ and $\mu(i)$. More precisely, let

m be the number of distinct pairs $(\lambda(i), \mu(i))$ for $i \in S$. If we denote these m different pairs by $(u(1), v(1)), \dots, (u(m), v(m))$, we obtain the partition B_1, \dots, B_m of the state space S by defining B_l as

$$B_l = \{i \in S \mid (\lambda(i), \mu(i)) = (u(l), v(l))\}.$$

For $l = 1, \dots, m$ and $t > 0$, we denote by $s_l(t)$ the quantities

$$s_l(t) = y e^{-v(l)t} + \frac{u(l)(1 - e^{-v(l)t})}{v(l)}.$$

We then have from Relation (3)

$$Q(t) = s_l(t) \iff X^*(s) \in B_l, \quad \forall s \in [0, t]$$

It follows that

$$\Pr\{Q(t) = s_l(t)\} = \pi_{B_l} e^{A_{B_l B_l} t} \mathbb{1},$$

where $A_{B_l B_l}$ is the sub-infinitesimal generator of dimension $|B_l|$ obtained from A by considering only the internal transitions of the subset B_l and π_{B_l} is the subvector of dimension $|B_l|$ obtained from vector π by considering the stationary probabilities of the subset B_l . The vector $\mathbb{1}$ is the column vector with all its entries equal 1, its dimension being given by the context.

3 DISTRIBUTION OF THE FLUID LEVEL IN THE QUEUE

We denote by $F_i(t, x)$ the cumulative distribution function of $Q(t)$ given that $X^*(0) = i$, that is, $F_i(t, x) = \Pr\{Q(t) \leq x \mid X^*(0) = i\}$. We denote by $F(t, x)$ the column vector $(F_i(t, x))_{i \in S}$, by D the diagonal matrix containing the $\mu(i)$'s and by Λ the diagonal matrix containing the $\lambda(i)$'s.

The distribution $F(t, x)$ of $Q(t)$ verifies the following differential equation.

Theorem 3.1 *For every (t, x) such that $y e^{-\mu(i)t} + \lambda(i)(1 - e^{-\mu(i)t})/\mu(i) \neq x$ for all $i \in S$ we have*

$$\partial_t F(t, x) = A^* F(t, x) + (Dx - \Lambda) \partial_x F(t, x). \quad (4)$$

Proof. Let us denote by P^* the transition probability matrix of the uniformized discrete-time Markov chain associated with X^* . We then have $P^* = I + A^*/\nu$, where I is the identity matrix and ν is the uniformization rate satisfying $\nu \geq \max\{-a_{i,i}^*, i \in S\}$. Let T_1 be the first instant of jump of X^* . T_1 is linked to the uniformized Markov chain via the equality

$$d \Pr\{X^*(T_1) = j, T_1 = u \mid X^*(0) = i\} = p_{i,j}^* \nu e^{-\nu u} du.$$

Defining $G_{i,j}(t, u, x) = \Pr\{Q(t) \leq x \mid X^*(T_1) = j, T_1 = u, X^*(0) = i\}$, we obtain

$$\begin{aligned} F_i(t, x) &= \sum_{j \in S} \int_0^\infty G_{i,j}(t, u, x) \\ &\quad d\Pr\{X^*(T_1) = j, T_1 = u \mid X^*(0) = i\} \\ &= \nu \sum_{j \in S} p_{i,j}^* \int_0^\infty G_{i,j}(t, u, x) e^{-\nu u} du. \end{aligned} \quad (5)$$

Let us define for all $t \geq 0$

$$I_1(i, t, x) = \nu \sum_{j \in S} p_{i,j}^* \int_0^t G_{i,j}(t, u, x) e^{-\nu u} du$$

$$\text{and } I_2(i, t, x) = \nu \sum_{j \in S} p_{i,j}^* \int_t^\infty G_{i,j}(t, u, x) e^{-\nu u} du.$$

