# AN ALGORITHMIC SOLUTION TO THE M/PH/c QUEUE WITH BATCH ARRIVALS 

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#### Abstract

This paper discusses algorithms for deriving the steady state features of the $\mathrm{M} / \mathrm{PH} / \mathrm{c}$ queue with batch arrivals. Many characteristic quantities such as the mean and variance of queue length in continuous time, the mean waiting time, the waiting probability, etc. are obtained in computationally tractable form. Numerical examples show that the effects of changing various parameters of queueing model may be examined at a small computational cost.


## 1. Introduction

Batch arrivals constitute an important class of input processes in the theory of queues. A queueing system is generally represented by $G I / G / C$, where $G I, G, C$ and $X$ denote an interarrival time distribution, a service time distribution, the number of servers and arrival group of random size, respectively. Especially, multiserver queues with batch arrivals have been investigated by a number of authors. Kabak [9,10] obtained the steady state results of $M^{X} / M / C$. Cromie et al. [6] extended and corrected Kabak's results. They also derived how to calculate percentiles or fractiles for the queue length distribution and the waiting time distribution. Holman et al. [8] obtained the moments of queue length of $E_{k}{ }^{X} / M / C$ queue using the roots of the characteristic equation. Baily and Neuts [2] studied the $G I^{X} / M / C$ queue with bounded batch arrivals. They discussed algorithms for the computation of the steady state features and obtained queue length densities at prior to arrivals and at arbitrary times in a modified matrix-geometric form. But all of the above authors assumed that the service time distribution was exponential.

In this paper, we shall discuss algorithms for the computation of the steady state features of the $M^{X} / P H / C$ queue. $P_{H}$ denotes the phase type distribution introduced by Neuts [12]. The phase type distribution is any continuous probability distribution on $[0, \infty)$ which is obtainable as the distribution of the absorption time in a continuous time finite state Markov chain with a single absorbing state. The class of such distributions includes many well-known distribution such as generalized Erlang and hyperexponential (i.e., a mixture of a finite number of exponential) distributions.

The random variable $X$ represents the batch size, and obeys the probability distribution with finite support on positive integers or geometric distribution. This restriction is not essential. But, for the simplicity of algorithms, we shall only treat these cases.

Recently Lucantoni [11] derived an algorithm for computing the stationary probability vector of an infinite state Markov chain whose transition matrix has a block-partitioned structure. We shall first show that the states of $M^{X} / P H / C$ queue have this property by devising the representation of the states. Based on this algorithm, we shall obtain many characteristic quantities such as the mean and variance of queue length in continuous time, the mean waiting time, the waiting probability, etc. These quantities are obtained in computationally tractable forms. We shall also show various numerical examples and obtain qualitative insight into the effect of varying the parameter values. This may be done at a small fraction of the cost for the Monte Carlo simulation of the models.
2. The stationary distributions of the $M^{X} / P H / c$ queue

Consider the $N^{X} / P H / C$ queueing model, in which customers arrive in batches at a c-server unit. The $c$-servers have independent phase type distributed processing times with a representation $(\underline{\alpha}, T)$, where $T$ is a matrix of order $M$. The times between batch arrivals are independent exponentially distributed with common arrival rate $\lambda$. Consecutive batch sizes are independent and obey the probability distribution with finite support on positive integers or geometric distribution. This probability distribution is represented by $\left\{g_{i}\right\}_{i=1}^{\infty}$ with mean $g=\sum_{i=1}^{\infty} i g_{i}$.

In this section, we discuss the stationary distributions of the number of customers in the system at an arbitrary time $t$. In order to obtain the stationary distribution of the $M^{X} / P H / C$ queue, we shall consider the con-
tinuous time Markov chain which represents the transitions of the states of $M^{X} / P H / c$ queue at an arbitrary time. In order to define the states of this Markov chain, it is convenient to define that the index $i \quad(i \geq 0)$ denotes the total number of customers in the system and $j_{k}(1 \leq k \leq M)$ the total number of customers in the $k$-th phase of service. The the state of the system can be represented by an ordered ( $M+1$ )-tuple of nonnegative integers

$$
(2.1) \quad\left(i ; j_{1}, \ldots, j_{M}\right)
$$

Let $i$ be the set of all possible states such that the total number of customers in the system is equal to $i$, and $s_{i}$ the number of states in $i=$ Since $\sum_{k=1} j_{k}=\min (c, i), s_{i}$ is given by

$$
\begin{equation*}
s_{i}=\binom{\min (c, i)+M-1}{M} \tag{2.2}
\end{equation*}
$$

We will number the states in $\underset{i}{ }$ by a suitable rule and refer them by pairs

$$
\text { (2.3) } \quad(i ; m), \quad m=1,2, \ldots, s_{i}, \quad i==0,1,2, \ldots \text {. }
$$

Therefore the infinitesimal generator of this system is given by the matrix

$$
\begin{aligned}
& \underline{0} \quad \underline{1} \quad \underline{2} \cdots \quad \underline{c-1} \quad \underline{c} \quad \underline{c+1} \quad \underline{c+2} \quad \cdots
\end{aligned}
$$

We denote the invariant probability vector of $Q$ by $\underline{x}$, which we may write in the partitioned form $\left\{\underline{x}_{0}, \underline{x}_{1}, \ldots, \underline{x}_{i}, \ldots\right\}$, where $\underline{x}_{i}(i \geq 0)$ are $s_{i}$-vectors.

