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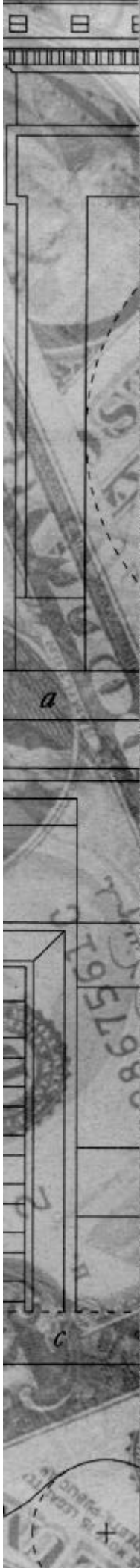

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A Single-Server Queue with Markov Modulated Service Times*

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Abstract

We study an $M/MMPP/1$ queueing system, where the arrival process is Poisson and service requirements are Markov modulated. When the Markov Chain modulating service times has two states, we show that the distribution of the number-in-system is a superposition of two matrix-geometric series and provide a simple algorithm for computing the rate and coefficient matrices. These results hold for both finite and infinite waiting space systems and extend results obtained in Neuts [5] and Naoumov [4].

Numerical comparisons between the performance of the $M/MMPP/1$ system and its $M/G/1$ analogue lead us to make the conjecture that the $M/MMPP/1$ system performs better if and only if the total switching probabilities between the two states satisfy a simple condition. We give an intuitive argument to support this conjecture.

1 Overview

Consider the following FCFS single-server queue: the arrival process is Poisson and service times are exponentially distributed. However, the rates of these exponential service times are determined by an underlying Markov chain. Transitions of the Markov chain take place at service completions.

Suppose the Markov chain has m states. When a service is completed, the Markov chain makes a transition. If the new state of the Markov chain is i, $1 \leq i \leq m$, then the rate of next exponential service time will be μ_i. We will call this an $M/MMPP/1$ queueing system.

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Our interest in this type of queueing system comes from the study of service systems with human servers. Employee learning and turnover cause the sequence of service-time distributions to exhibit systematic non-stationarities: as an employee learns, his or her service speed increases; when an employee turns over, s/he is usually replaced by a new person with lower service speeds. We wish to understand the effect of employee learning and turnover on measures of system performance such as average waiting time and queue length.

We model employee learning and turnover as transitions through states of a Markov chain. After each service an employee may learn and advance to a higher skill level with a pre-specified probability. After each service an employee may also turn over with another pre-specified probability, in which case s/he is replaced by a new employee at the lowest skill level. Skill levels correspond to states of the Markov chain and the Markov chain modulates the service-time distribution. In the simplest case, when there is only one employee, the human server queueing system becomes an $M/MMPP/1$ system.

In addition to modeling server "learning and turnover", the $M/MMPP/1$ queue may be used to model a processor in a data network. The processor works at a constant speed but processes jobs from several sources. The aggregate arrival process is a stationary Poisson process, but the source from which a particular job comes (the job "type") is determined by an underlying Markov chain. Jobs from different sources carry with them exponentially distributed amounts of work with different means.

When the waiting space is infinite, the dynamics of the two systems are equivalent. When there is a finite limit on the waiting space, however, the behavior of the two systems differs. In the data-processor model, arriving jobs that are lost still generate transitions of the modulating Markov chain, and changes in the service-time distribution from one job to the next depend on whether or not the waiting space is full. Alternatively, in the human-server model it is service completions that generate transitions of the modulating Markov chain, and these transitions are unaffected by lost arrivals.

Using a matrix difference equation approach, we are able to obtain a complete characterization of the system's behavior when the Markov chain has two states ($m = 2$). In this case, we can also use closed-form solutions to the resulting cubic equations to obtain *exact* solutions for the computation of required rate coefficient matrices in the numerical study. Our analysis yields the following results.

We obtain traditional measures of queueing performance for this $M/MMPP/1$ system: the

distribution of the number of customers in the system and, in turn, the system utilization, the average number in the system, the average waiting time in queue and in the system. In the case of systems with finite waiting rooms we also obtain the loss probability.