We first consider $I_1(i, t, x)$, where we integrate $G_{i,j}(t, u, x) e^{-\nu u}$ for $u \in [0, t]$. Then, when u lies in that interval and $T_1 = u$ and $X^*(0) = i$, we have

$$\begin{aligned} Q(t) &= y \exp\left(-\int_0^t \mu(X^*(s)) ds\right) \\ &\quad + \int_0^t \exp\left(-\int_0^s \mu(X^*(v)) dv\right) \lambda(X^*(s)) ds \\ &= y \exp\left(-\int_0^u \mu(X^*(s)) ds - \int_u^t \mu(X^*(s)) ds\right) \\ &\quad + \int_0^u \exp\left(-\int_0^s \mu(X^*(v)) dv\right) \lambda(X^*(s)) ds \\ &\quad + \int_u^t \exp\left(-\int_0^s \mu(X^*(v)) dv\right) \lambda(X^*(s)) ds \\ &= y e^{-\mu(i)u} \exp\left(-\int_u^t \mu(X^*(s)) ds\right) \\ &\quad + \frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)} \\ &\quad + \int_u^t \exp\left(-\int_0^s \mu(X^*(v)) dv\right) \lambda(X^*(s)) ds \\ &= y e^{-\mu(i)u} \exp\left(-\int_u^t \mu(X^*(s)) ds\right) \\ &\quad + \frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)} \\ &\quad + e^{-\mu(i)u} \int_u^t \exp\left(-\int_u^s \mu(X^*(v)) dv\right) \\ &\quad \quad \lambda(X^*(s)) ds \\ &= \frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)} + e^{-\mu(i)u} Q_u(t), \end{aligned}$$

where

$$\begin{aligned} Q_u(t) &= y \exp\left(-\int_u^t \mu(X^*(s)) ds\right) \\ &\quad + \int_u^t \exp\left(-\int_u^s \mu(X^*(v)) dv\right) \lambda(X^*(s)) ds. \end{aligned}$$

Hence for $u \in [0, t]$, we have

$$\begin{aligned} G_{i,j}(t, u, x) &= \Pr\{Q(t) \leq x \mid X^*(T_1) = j, T_1 = u, X^*(0) = i\} \\ &= \Pr\left\{\frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)} + e^{-\mu(i)u} Q_u(t) \leq x \mid X^*(T_1) = j, T_1 = u, X^*(0) = i\right\}. \end{aligned}$$

Now from the Markov property and the homogeneity of X^* we get that the distribution of $Q_u(t)$ given $X^*(u)$ is the same as the distribution of $Q(t - u)$ given $X^*(0)$, thus

$$\begin{aligned} G_{i,j}(t, u, x) &= \Pr\left\{\frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)} + e^{-\mu(i)u} Q(t - u) \leq x \mid X^*(0) = j\right\} \\ &= \Pr\{Q(t - u) \leq e^{\mu(i)u} (x - \frac{\lambda(i)(1 - e^{-\mu(i)u})}{\mu(i)}) \mid X^*(0) = j\} \\ &= F_j(t - u, x e^{\mu(i)u} + \lambda(i)(1 - e^{\mu(i)u})/\mu(i)). \end{aligned} \quad (6)$$

Let us now consider $I_2(i, t, x)$. For $u \geq t$, the expression of $G_{i,j}(t, u, x)$ is given by

$$\begin{aligned} G_{i,j}(t, u, x) &= \Pr\{y e^{-\mu(i)t} + \lambda(i)(1 - e^{-\mu(i)t})/\mu(i) \leq x \mid X^*(T_1) = j, T_1 = u, X^*(0) = i\} \\ &= 1_{\{y e^{-\mu(i)t} + \lambda(i)(1 - e^{-\mu(i)t})/\mu(i) \leq x\}}. \end{aligned} \quad (7)$$

We denote this indicator function by $\eta(i, t, x)$. $\eta(i, t, x)$ is differentiable in t and x for all (t, x) in the domain $\{(t, x) \mid y e^{-\mu(i)t} + \lambda(i)(1 - e^{-\mu(i)t})/\mu(i) \neq x\}$. Since $\eta(i, t, x)$ is a constant equal to 0 or 1 in this domain, its derivatives in t and x are both equal to 0.

Hence from (6) and (7) we have

$$\begin{aligned} I_1(i, t, x) &= \nu \sum_{j \in S} p_{i,j}^* \int_0^t F_j(t - u, x e^{\mu(i)u}) \\ &\quad + \lambda(i)(1 - e^{\mu(i)u})/\mu(i) e^{-\nu u} du \\ &= \nu e^{-\nu t} \sum_{j \in S} p_{i,j}^* \int_0^t F_j(u, x e^{\mu(i)(t-u)}) \\ &\quad + \lambda(i)(1 - e^{\mu(i)(t-u)})/\mu(i) e^{\nu u} du, \\ I_2(i, t, x) &= \sum_{j \in S} p_{i,j}^* \eta(i, t, x) e^{-\nu t} \\ &= \eta(i, t, x) e^{-\nu t} \end{aligned}$$

where we made the change variable $u := t - u$ in the expression of $I_1(i, t, x)$.