Let $\tau$ be the real number such that

and $I$ the identity matrix, then the discrete time Markov chain with transition matrix

$$
\begin{aligned}
& \underline{0} \quad \underline{2} \cdots \quad \underline{c-1} \quad \underline{c} \quad \underline{c+1} \quad \underline{c+2} \quad \cdots
\end{aligned}
$$

where $c_{i}=I+\tau^{-1} \tilde{C}_{i} \quad(0 \leqq i \leq c-1), C=I+\tau^{-1} \mathcal{C}^{\prime}, B_{i}=\tau^{-1} \tilde{B}_{i} \quad(1 \leqq i \leqq c)$, $B=\tau^{-1} \tilde{B}_{B}, D_{i j}=\tau^{-1} \tilde{D}_{i j} \quad\left(0 \leqq i \leqq c^{-2}, i+1 \leqq j \leqq c^{-1}\right), D_{i}=\tau^{-1} \tilde{D}_{i}$ ( $0 \leqq i \leqq C^{-1}$ ) and $D=\tau^{-1} \tilde{D}$, has the same invariant probability vector as the continuous time Markov chain whose infinitesimal generator is $Q$. In this paper, we shall analyze about the discrete time Markov chain with transition matrix $p$ instead of the continuous time Markov chain with infinitesimal generator $Q$.

Recently Lucantoni [11] derived an algorithm for computing the stationary probability vector of an infinite state Markov chain whose transition matrix has a block-partitioned structure. The transition matrix (2.6) has this property by devising the representation of the states in the following way.

Let us define dome matrices and vectors given by

$$
\begin{aligned}
& y_{0}=\left(\underline{x}_{0}, \underline{x}_{1}, \ldots, \underline{x}_{C-1}\right) \\
& F=\left(\begin{array}{lllll}
C_{0} & D_{01} & D_{02} & \cdots & D_{0, c-1} \\
B_{1} & C_{1} & D_{12} & \cdots & D_{1, c-1} \\
\vdots & \vdots & \vdots & & \vdots \\
0 & 0 & 0 & \cdots & c_{c-1}
\end{array}\right), \quad G_{i}=\left(\begin{array}{c}
g_{c+i-1} D_{0} \\
g_{C+i-2}{ }^{D} \\
\vdots \\
g_{i}^{D} \\
C-1
\end{array}\right) \quad(i \geq 1), \\
& E=\left(0, \ldots, 0, B_{C}\right) .
\end{aligned}
$$

Then the stochastic matrix $P$ is written by

$$
P=\left(\begin{array}{lllll}
F & G_{1} & G_{2} & G_{3} & \cdots  \tag{2.8}\\
E & C & g_{1} D & g_{2} D & \cdots \\
0 & B & C & g_{1} D & \cdots \\
0 & 0 & B & C & \cdots \\
\vdots & \vdots & \vdots & &
\end{array}\right)
$$

Using the stochastic matrix $P$, we state below a_practical algorithm to calculate the stationary distribution of the $M^{X} / P H / C$ queue by improving the algorithm discussed in Lucantoni [11].

A practical alogirithm
Step 1. Calculate the sequence of matrices $\{H(n), n \geq 0\}$ by
(2.9) $\quad H(0)=B, \quad H(n+1)=B+C H(n)+\sum_{i=1}^{\infty} g_{i} D[H(n)]^{i+1}$.

By above successive substitutions, the sequence $\{H(n)\}$ converges to a matrix $H$, which satisfies
(2.10) $\quad H=B+C H+\sum_{i=1}^{\infty} g_{i} D H^{i+1}$.

Especially the batch size distribution is the probability distribution with finite support on positive integers, we call this Case 1, where $\left\{g_{i}\right\}_{i=1}^{K}$ with mean $g={ }_{i=1}^{K}{ }_{i}^{K} i g_{i}$, then (2.9) reduces to
$H(0)=B, \quad H(n+1)=B+C H(n)+\sum_{i=1}^{K} g_{i} D[H(n)]^{i+1}$,
and the batch size distribution is geometric, we call this Case 2 , where $g_{i}=(1-p) p^{i-1} \quad(i \geqq 1)$ with mean $g=1 /(1-p)$, then (2.9) reduces to
(2.12) $H(0)=B, H(n+1)=B+C H(n)+(1-p) D[I-p H(n)]^{-1}[H(n)]^{2}$.

Step 2. Calculation of the vector $\underline{h}$ of stationary probabilities corresponding to the stochastic matrix $H$.

Step 3. We introduce the square matrix $\tilde{H}$ of order $S_{C}$, whose rows are all identical and equal to the vectior $\underline{h}$, and the vector $\underline{\beta}$ defined by $\underline{\beta}=C \underline{e}+\sum_{i=2}^{\infty} i g_{i-1} D \underline{e}$
$\underline{\mu}=(I-H+\tilde{H})[I-A+\tilde{H}-\Delta(\underline{\beta}) \tilde{H}]^{-1} \underline{e}$,
where $A=B+C+D$ and $\Delta(\beta)$ is the diagonal matrix of order $s_{c}$, with diagonal entries $\beta_{1}, \beta_{2}, \ldots, \beta_{s_{c}}$.
Step 4. Calculate some matrices defined by

$$
=\left[I-C-\sum_{i=1}^{K} g_{i} D H^{i}\right]^{-1} E \quad \text { for Case } 1
$$