More fundamentally we show that, for systems with either infinite or finite waiting spaces, the steady-state distribution of the number of customers in the system can be represented as the superposition of two, matrix-geometric series: $X_n = (R_1^n K_1 + R_2^n K_2) X_0$. Here R_1 and R_2 are two square matrices and X_n is the vector of steady-state system probabilities for states which have n customers in the system.

Furthermore, we prove that even when system utilization is strictly less than one, the spectral radius of at least one of the rate matrices will *always* be at least one. In this case, the process is ergodic and exhibits a unique, positive steady-state distribution, even though an eigenvalue lies outside the interior of the unit disk.

Moreover, our analysis develops explicit, computable analytical expressions for both the rate and coefficient matrices of the geometric series. Thus, for the case of a 2-state Markov chain, we obtain an *efficient computational procedure* for calculating the steady-state distribution of the number-in-system for $M/MMPP/1$ systems with both finite and infinite waiting rooms. In the discussion at the end of this paper, we also discuss how this procedure may be extended to $M/MMPP/1$ systems whose underlying Markov chain has $m \geq 3$ states.

For the infinite waiting space system, we compare the $M/MMPP/1$ model with an analogous $M/G/1$ model with the same arrival rate and the same first two moments of service time. Through numerical examples we show that the $M/G/1$ system, which has independent service times, does not necessarily out-perform the $M/MMPP/1$ system with correlated service times. When the transition probabilities of the modulating Markov chain are invariant across states, the $M/MMPP/1$ system is equivalent to an $M/H_2/1$ system, and therefore it has the same expected backlog as its $M/G/1$ analogue. When the modulating Markov chain's transition probabilities out of the current state fall below these $M/H_2/1$ transition probability levels, however, numerical results show that $M/MMPP/1$ performance suffers. Conversely, when the transition probabilities out of the current state exceed these levels, then the expected backlog in the $M/MMPP/1$ system is smaller than in the $M/H_2/1$ system. In the finite waiting space case, loss probabilities of the $M/MMPP/1$ system and its $M/G/1$ analogue exhibit the same pattern.

This numerical evidence leads us to believe that the pattern of observed differences between the

$M/MMPP/1$ system and its $M/G/1$ analogue is provably true. We give an intuitive argument to support this conjecture.

2 Literature Review

The $M/MMPP/1$ system is a special case of a "Quasi Birth and Death" (QBD) process. QBD processes can be used to model a wide variety of stochastic systems, in particular many telecommunications systems. For background and examples, see Neuts [5] and Servi [7].

Neuts's [5] seminal work characterizes QBD systems with countable state spaces as having, when a certain boundary condition holds, a steady-state distribution of the number-in-system that can be described as a single, matrix-geometric series: $X_n = R^n X_0$. The rate matrix R may be difficult to calculate, however, and the required boundary condition that R must satisfy is difficult to verify and not guaranteed to hold.

For finite QBD processes with a limit of N in the system, Naoumov [4] develops results that are similar to ours. He demonstrates that the steady-state distribution of the number-in-system can be represented as the superposition of two matrix geometric series. His results differ from ours, however, in two important ways. First, his characterization relies on finiteness of the QBD process and cannot be generalized in a straightforward fashion to infinite QBD systems. Second, his determination of the rate matrices, R_1 and R_2, requires the computation of two infinite series of (recursively defined) matrices. Hence his solution is not easily computable.

Thus, for $M/MMPP/1$ systems with $m = 2$, we have developed a characterization of system performance that represents a link between Neuts's single-geometric-series characterization of infinite QBD processes and Naoumov's dual-geometric-series characterization of finite QBD systems. It is a single characterization of system performance that covers both the finite and countable-state-space cases. In addition, it requires no assumptions concerning the rate matrices, and its rate matrices are easy to compute.

For $M/MMPP/1$ systems with $m \geq 3$, however, our characterization has not been proved. In particular, the determination of the rate matrices becomes more difficult. (For a further discussion, see the Conclusion, §6.) Servi[7] provides efficient numerical procedures for solving QBD systems such as these.