Let us now derive (5) with respect to t . We have $\partial_t F_i(t, x) = \partial_t I_1(i, t, x) + \partial_t I_2(i, t, x)$, and direct calculation yields

$$\begin{aligned} \partial_t I_1(i, t, x) &= -\nu I_1(i, t, x) + \nu \sum_{j \in S} p_{i,j}^* F_j(t, x) \\ &+ \nu e^{-\nu t} (\mu(i)x - \lambda(i)) \sum_{j \in S} p_{i,j}^* \int_0^t \partial_x F_j(u, \\ &xe^{\mu(i)(t-u)} + \lambda(i)(1 - e^{\mu(i)(t-u)})/\mu(i)) e^{\nu u} du \\ &= -\nu I_1(i, t, x) + \nu \sum_{j \in S} p_{i,j}^* F_j(t, x) \\ &+ (\mu(i)x - \lambda(i)) \partial_x \left[\nu e^{-\nu t} \sum_{j \in S} p_{i,j}^* \int_0^t F_j(u, \right. \\ &xe^{\mu(i)(t-u)} + \lambda(i)(1 - e^{\mu(i)(t-u)})/\mu(i)) e^{\nu u} du \left. \right] \\ &= -\nu I_1(i, t, x) + \nu \sum_{j \in S} p_{i,j}^* F_j(t, x) \\ &+ (\mu(i)x - \lambda(i)) \partial_x I_1(i, t, x). \end{aligned}$$

and

$$\begin{aligned} \partial_t I_2(i, t, x) &= -\nu \eta(i, t, x) e^{-\nu t} \\ &= -\nu I_2(i, t, x). \end{aligned}$$

By adding these terms, we get

$$\begin{aligned} \partial_t F_i(t, x) &= -\nu F_i(t, x) \\ &+ \nu \sum_{j \in S} p_{i,j}^* F_j(t, x) + (\mu(i)x - \lambda(i)) \partial_x I_1(i, t, x). \end{aligned}$$

But since $\partial_x I_2(i, t, x) = 0$, we obtain

$$\begin{aligned} \partial_t F_i(t, x) &= -\nu F_i(t, x) \\ &+ \nu \sum_{j \in S} p_{i,j}^* F_j(t, x) + (\mu(i)x - \lambda(i)) \partial_x F_i(t, x), \end{aligned}$$

and the results follow by using the relation $P^* = I + A^*/\nu$. ■

3.1 Moments evaluation

We consider in this section the moments of the transient buffer level $Q(t)$. Let us note that, since the jumps of the cumulative distribution function of $Q(t)$ are known, the equation (4) has a unique solution provided that the initial conditions are fixed. However, we succeed in finding an expression of the moments of $Q(t)$ and an expression of its Laplace transform, without solving this equation.

We first recall the following well-known result

Lemma 3.2 *Let H be the cumulative distribution function of a non negative random variable. For every $r \geq 1$, if the r -th order moment exists, we have*

$$\int_0^\infty x^r dH(x) = r \int_0^\infty x^{r-1} (1 - H(x)) dx.$$

Proof. See for instance [Feller, 1957]. ■

Let us denote by $v_i(t, k)$ the k th moment of $Q(t)$ given that the initial state of the Markov chain X^* is i , that is

$$v_i(t, k) = E(Q(t)^k \mid X^*(0) = i).$$

We denote by $V(t, k)$ the column vector containing the $v_i(t, k)$. By definition, we have $V(t, 0) = \mathbb{1}$. In the following corollary of Theorem 3.1, we give an expression for all the moments of the buffer level $Q(t)$.