(2.15) $\quad=\left[I-C-\sum_{i=1}^{K} g_{i} D H^{i}\right]^{-1} \quad$ for Case 1

$$
=\left[I-c-(1-p) D(I-p H)^{-1}\right]^{-1} E \quad \text { for Case } 2,
$$

$$
N=\left[I-C-\sum_{i=1}^{\infty} g_{i} D H^{i}\right]^{-1} E
$$

$$
L=F+\sum_{i=1}^{\infty} G_{i} H^{i-1} N
$$

$$
\begin{equation*}
=F+\sum_{i=1}^{K} G_{i} H^{i-1}{ }_{N} \quad \text { for Case } 1 \tag{2.16}
\end{equation*}
$$

$$
=F+G_{1}(I-p H)^{-1} N \quad \text { for Case } 2
$$

$$
K=E(I-F)^{-1} \sum_{i=1}^{\infty} G_{i} H^{i-1}+C+\sum_{i=1}^{\infty} g_{i} D H^{i}
$$

$$
=E(I-F)^{-1} \sum_{i=1}^{K} G_{i} H^{i-1}+C+\sum_{i=1}^{K} g_{i} D H^{i} \quad \text { for Case } 1
$$

$$
=E(I-F)^{-1} G_{1}(I-p H)^{-1}+C+(1-p) D(I-p H)^{-1} H \quad \text { for Case } 2
$$

Step 5. The matrices $N, L$ and $K$ are stochastic. (see Lucantoni [11]) Calculate the invariant probability vectors $\underline{d}$ and $\underline{k}$ of the matrices $L$ and $K$.

Step 6. Calculate some vectors defined by

$$
\begin{aligned}
\underline{r}^{*}= & {\left[I-C-\sum_{i=1}^{\infty} g_{i} D H^{i}\right]^{-1}\left[\underline{e}+\left\{A-B-C-\sum_{i=1}^{\infty} g_{i} D H^{i}+\sum_{i=1}^{\infty} i g_{i} D \tilde{H}\right\}\right.} \\
& \left.(I-H-\tilde{H})^{-1} \underline{\mu}\right]
\end{aligned}
$$

$$
\begin{align*}
& =\left[I-C-\sum_{i=1}^{K} g_{i} D H^{i}\right]^{-1}\left[\underline{e}+\left\{A-B-C-\sum_{i=1}^{K} g_{i} D H^{i}+\sum_{i=1}^{K} i g_{i} D H\right\}\right.  \tag{2.18}\\
& \left.(I-H+\tilde{H})^{-1} \underline{\mu}\right] \quad \text { for Case } 1 \\
& =\left[I-C-(1-p) D(I-p H)^{-1} H\right]^{-1}\left[\underline{e}+\left\{A-B-C-(1-p) D(I-p H)^{-1} H\right\}\right. \\
& \left.\left.+(1-p)^{-1} D \tilde{H}\right\}(I-H+\tilde{H})^{-1} \mu\right] \quad \text { for case } 2 \text {, } \\
& \underline{d}^{*}=\underline{e}+\sum_{i=1}^{\infty} G_{i} H^{i-1} \underline{r}^{*}+\left[\sum_{i=1}^{\infty} G_{i}-\sum_{i=1}^{\infty} G_{i} H^{i-1}+\sum_{i=2}^{\infty}(i-1) G_{i} \not H^{\prime}\right] \\
& (I-H+\tilde{H})^{-1} \mu \\
& =\underline{e}+\sum_{i=1}^{K} G_{i} H^{i-1} \underline{r}^{*}+\left[\sum_{i=1}^{K} G_{i}-\sum_{i=1}^{K} G_{i} H^{i-1}+\sum_{i=2}^{K}(i-1) G_{i} \not H^{\prime}\right]  \tag{2.19}\\
& (I-H+\tilde{H})^{-1} \mu \quad \text { for Case } 1 \\
& =e+G_{1}(I-p H)^{-1} \underline{r} *+\left[(1-p)^{-1} G_{1}-G_{1}(I-p H)^{-1}+(1-p)^{-2} p G_{1} \tilde{H}\right] \\
& (I-H+\tilde{H})^{-1} \underline{\text { I }} \quad \text { for Case } 2
\end{align*}
$$

and

$$
\begin{aligned}
& K^{*}=\underline{e}+E(I-F)^{-1} \underline{e}+\left[E(I-F)^{-1}\left\{\sum_{i=1}^{\infty} G_{i}-\sum_{i=1}^{\infty} G_{i} H^{i-1}+\sum_{i=2}^{\infty}(i-1) G_{i} H\right\}\right. \\
& \left.+A-B-C-\sum_{i=1}^{\infty} g_{i} D H^{i}+\sum_{i=1}^{\infty} i g_{i} D \tilde{H}\right]\left(I-H+\not H^{-1} \underline{\mu}\right. \\
& =\underline{e}+E(I-F)^{-1} \underline{e}+\left[E(I-F)^{-1}\left\{\sum_{i=1}^{K} G_{i}-\sum_{i=1}^{K} G_{i} H^{i-1}+\sum_{i=2}^{K}(i-1) G_{i} H\right\}\right. \\
& \left.+A-B-C-\sum_{i=1}^{K} g_{i} D H^{i}+\sum_{i=1}^{K} i g_{i} D \tilde{H}\right](I-H+\tilde{H})^{-1} \underline{\mu} \quad \text { for Case } 1 \\
& =\underline{e}+E(I-F)^{-1}+\left[E ( I - F ) ^ { - 1 } \left\{(1-p)^{-1} G_{1}-G_{1}(I-p H)^{-1}\right.\right. \\
& \left.\left.+(1-p)^{-2} p G_{1} \widetilde{H}\right\}+A-B-C-(1-p) D(I-p H)^{-1} H+(1-p)^{-1} D \tilde{H}\right] \\
& (I-H+\tilde{H})^{-1} \mu \quad \text { for Case } 2
\end{aligned}
$$

Step 7. The stationary probability vectors $y_{0}$ and $\underline{x}_{C}$ are given by (2.21) $\quad y_{0}=\frac{\underline{d}}{\frac{d d^{*}}{}}, \quad \underline{x}_{C}=\frac{\underline{K}}{\underline{K K}^{*}}$.