Morrice et al. [3] study Markovian queueing systems in which inter-arrival times and service

times are modulated according to a deterministic, cyclic structure. For the case of cyclic service times (and stationary inter-arrival times) this model is a special case of ours.

Prabhu [6] develops a Markov-modulated model that applies to the infinite waiting space, data-processor systems described in the introduction. The analysis yields elegent, Wiener-Hopf representations of the waiting-time distribution of jobs. Zhu and Li [9] develop MacLaurin series expansions to describe these quantities. In that they characterize waiting times, rather than the distribution of the number-in-system, these works complement ours. We also note that the analyses apply only to systems with infinite waiting spaces, while we characterize both infinite and finite waiting-space systems.

The rest of the paper will be organized as follows. In §3.1-§3.3 we give a complete solution to the steady-state probability distribution of the number-in-system of an $M/MMPP/1$ system. Then in §3.4 we compute important queueing performance measures, such as average number in the system. In §4 we analyze the finite waiting space queueing system, $M/MMPP/1/N$. In §5 we present numerical analyses which compare both the infinite and finite systems to their analogues that have *i.i.d.* service times. Finally, in §6 we discuss possible extensions of our results.

3 $M/MMPP/1$ queueing system solution

3.1 The steady-state probability distribution.

In the following analysis, $m = 2$, i.e., the underlying Markov chain has only two states. We denote the two states of the Markov chain as fast, F, and slow, S.

Jobs arrive according to a Poisson process of rate λ, and service times are exponentially distributed. When the Markov chain is in state F, the server works at a rate of μ_F, and when the Markov chain is in state S, the server works at rate $\mu_S < \mu_F$. When the server is in state F and completes a service it remains fast with probability p_{FF} and becomes slow with probability $p_{FS} = 1 - p_{FF}$. Similarly, when the server is in state S and completes a service, it remains slow with probability p_{SS} and becomes fast with probability $p_{SF} = 1 - p_{SS}$.

We let $P_{S,n}, n = 0, 1, ...$ denote the steady-state probability that the server is slow and there are n jobs in the system. Similarly, $P_{F,n}$ denotes the steady-state probability that the server is fast and there are n jobs in the system.

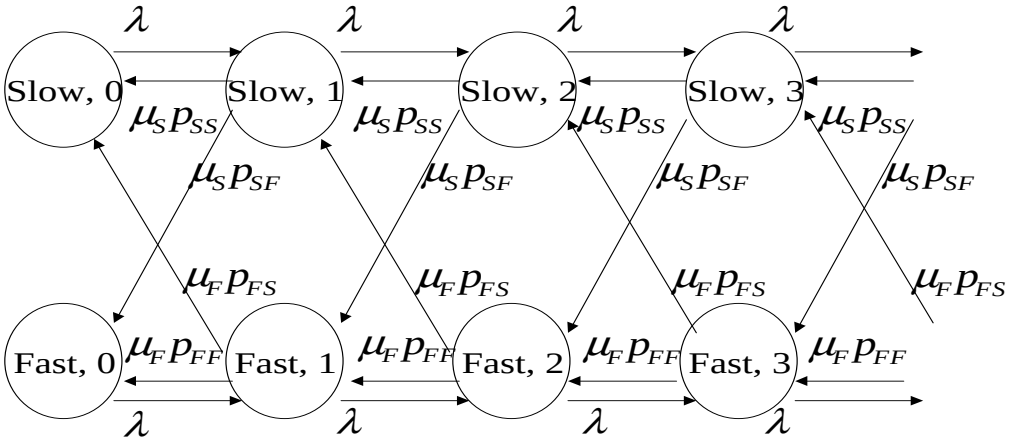

Figure 1: State-transition diagram of the Continuous Time Markov Chain

The state-transition equations of the $M/MMPP/1$ system's associated Continuous Time Markov Chain (CTMC) are presented below. While they are easy to formulate, they are difficult to solve, due to the high-dimensionality of the recursive equations. The corresponding state-transition diagram can be found in Figure 1.