Corollary 3.3 *For every $k \geq 1$, we have the following recursion for the process $\{V(t, k), t \geq 0\}$*

$$\begin{aligned} V(t, k) &= e^{(A^* - kD)t} y^k \mathbb{1} \\ &+ e^{(A^* - kD)t} \int_0^t e^{-(A^* - kD)s} k \Lambda V(s, k-1) ds \end{aligned} \quad (8)$$

Proof. Since $A^* \mathbb{1} = 0$, relation (4) can be written as

$$\begin{aligned} -\partial_t (\mathbb{1} - F(t, x)) &= -A^* (\mathbb{1} - F(t, x)) \\ &+ (Dx - \Lambda) \partial_x F(t, x). \end{aligned}$$

Multiplying both sides by x^{k-1} , for $k \geq 1$, and after integration, we get

$$\begin{aligned} -\partial_t \int_0^\infty x^{k-1} (\mathbb{1} - F(t, x)) dx &= -A^* \int_0^\infty x^{k-1} (\mathbb{1} - F(t, x)) dx \\ &+ D \int_0^\infty x^k \partial_x F(t, x) dx \\ &- \Lambda \int_0^\infty x^{k-1} \partial_x F(t, x) dx. \end{aligned}$$

Using Lemma 3.2, we easily get

$$V'(t, k) = (A^* - kD)V(t, k) + k\Lambda V(t, k-1).$$

It is easily checked that the solution to this equation is (8), which completes the proof. ■

The k th moment of $Q(t)$ is then easily given by $E(Q(t)^k) = \pi V(t, k)$. Note that in the case $k = 1$ simple computation yields the following expression for $E(Q(t))$:

$$E(Q(t)) = \gamma \pi e^{(A^* - D)t} \mathbb{1} + \pi (A^* - D)^{-1} [e^{(A^* - D)t} - I] \Lambda \mathbb{1}.$$

It is easy to verify that in the case $\mu(i) = \mu$ (i.e. $D = \mu I$) we have

$$E(Q(t)) = ye^{-\mu t} - \frac{1}{\mu}[e^{-\mu t} - 1]\pi\Lambda\mathbb{1}.$$

We now easily deduce the Laplace transform $\phi(t, \theta) = E(\exp(\theta Q(t)))$ of $Q(t)$ for all t :

Corollary 3.4 *For every $\theta \in \mathbb{R}$, we have*

$$\phi(t, \theta) = \pi \sum_{k=0}^{\infty} \frac{V(t, k)\theta^k}{k!}.$$

Proof. First note that it is easy to see that $Q(t)$ is upper bounded by the deterministic value $c(t, y) = y + t \sup_{i \in S} \lambda(i)$. Besides we have $\partial_{\theta}^k \phi(t, 0) = E(Q(t)^k) = \pi V(t, k)$. Hence we have for all $N \geq 0$

$$\begin{aligned} & \left| \phi(t, \theta) - \sum_{k=0}^N \frac{\partial_{\theta}^k \phi(t, 0)\theta^k}{k!} \right| \\ &= \left| E \left(\exp(\theta Q(t)) - \sum_{k=0}^N \frac{Q(t)^k \theta^k}{k!} \right) \right| \\ &= \left| E \left(\sum_{k=N+1}^{\infty} \frac{Q(t)^k \theta^k}{k!} \right) \right| \\ &\leq \sum_{k=N+1}^{\infty} c(y, t)^k \frac{\theta^k}{k!} \\ &\longrightarrow 0 \quad \text{as } N \rightarrow \infty. \end{aligned}$$

This completes the proof. ■

REFERENCES

Anick D., Mitra D. and Sondhi M. M. 1982, “Stochastic theory of a data-handling system with multiple sources” *The Bell System Tech. Journal*, Vol. 61. Pp1871-1894.

Asmussen S. and Kella O. 1996 “Rate modulation in dams and ruin problem” *Journal of Applied Probability*, Vol. 33(2). Pp523-535.

Feller W. 1957 *An introduction to probability theory and its applications. Vol. 1.* Wiley series in probability and mathematical statistics.

Kella O. and Stadjie W. 2002 “Markov modulated linear fluid networks with Markov additive input” *Journal of Applied Probability*, Vol. 39(2). Pp413-420.

Kella O. and Whitt W. 1999 “Linear Stochastic Fluid Networks” *Journal of Applied Probability*, Vol. 36(1). Pp244-260.

BIOGRAPHY



LANDY RABEHASAINA is a PhD student in Applied Mathematics at the University of Rennes I. His current work deals with stochastic processes applied to fluid queues and stochastic networks.



BRUNO SERICOLA received the Ph.D. degree in computer science from the University of Rennes I in 1988. He has been with INRIA (Institut National de Recherche en Informatique et Automatique, a public research French laboratory) since 1989. His main research activity is in computer and communication systems performance evaluation, dependability and performability analysis of fault-tolerant architectures and applied stochastic processes.