Using this algorithm, we can obtain the stationary probability vectors ${\underset{y}{0}}_{0}$ and $\underline{x}_{C}$.
3. Moments of queue Length

In this section, we obtained the stationary probability vectors $y_{0}$ and $\underline{x}_{c}$. Using these vectors, we shall obtain the first two moments of the queue length.

Let us recall the stochastic matrix (2.8):

$$
P=\left(\begin{array}{lllll}
F & G_{1} & G_{2} & G_{3} & \cdots \\
E & C & g_{1} D & g_{2} D & \cdots \\
0 & B & C & g_{1} D & \cdots \\
\vdots & \vdots & \vdots & \vdots &
\end{array}\right)
$$

The steady state equations with respect to $P$ are given by

$$
\begin{align*}
& \underline{y}_{0}=\underline{y}_{0} F+\underline{x}_{C} E \\
& \underline{x}_{C}=\underline{y}_{0} G_{1}+\underline{x}_{C} C+\underline{x}_{c+1}{ }^{B}  \tag{3.1}\\
& \underline{x}_{c+i}=\underline{y}_{0} G_{i+1}+\sum_{j=1}^{i} \underline{x}_{c+j-1} g_{i-j+1} D+\underline{x}_{c+i} c+\underline{x}_{c+i+1}{ }^{B} \quad(i \geq 1) .
\end{align*}
$$

We introduce the vector generating function $\underline{X}(z)$ for $0 \leqq z \leqq 1$ in the following way.
(3.2) $\quad \underline{X}(z)=\sum_{i=c}^{\infty} \underline{X}_{i} z^{i-c}$.

Multiplying both hands in (3.1) by $z^{i}$ and summing over $i \geqq 1$, we can easily obtain that $\underline{X}(z)$ satisfies the equation

$$
\begin{align*}
& \underline{X}(z)=y_{0} \sum_{i=1}^{\infty} G_{i} z^{i-1}+\sum_{i=1}^{\infty} \sum_{j=1}^{i} \underline{x}_{c+j-1} g_{i-j+1} D z^{i}+\sum_{i=0}^{\infty} \underline{X}_{c+i} C z^{i} \\
& +\sum_{i=1}^{\infty} \underline{x}_{C+i}^{B z}{ }^{i-1} \\
& =\underline{y}_{0} \sum_{i=1}^{\infty} G_{i} z^{i-1}+\sum_{j=1}^{\infty} \frac{x_{C+j-1}}{} z^{j-1} \sum_{i=j}^{\infty} g_{i-j+1} \mathrm{Dz}^{i-j+1}+\sum_{i=0}^{\infty} \frac{x_{C+i}}{} z^{i}{ }_{C}  \tag{3.3}\\
& +\sum_{i=0}^{\infty} \underline{x}_{c}+i^{B z^{i-1}}-z^{-1} \underline{x}_{c}^{B} \\
& =y_{0} \sum_{i=1}^{\infty} G_{i} z^{i-1}+z^{-1} \underline{X}(z) A(z)-z^{-1} \underline{X}_{C} B, \\
& \text { where } A(z)=B+C z+\sum_{i=1}^{\infty} g_{i} D z^{i+1} \text {. }
\end{align*}
$$

In deriving the moments of queue length, some explicit expressions of the derivatives of the Perron-Frobenius eigenvalues and the associated eigenvectors of the $A(z)$ may be necessary.

For $0 \leqq z \leq 1$, the matrix $A(z)$ has the Perron-Frobenius eigenvalue $\delta(z)$ uniquely. Let $\underline{u}(z)$ and $\underline{v}(z)$ be the corresponding right and left eigenvectors such as

$$
\begin{equation*}
[A(z)-\delta(z) I] \underline{u}(z)=\underline{v}(z)[A(z)-\delta(z) I]=0 \tag{3.4}
\end{equation*}
$$

The following relations are assumed to be hold.

$$
\begin{equation*}
\underline{v}(z) \underline{u}(z)=\underline{v}(z) \underline{e}=1, \quad \underline{v}(1)=\underline{\pi}, \quad \text { and } \underline{u}(1)=\underline{e}, \tag{3.5}
\end{equation*}
$$

where $\pi$ is the steady state vector of the stochastic matrix $A(1)$, and $e$ is the column vector with all entries equal to 1 . We denote by $A^{(j)}(z)$ the matrix obtained by differentiating $;$ times each entry of $A(z)$.

We have to prepare the following.
Proposition 3.1. [11] The derivatives $\delta^{(j)}(1), \underline{u}^{(j)}(1), \underline{v}^{(j)}(1)$, $j \geqq 0$, may be computed recursively for each $j$. These recursion formulae are follows.

$$
\begin{align*}
& \delta^{(0)}(1)=1, \underline{u}^{(0)}(1)=\underline{e}, \underline{v}^{(0)}(1)=\underline{\pi} \\
& \delta^{(1)}(1)=\underline{\pi}^{(1)}(1) \underline{e} \\
& \underline{u}^{(1)}(1)=[I-A(1)+\pi]^{-1}\left[A^{(1)}(1)-\delta^{(1)}(1) I\right]_{\underline{e}}  \tag{3.6}\\
& \left.\underline{v}^{(1)}(1)=\underline{\pi}^{(1)}(1)-\delta^{(1)}(1) I\right][I-A(1)+\Pi]^{-1}
\end{align*}
$$