We have, for $n = 0$, that

$$\lambda P_{S,0} = \mu_S p_{SS} P_{S,1} + \mu_F p_{FS} P_{F,1} \quad (1)$$

$$\lambda P_{F,0} = \mu_S p_{SF} P_{S,1} + \mu_F p_{FF} P_{F,1}, \quad (2)$$

and for $n \geq 1$,

$$(\mu_S + \lambda) P_{S,n} = \lambda P_{S,n-1} + \mu_S p_{SS} P_{S,n+1} + \mu_F p_{FS} P_{F,n+1} \quad (3)$$

$$(\mu_F + \lambda) P_{F,n} = \lambda P_{F,n-1} + \mu_S p_{SF} P_{S,n+1} + \mu_F p_{FF} P_{F,n+1}. \quad (4)$$

We can present the balance equations in a matrix-vector notation. Let

$$X_n = \begin{pmatrix} P_{S,n} \\ P_{F,n} \end{pmatrix}, \qquad A = \begin{pmatrix} \mu_S p_{SS} & \mu_F p_{FS} \\ \mu_S p_{SF} & \mu_F p_{FF} \end{pmatrix}, \qquad \text{and} \quad B = \begin{pmatrix} \lambda + \mu_S & 0 \\ 0 & \lambda + \mu_F \end{pmatrix}.$$

Then the balance equations (1), (2), (3), (4) become

$$\begin{aligned} BX_{n+1} &= \lambda X_n + AX_{n+2} \quad \forall n \geq 0 \\ \lambda X_0 &= AX_1, \end{aligned}$$

Furthermore, we can define $C = \lambda A^{-1}$ and $D = A^{-1}B$, and equivalently represent the balance equations as:

$$X_{n+2} - DX_{n+1} + CX_n = 0, \qquad \forall n \geq 0 \tag{5}$$

$$X_1 = CX_0. \tag{6}$$

We note that when $p_{SF}+p_{FS} = 1$ ($p_{SF} = p_{FF}, p_{SS} = p_{FS}$), the service times become *i.i.d.* hyper-exponential random variables. In this case, the $M/MMPP/1$ system becomes an $M/H_2/1$ system, which is simpler to analyze and has been studied by many before (see, for example, Kleinrock [1, page 205]). Furthermore, if either p_{SF} or p_{FS} is zero, then in the steady-state, the system operates as an $M/M/1$ queue, which has been well studied (see also Kleinrock [1] for an example). In this paper we will focus on the case in which $p_{SF} + p_{FS} \neq 1$ and $p_{SF} \cdot p_{FS} \neq 0$.

Given the representation (5) and (6), we are ready to state our main result.

Theorem 1 *When $p_{SF} + p_{FS} \neq 1$ (i.e. $p_{SF} \neq p_{FF}, p_{SS} \neq p_{FS}$) and $p_{SF} \cdot p_{FS} \neq 0$, the solution to (5) and (6) is of the form*

$$X_n = (R_1^n K_1 + R_2^n K_2)X_0, \tag{7}$$

where R_1, R_2, K_1, and K_2 are such that

$$R_i^2 - DR_i + C = 0 \qquad i = 1, 2 \tag{8}$$

$$K_1 + K_2 = I \tag{9}$$

$$R_1 K_1 + R_2 K_2 = C. \tag{10}$$

Once the matrices R_1, R_2, K_1, and K_2 satisfying (8)-(10) are found, $\{X_n\}_{n=0}^{\infty}$ as defined by (7) is clearly a solution to (5). Moreover, given X_0, (5) and (6) uniquely determine all other probabilities X_n, $\forall n > 0$. So it suffices to prove the existence of a solution of the form (7) such that (8)-(10) are satisfied.

We constructively prove the existence of R_1, R_2, K_1, and K_2. Because we consider the proof to be an important result of this paper, and because it is quite long and technical, we will present it

in §3.2. Readers mainly interested in how we use Theorem 1 to derive the $M/MMPP/1$ queueing measures should go directly to §3.3.

3.2 Proof of Theorem 1

Lemma 1 *Suppose R satisfies (8), then if γ is its eigenvalue, it satisfies*

$$\det\left(\gamma^2 I - \gamma D + C\right) = 0. \tag{11}$$

Proof Let V be the corresponding eigenvector, i.e., $RV = \gamma V$. Then $R^2 - DR + C = 0$ implies $(R^2 - DR + C)V = 0$. Therefore

$$(\gamma^2 I - \gamma D + C)V = 0 \tag{12}$$

Since eigenvectors are non-zero, this implies (11).

△

Lemma 1 shows that the eigenvalues and eigenvectors of any solution to (8) satisfy (11) and (12). Moreover, it shows that they can be directly computed from (11) and (12). The following two propositions show how to construct the two solutions to (8), $R_{1,2}$, based on the solutions to (11) and (12).

Since $p_{SF} + p_{FS} \neq 1$, there are four roots to equation (11): γ_1, γ_2, γ_3, and γ_4. Let V_1, V_2, V_3, and V_4 be the corresponding vectors given by (12).

Proposition 1 *If V_i and V_j are linearly independent, then $R = (V_i, V_j)\begin{pmatrix} \gamma_i & 0 \\ 0 & \gamma_j \end{pmatrix}(V_i, V_j)^{-1}$ is a solution to (8).*

Proof It can be verified as follows:

$$\begin{aligned}
(R^2 - DR + C)(V_i, V_j) &= (V_i, V_j)\begin{pmatrix} \gamma_i^2 & 0 \\ 0 & \gamma_j^2 \end{pmatrix} - D(V_i, V_j)\begin{pmatrix} \gamma_i & 0 \\ 0 & \gamma_j \end{pmatrix} + C(V_i, V_j) \\
&= (\gamma_i^2 V_i, \gamma_j^2 V_j) - D(\gamma_i V_i, \gamma_j V_j) + C(V_i, V_j) \\
&= \mathbf{0}
\end{aligned}$$

from (12). Therefore $(R^2 - DR + C) = 0$, as (V_i, V_j) is invertible.

△

If a solution to (8), R, is non-diagonalizable, then let $\hat{\gamma}$ be its multiple eigenvalues. Since clearly $R \neq \hat{\gamma} I$, R can be transformed into a Jordan form: $\exists (V,U)$ such that $R = (V,U) \begin{pmatrix} \hat{\gamma} & 1 \\ 0 & \hat{\gamma} \end{pmatrix} (V,U)^{-1}$, i.e.,

$$RV = \hat{\gamma} V \tag{13}$$

$$RU = V + \hat{\gamma} U. \tag{14}$$

The following proposition shows that the inverse is also true. See Appendix A for its proof.

Proposition 2 *If $\hat{\gamma}$ is a multiple root of (11) and V is its corresponding solution in (12), then there exists a U, linearly independent of V, such that $R = (V,U) \begin{pmatrix} \hat{\gamma} & 1 \\ 0 & \hat{\gamma} \end{pmatrix} (V,U)^{-1}$ is a solution to (8).*

Now, define

$$\rho = \lambda \left[\left(\frac{p_{FS}}{p_{SF} + p_{FS}} \right) \frac{1}{\mu_S} + \left(\frac{p_{SF}}{p_{SF} + p_{FS}} \right) \frac{1}{\mu_F} \right]. \tag{15}$$

The following lemma is needed for Proposition 3. Its proof can also be found in Appendix A.

Lemma 2

1. *When $\rho \neq 1$, one and only one of the four γ's is 1. Furthermore, the other three eigenvalues cannot all be the same, and, none equals 0.*
2. *The eigenvector corresponding to the eigenvalue 1 is $(\mu_F p_{FS}, \mu_S p_{SF})'$, and it is linearly independent of the eigenvectors of other eigenvalues.*
3. *If $\gamma_i = \gamma_j$, then V_i and V_j are linearly dependent.*
4. *If $\gamma_i \neq \gamma_j$ and V_i and V_j are linearly dependent, $1 \leq i \neq j \leq 4$, then $\gamma_i \gamma_j$ is an eigenvalue of C.*
5. *If V_i, V_j, and V_k are linearly dependent, $1 \leq i \neq j \neq k \leq 4$, then γ_i, γ_j, and γ_k cannot be all distinct.*

The following proposition uses the results of Propositions 1 and 2 to provide a procedure for determining solution to (7)-(10). Thus it provides a constructive proof of Theorem 1. Without loss of generality, we can let $\gamma_1 = 1$.