and for $j \geq 2$

$$
\begin{align*}
\delta^{(j)}(1) & =\sum_{i=1}^{j}\binom{j}{i} \underline{\underline{T}}^{(i)}(1) \underline{u}^{(j-i)}(1)-\sum_{i=1}^{j-1} \delta^{(i)}(1) \underline{\underline{u} u}^{(j-i)}(1) \\
\underline{u}^{(j)}(1) & =[I-A(1)+\Pi]^{-1} \sum_{i=1}^{j}\binom{j}{i}\left[A^{(i)}(1)-\delta^{(i)}(1) I\right]_{\underline{u}}^{(j-i)}(1)  \tag{3.7}\\
& -\left[\sum_{i=1}^{j-1}\binom{j}{i} \underline{v}^{(i)}(1) \underline{A}^{(j-i)}(1)\right] \underline{e} \\
\underline{v}^{(j)}(1) & =\sum_{i=0}^{j-1}\binom{j}{i} \underline{v}^{(i)}(1)\left[A^{(j-i)}(1)-\delta^{(j-i)}(1) I\right][I-A(1)+\pi]^{-1},
\end{align*}
$$

where $I I$ is the square matrix of order $s_{C}$, and each row of it is $\pi$.
We want to derive the first two moments of the queue size, i.e., we shall deduce the formulae for computing $\underline{x}^{(1)}(1) \underline{e}$ and $\underline{x}^{(2)}(1) \underline{e}$. Let us recall the equation (3.3):

$$
\underline{X}(z)=\underline{y}_{0} \sum_{i=1}^{\infty} G_{i} z^{i-1}+z^{-1} \underline{X}(z) A(z)-z^{-1} \underline{x}_{C} B .
$$

Rearranging this equation, we have

$$
\begin{equation*}
\underline{x}(z)[z I-A(z)]=\underline{y}_{0} \sum_{i=1}^{\infty} G_{i} z^{i}-\underline{x}_{C}^{B} . \tag{3.8}
\end{equation*}
$$

If we let $z$ tend to 1 , we get
(3.9) $\quad \underline{X}(1)[I-A(1)]=y_{0} \sum_{i=1}^{\infty} G_{i}-\underline{x}_{C} B$.

Adding $\underline{X}(1) \pi=(\underline{X}(1) \underline{e}) \underline{\pi}=\left(1-\underline{y}_{0} \underline{e}\right) \underline{\pi}$ to both sides of equation (3.9) and recognizing that $\underline{\pi}[I-A(1)+\Pi]^{-1}=\underline{I}$, we have
(3.10) $\underline{X}(1)=\left[\underline{y}_{0} \sum_{i=1}^{\infty} G_{i}-\underline{x}_{C} B\right][I-A(1)+\Pi]^{-1}+\left(1-\underline{y}_{0} e\right) \underline{\pi}$.

Differentiating (3.8) once with respect to $z$ yields
(3.11) $\underline{X}^{(1)}(z)[z I-A(z)]+\underline{X}(z)\left[I-A^{(1)}(z)\right]=y_{0} \sum_{i=1}^{\infty} i G_{i} z^{i-1}$.

Hence as $z \rightarrow 1$, we get
(3.12) $\underline{x}^{(1)}(1)[I-A(1)]+\underline{X}(1)\left[I-A^{(1)}(1)\right]=y_{0} \sum_{i=1}^{\infty} i G_{i}$.

We note that $I-A(1)$ is singular but $I-A(1)+I I$ is nonsingular and $\underline{X}^{(1)}(1) \pi=\underline{X}^{(1)}(1) \underline{e} \underline{\pi}$. Therefore (3.12) becomes
(3.13) $\underline{X}^{(1)}(1)=\left[-\underline{X}(1)\left\{I-C-\sum_{i=1}^{\infty}(i+1) g_{i} D\right\}+\underline{y}_{0} \sum_{i=1}^{\infty} i G_{i}\right][I-A(1)+\Pi]^{-1}$

$$
\left.+\underline{(x}^{(1)}(1) \underline{e}\right) \underline{\pi}
$$

Using (3.10) and (3.13), we have the next theorem.
Theorem 3.2. The first and second factorial moments of the queue size are given by
(3.14)

$$
\begin{aligned}
\underline{x}^{(1)}(1) \underline{e} & \left.=-\underline{X}(1) \underline{u}^{(1)}(1)+\frac{1}{2[1-\delta}(1)(1)\right]
\end{aligned} \delta^{(2)}(1) \underline{x}(1) \underline{e} .
$$

(3.15) $\quad \underline{x}^{(2)}(1) \underline{e}=-\underline{x}^{(1)} \underline{u}^{(2)}(1)-2 \underline{x}^{(1)}(1) \underline{u}^{(1)}(1)$

$$
\begin{aligned}
& +\frac{1}{3\left[1-\delta^{(1)}(1)\right]}\left[3 \delta^{(2)}(1) \underline{x}(1) \underline{e}+3 \delta^{(2)}(1) \underline{x}^{(1)} \underline{u}^{(1)}(1)\right. \\
& +\delta^{(3)}(1) \underline{x}(1) \underline{e}+\underline{y}_{0} \sum_{i=1}^{\infty} i(i-1)(i-2) G_{i} \underline{e}+ \\
& +3 \underline{y}_{0} \sum_{i=1}^{\infty} i(i-1) G_{i} \underline{u}^{(1)}(1)+3 \underline{u}_{0_{i}} \sum_{i=1}^{\infty} i G_{i}{ }^{(2)}(1) \\
& \left.+\underline{y}_{0} \sum_{i=1}^{\infty} G_{i} \underline{u}^{(3)}(1)-\underline{x}_{c} \underline{u}^{(3)}(1)\right] .
\end{aligned}
$$

Proof: Multiplying (3.8) on the right by $\underline{u}(z)$, we get

$$
\begin{equation*}
[z-\delta(z)] \underline{x}(z) \underline{u}(z)=\underline{y}_{0_{i}} \sum_{i=1}^{\infty} G_{i} z^{i} \underline{u}(z)-\underline{x}_{C} B \underline{u}(z) . \tag{3.16}
\end{equation*}
$$