Proposition 3

1. *Let $\gamma_i, V_i, i = 1, 2, 3, 4$, be given by (11) and (12), and let $\gamma_1 = 1$. There are two possibilities:*

   (a) *Suppose there exist a pair of linearly independent vectors in V_2, V_3 and V_4, say V_3 and V_4. There are two possible cases. In the first, γ_2 is different from both γ_3 and γ_4, then $R_1 = (V_1, V_2) \begin{pmatrix} \gamma_1 & 0 \\ 0 & \gamma_2 \end{pmatrix} (V_1, V_2)^{-1}$ and $R_2 = (V_3, V_4) \begin{pmatrix} \gamma_3 & 0 \\ 0 & \gamma_4 \end{pmatrix} (V_3, V_4)^{-1}$ are both solutions to (8). In the other case, $\gamma_2 = \gamma_3$ or γ_4. Without loss of generality, let $\gamma_2 = \gamma_3$. Then $R_1 = (V_1, V_4) \begin{pmatrix} \gamma_1 & 0 \\ 0 & \gamma_4 \end{pmatrix} (V_1, V_4)^{-1}$ and $R_2 = (V_2, U_2) \begin{pmatrix} \gamma_2 & 1 \\ 0 & \gamma_2 \end{pmatrix} (V_2, U_2)^{-1}$ are both solutions to (8), where U_2 is found via Proposition 2 (equation (36)).*

   (b) *Suppose V_2, V_3 and V_4 are pair-wise linearly dependent, then γ_2, γ_3, and γ_4 can be neither all distinct nor all the same. Suppose $\gamma_3 = \gamma_4 = \gamma \neq \gamma_2$. Then, $R_1 = (V_1, V_2) \begin{pmatrix} \gamma_1 & 0 \\ 0 & \gamma_2 \end{pmatrix} (V_1, V_2)^{-1}$ and $R_2 = (V_3, U_3) \begin{pmatrix} \gamma & 1 \\ 0 & \gamma \end{pmatrix} (V_3, U_3)^{-1}$ are both solutions to (8), where U_3 is found via Proposition 2.*

2. *R_1 and R_2, as constructed in (1a) and (1b), have no common eigenvalues.*

3. *Let R_1 and R_2 be given in (1a) and (1b). Then there exist K_1 and K_2 such that (9) and (10) are satisfied.*

Proof To prove part (1a), we note that in the latter case, V_1 and V_4 are linearly independent according to part 2 of Lemma 2. Part (1a) then follows from Proposition 1 in the former case and Propositions 1 and 2 in the latter case.

To prove part (1b), we note that parts 1 and 5 of Lemma 2 together show that γ_2, γ_3, and γ_4 can be neither all distinct nor all the same. The rest follows again from Propositions 1 and 2.

From our construction of R_1 and R_2 in (1a) and (1b), it is clear that they have no common eigenvalues in all cases. We note that, in the latter case of (1a), $1 = \gamma_1 \neq \gamma_2$ and $\gamma = \gamma_3 \neq \gamma_4$ from part 3 of Lemma 2.

We will defer the proof of part 3 to Appendix A.

△

3.3 Complete Solution of the Steady State Probability Distribution

From Theorem 1, we see that, once we know $X_0 = (P_{S,0}, P_{F,0})'$, then all the other probabilities can be obtained from equation (7). The following two propositions provide two independent equations to determine $P_{S,0}$ and $P_{F,0}$ and, in turn, the entire probability distribution.