Differentiating this with respect to $z$ and rearranging the results,

$$
\begin{align*}
\underline{x}^{(1)}(z) \underline{u}(z) & =-\underline{x}(z) \underline{u}^{(1)}(z)+\frac{1}{z-\delta(z)}\left[-\left\{1-\delta \delta^{(1)}(z)\right\} \underline{x}(z) \underline{u}(z)\right.  \tag{3.17}\\
& \left.+\underline{y}_{0} \sum_{i=1}^{\infty} i G_{i} z^{i-1} \underline{u}(z)+\underline{y}_{0} \sum_{i=1}^{\infty} G_{i} z^{i} \underline{u}^{(1)}(z)-\underline{x}_{C} \underline{u}^{(1)}(z)\right] .
\end{align*}
$$

Letting $z \rightarrow 1$ and using L'Hospital's rule, we have (3.14) after some tedious computations.

Differentiating (3.16) twice with respect to $z$ and rearranging the terms, we get

$$
\begin{align*}
\underline{x}^{(2)}(z) \underline{u}(z) & =-{\underline{\underline{x}}(z) \underline{u}^{(2)}(z)-2 \underline{x}^{(1)}(z) \underline{u}^{(1)}(z)}+\frac{1}{z-\delta(z)}\left[\delta^{(2)}(z) \underline{x}(z) \underline{u}^{(z)}-2\left\{1-\delta^{(1)}(z)\right\} \underline{x}^{(1)}(z) \underline{u}(z)\right.  \tag{3.18}\\
& -2\left\{1-\delta^{(1)}(z)\right\} \underline{x}^{(z)} \underline{\underline{u}}^{(1)}(z)+\underline{y}_{0} \sum_{i=1}^{\infty} i(i-1) G_{i} z^{i-2} \underline{u}^{(z)} \\
& \left.+2 \underline{u}_{0} \sum_{i=1}^{\infty} i G_{i} z^{i-1} \underline{u}^{(1)}(z)+\underline{u}_{0} \sum_{i=1}^{\infty} G_{i} z^{i} \underline{u}^{(2)}(z)-\underline{x}_{c} \underline{\underline{u}}^{(2)}(z)\right] .
\end{align*}
$$

Letting $z \rightarrow 1$ and using L'Hospital's rule, we have (3.15) after tedious computations.

Especially, we have the next corollary for Case 1 and Case 2 defined in Section 2.

Corollary 3.3. For Case 1,

$$
\begin{align*}
\underline{x}^{(1)}(1) \underline{e} & =-\underline{X}^{\left.(1) \underline{u}^{(1)}(1)+\frac{1}{2[1--\delta}{ }^{(1)}(1)\right]}\left[\delta^{(2)}(1) \underline{x}(1) \underline{e}\right.  \tag{3.19}\\
& +\underline{y}_{0} \sum_{i=1}^{K} i(i-1) G_{i} \underline{e}+2 \underline{u}_{0} \sum_{i=1}^{K} i G_{i} \underline{u}^{(1)}(1)+\underline{y}_{0} \sum_{i=1}^{K} G_{i} \underline{u}^{(2)}(1)
\end{align*}
$$

$$
\left.-\underline{x}_{C}^{B \underline{u}^{(2)}}(1)\right]
$$

(3.20)

$$
\begin{align*}
\underline{x}^{(2)}(1) \underline{e} & =-\underline{x}^{(1) \underline{u}^{(2)}(1)-2 \underline{x}^{(1)}(1) \underline{u}^{(1)}(1)} \\
& +\frac{1}{3\left[1-\delta^{(1)}(1)\right]}\left[3 \delta^{(2)}(1) \underline{x}^{(1)}(1) \underline{e}+3 \delta^{(2)}(1) \underline{x}^{(1) \underline{u}^{(1)}(1)}\right. \\
& +\delta^{(3)}(1) \underline{x}^{(1) \underline{e}+\underline{y}_{0} \sum_{i=1}^{K} i(i-1)(i-2) G_{i} \underline{e}} \\
& +3 \underline{y}_{0} \sum_{i=1}^{K} i(i-1) G_{i} \underline{u}^{(1)}(1)+3 \underline{y}_{0} \sum_{i=1}^{K} i G_{i} \underline{u}^{(2)}(1)  \tag{1}\\
& +\underline{y}_{0} \sum_{i=1}^{K} G_{i} \underline{u}^{(3)}(1)-{\left.\underline{x}_{C} B \underline{u}^{(3)}(1)\right] .}^{l} .
\end{align*}
$$

For Case 2,
(3.21) $\quad \underline{x}^{(1)}(1) \underline{e}=-\underline{x}^{(1)} \underline{u}^{(1)}(1)+\frac{1}{2\left[1-\delta^{(1)}(1)\right]}\left[\delta^{(2)}(1) \underline{x}(1) \underline{e}\right.$

$$
\begin{aligned}
& +2 p(1-p)^{-3} \underline{y}_{0} G_{1} \underline{e}+2(1-p)^{-2} \underline{y}_{0} G_{1} \underline{u}^{(1)}(1) \\
& \left.+(1-p)^{-1} \underline{y}_{0} G_{1} \underline{u}^{(2)}(1)-\underline{x}_{c} \underline{\underline{u}}^{(2)}(1)\right]
\end{aligned}
$$

(3.22) $\quad \underline{x}^{(2)}(1) \underline{e}=-\underline{x}^{(1)} \underline{u}^{(2)}(1)-2 \underline{x}^{(1)}(1) \underline{u}^{(1)}(1)$

$$
\begin{aligned}
& +\frac{1}{3\left[1-\delta^{(1)}(1)\right]}\left[3 \delta^{(2)}(1) \underline{x}^{(1)}(1) \underline{e}+3 \delta^{(2)} \underline{x}^{(1)} \underline{u}^{(1)}(1)\right. \\
& +\delta^{(3)}(1) \underline{x}(1) \underline{e}+6 p^{2}(1-p)^{-4} \underline{y}_{0} G 1 \underline{e}+6 p(1-p)^{-3} \underline{y}_{0} G_{1} \underline{u}^{(1)}(1) \\
& \left.+3(1-p)^{-2} \underline{u}_{0} G_{1} \underline{u}^{(2)}(1)+(1-p)^{-1} \underline{u}_{0} G_{1} \underline{u}^{(3)}(1)-\underline{x}_{C} \underline{u}^{(3)}(1)\right]
\end{aligned}
$$

The higher factorial moments of the queue size can be computed in the same manner but the formulae become uninspiringly complicated. Thus they will not be shown here.

Burke [5] shows, using a result from renewal theory, that the probability of an arbitrary customer being in the $n$-th position is given by (3.23) $\quad r_{n}=\frac{1}{9} \sum_{i=n}^{\infty} g_{i}=\frac{1}{9}\left(1-\sum_{i=1}^{n-1} g_{i}\right)$.

The probability that a randomly chosen customer is in the $k$-th position in line (including the ones being served) immediately following an arrival is equal to

$$
\begin{equation*}
\hat{p}_{k}=P(k-\text { th in line })=\sum_{i=0}^{k-1} \underline{x}_{i} \underline{e r}_{k-i} \tag{3.24}
\end{equation*}
$$

Let $W_{1}$ snd $W$ be the time until the first customer of the batch and an arbitrary customer of the batch enter the service, respectively. Using (3.23) and (3.24), we have

$$
\begin{align*}
& P\left(W_{1}>0\right)=\sum_{i=c}^{\infty} \underline{x}_{i} e=1-\sum_{i=0}^{c-1} \underline{x}_{i} e,  \tag{3.25}\\
& P(W>0)=\sum_{i=c+1}^{\infty} \hat{p}_{i}=1-\sum_{i=0}^{c} \hat{p}_{i} . \tag{3.26}
\end{align*}
$$

## 4. Numerical results

Using the results obtained in section 2 and 3 , we can get many characteristic quantities such as mean queue length and mean system length in continuous time, variance of queue length and variance of system length in continuous time, mean waiting time, mean system time, and the waiting probability of the first customer of the batch and an arbitrary customer of the batch. For example, mean waiting time is obtained by using (3.8) and Little's formula. We calculated mean waiting times for various service time distribution, the number of servers, mean batch size, and arrival batch type (constant or geometric).

Figure 1 gives the mean waiting times for $g=4$ and constant and geometric batch sizes. Note that the geometric distribution leads to longer mean waiting time than the constant batch sizes. Since geometric distribution has higher variance than constant, this means that the higher the variance of the batch size, the longer the mean waiting time, which is an intuitively appealing result. When $c$ is larger than 1 , it was also found that, in the heavy traffic case, the larger the coefficient of variation of the service time distribution, the longer the mean waiting time. But, in the light traffic case, the smaller the coefficient of variation of the service time distribution, the longer the mean waiting time. This result does not hold in the single server case ( $c=1$ ).

Table 1 gives some other measures for the constant and geometric case if $g=8$ and $c=4$.

More numerical results are shown in the extended version of this paper [2].

Fig. 1. Sample charts for measures of efficiency $M^{X} / P H / C$ for $g=4$ and mean waiting time. ( $H_{2}$ denotes a hyperexponential distribution with two phases and its coefficient of variation is $\sqrt{2} . \rho$ denotes the traffic intensity and is given by $\rho=\frac{\lambda g}{\mu c}$, where $\frac{1}{\mu}$ is mean service time.)


Table 1. Various measures of the $M^{X} / P H / C$ queue

|  | Constant batch size | $M^{X} / E_{2} / 4$ | Batch size 8 |  |
| :---: | :---: | :---: | :---: | :---: |
| $\rho$ | $P(W>0)$ | $E W$ | $E L$ | $V L$ |
| 0.1 | 0.55000 | 0.51754 | 0.60702 | 3.66512 |
| 0.2 | 0.60000 | 0.66419 | 1.33135 | 8.67589 |
| 0.3 | 0.65000 | 0.85302 | 2.22362 | 15.91077 |
| 0.4 | 0.70000 | 1.10510 | 3.36816 | 27.07257 |
| 0.5 | 0.75000 | 1.45838 | 4.91677 | 45.79947 |
| 0.6 | 0.80000 | 1.98876 | 7.17303 | 80.98025 |
| 0.7 | 0.85000 | 2.87332 | 10.84530 | 159.08914 |
| 0.8 | 0.90000 | 4.64331 | 18.05859 | 389.65244 |
| 0.9 | 0.95000 | 9.95498 | 39.43792 | 1681.55060 |


| Constant batch size $M^{\text {X }} / H_{2} / 4$ Batch size 8 |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| $\rho$ | $P(W>0)$ | EW | EL | $V L$ |
| 0.1 | 0.55000 | 0.36881 | 0.54672 | 2.80784 |
| 0.2 | 0.60000 | 0.51805 | 1.21444 | 7.12798 |
| 0.3 | 0.65000 | 0.72076 | 2.06491 | 14.12545 |
| 0.4 | 0.70000 | 0.99954 | 3.19927 | 26.09998 |
| 0.5 | 0.75000 | 1.39886 | 4.79773 | 48.01257 |
| 0.6 | 0.80000 | 2.00786 | 7.21887 | 92.04675 |
| 0.7 | 0.85000 | 3.03473 | 11.29725 | 194.59997 |
| 0.8 | 0.90000 | 5.10435 | 19.53393 | 506.57233 |
| 0.9 | 0.95000 | 11.34641 | 44.42981 | 2282.53285 |
| Geometric batch size $M^{X} / E_{2} / 4$ Mean batch size 8 |  |  |  |  |
| $\rho$ | $P(W>0)$ | EW | EL | $V L$ |
| 0.1 | 0.62627 | 1.49308 | 0.99723 | 15.18963 |
| 0.2 | 0.66667 | 1.76103 | 2.20883 | 35.88925 |
| 0.3 | 0.70738 | 2.10590 | 3.72708 | 65.47637 |
| 0.4 | 0.74839 | 2.56613 | 5.70581 | 110.37438 |
| 0.5 | 0.78968 | 3.21091 | 8.42183 | 184.05185 |
| 0.6 | 0.83124 | 4.17864 | 12.42873 | 318.80830 |
| 0.7 | 0.87306 | 5.79222 | 19.01822 | 609.07628 |
| 0.8 | 0.91513 | 9.02041 | 32.06532 | 1438.25712 |
| 0.9 | 0.95745 | 18.70696 | 70.94507 | 5924.60627 |
| Geometric batch size |  |  | $M^{X} / \mathrm{H}_{2} / 4$ Mean batch size 8 |  |
| $\rho$ | $P(W>0)$ | EW | EL | $V L$ |
| 0.1 | 0.62545 | 1.26382 | 0.90553 | 12.99231 |
| 0.2 | 0.66531 | 1.54429 | 2.03543 | 31.94990 |
| 0.3 | 0.70570 | 1.90971 | 3.49165 | 60.73721 |
| 0.4 | 0.74658 | 2.40224 | 5.44358 | 106.99879 |
| 0.5 | 0.78790 | 3.09776 | 8.19551 | 186.38537 |
| 0.6 | 0.82694 | 4.14805 | 12.35331 | 337.01922 |
| 0.7 | 0.87174 | 5.90725 | 19.34030 | 670.69670 |
| 0.8 | 0.91419 | 9.43785 | 33.40112 | 1643.25714 |
| 0.9 | 0.95695 | 20.05233 | 75.78837 | 6978.95779 |

EW : Mean waiting time, EL : Mean system length
$V L$ : Variance of system length

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## References

[1] Baba, Y.: Algorithmic Methods for PH/PH/1 Queues with Batch Arrivals or Services. Journal of Operations Research Society of Japan, Vol. 26 (1983), (to appear).
[2] Baba, Y.: An Algorithmic Solution to the $M^{X} / \mathrm{PH} / \mathrm{c}$ Queue. Research Reports on Information Sciences, B-112, Department of Information Sciences, Tokyo Institute of Technology.
[3] Baily, D. E. and Neuts, M. F.: Algorithmic Methods for Multi-Server Queues with Group Arrivals and Exponential Servers. European Journal of Operations Research, Vol. 8 (1981), 184-196.
[4] Bellman, R.: Introduction to Matrix Analysis. MacGraw-Hil1, New York, 1960.
[5] Burke, P. J.: Delays in Single Server Queues with Batch Input. Operations Research, Vol. 23 (1975), 830-833.
[6] Cromie, M. V., Chaudhry, M. L. and Grassman, W. K.: Further Results for the Queueing System $M^{X} / M / c$. Journal of Operational Research Society, Vo1. 30 (1979), 755-763.
[7] Gross, D., and Harris, C. M.: Fundamentals of Queueing Theory. New York; John Wiley and Sons, 1974.
[8] Holman, D. F., Grassman, W. K., and Chaudhry, M. L.: Some Results of the Queueing System $\mathrm{E}_{\mathrm{k}}^{\mathrm{X}} / \mathrm{M} / \mathrm{c}$. Naval Research Logistics Quarterly, Vol. 27 (1980), 217-222.
[9] Kabak, I. W.: Blocking and Delays in $M^{(n)} / M / c$ Bulk Queueing Systems. Operations Research, Vol. 16 (1968), 830-840.
[10] Kabak, I. W.: Blocking and Delays in $M^{(X)} / M / c$ Bulk Arrival Queueing Systems. Management Science, Vo1.17 (1970), 112-115.
[11] Lucantoni, D.: Numerical Methods for a Class of Markov Chains Arising in Queueing Theory. M.S. Thesis, Department of Statistics and Computing Sciences, University of Delaware, 1978.
[12] Neuts, M. F.: Probability Distribution of Phase Type. In Liber Amicorum Professor Emeritus H. Florin, Department of Mathematics, University of Louvain, 1975, 173-206.
[13] Neuts, M. F.: Renewal Processes of Phase Type. Naval Research Logistics Quarterly, Vol. 25 (1978), 445-454.
[14] Neuts, M. F.: Markov Chains with Applications in Queueing Theory, Which Have a Matrix-Geometric Invariant Vector. Advanced Applied Probability, Vol. 10 (1978), 185-212.
[15] Neuts, M. F.: Some Algorithms for Queues with Group Arrivals or Group

Services. Proceedings of loth Annual Pittsburgh Conference. Modeling and Simulation, Vol.10, pt. 2 (1979), 311-314.
[16] Neuts, M. F.: Matrix-Geometric Solutions in Stochastic Models - An Algorithmic Approach. Johns Hopkins University Press, 1981.
[17] Ramaswami, V.: N/G/1 Queue and Its Detailed Analysis. Advanced Applied Probability, Vol. 17 (1980), 222-261.
[18] Takahashi, Y. and Takami, Y.: A Numerical Method for the Steady State Probabilities of a GI/G/c Queueing System in a General Class. Journal of Operations Research Society of Japan, Vol. 19 (1976), 147-157.

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