Proposition 4

(*i*) *The long-run average service time of the $M/MMPP/1$ system is $1/\mu$ where*

$$\frac{1}{\mu} = \frac{p_{FS}}{p_{SF}+p_{FS}}\frac{1}{\mu_S} + \frac{p_{SF}}{p_{SF}+p_{FS}}\frac{1}{\mu_F}. \tag{16}$$

(*ii*) *Let ρ be defined as in (15). Then $\rho = \lambda/\mu$. Moreover, when $\rho < 1$, the system is stable, and ρ is the long-run proportion of time the system is busy.*

(*iii*) *When $\rho \geq 1$, the system is unstable.*

Proof The transition probability matrix of the Embedded Markov Chain (EMC) at service completion epochs is $P = \begin{pmatrix} p_{SS} & p_{SF} \\ p_{FS} & p_{FF} \end{pmatrix}$, with the steady-state distribution $\pi = (\pi_S, \pi_F) = \left(\frac{p_{FS}}{p_{SF}+p_{FS}}, \frac{p_{SF}}{p_{SF}+p_{FS}}\right)$ such that $\pi = \pi P$. Note that (π_S, π_F) are also the long-run proportion of slow and fast services. More specifically, if we let $m(n)$ be the number of slow services in the first n services the server provides, then $\lim_{n\to\infty} m(n) = \infty$, $\lim_{n\to\infty} \frac{m(n)}{n} = \pi_S$ and $\lim_{n\to\infty} \frac{n-m(n)}{n} = \pi_F$ with probability one.

Let $S_1, S_2, \ldots$ denote the sequence of services provided by this server, and let $\Omega_n = \{i : i \leq n \text{ and } S_i \text{ is a slow service}\}$, then $m(n) = |\Omega_n|$, and

$$\begin{aligned}
\lim_{n\to\infty} \frac{\sum_{i=1}^n S_i}{n} &= \lim_{n\to\infty} \left(\frac{\sum_{i\in\Omega_n} S_i}{n} + \frac{\sum_{i\notin\Omega_n} S_i}{n} \right) \\
&= \lim_{n\to\infty} \left(\frac{\sum_{i\in\Omega_n} S_i}{m(n)} \cdot \frac{m(n)}{n} + \frac{\sum_{i\notin\Omega_n} S_i}{n-m(n)} \cdot \frac{n-m(n)}{n} \right) \\
&= \frac{\pi_S}{\mu_S} + \frac{\pi_F}{\mu_F} = \frac{p_{FS}}{p_{SF}+p_{FS}}\frac{1}{\mu_S} + \frac{p_{SF}}{p_{SF}+p_{FS}}\frac{1}{\mu_F}
\end{aligned}$$

with probability 1. Hence the long-run average service time $1/\mu$ is defined as in (16), and it follows from (15) that $\rho = \lambda/\mu$. When $\rho < 1$, by Little's Law, ρ is the long-run average fraction of time the system is busy.

To derive stability conditions, we define (in Loynes's [2] notation) $T_1, T_2, \ldots$ to be the sequence of inter-arrival times. Moreover, define $U_n = S_n - T_n$. Then

$$\lim_{n\to\infty} \frac{\sum_{k=1}^{n} U_k}{n} = \frac{1}{\mu} - \frac{1}{\lambda} \begin{cases} < 0 & \text{if } \rho < 1, \\ \geq 0 & \text{if } \rho \geq 1 \end{cases} \quad w.p.1.$$

Therefore, the system is stable when $\rho < 1$ and unstable when $\rho \geq 1$. This follows directly from Theorems 1 and 2 and Corollary 1 in Loynes [2].

$\triangle$

Proposition 4 provides the first equation relating $P_{S,0}$ and $P_{F,0}$:

$$P_{S,0} + P_{F,0} = 1 - \rho. \tag{17}$$

To provide the second equation, we use the fact that probabilities sum to one. Let $(a_M, b_M) = (1,1)\sum_{n=0}^{M} (R_1^n K_1 + R_2^n K_2)$. Then

$$1 = (1,1)\sum_{n=0}^{\infty} X_n = \lim_{M\to\infty} [(a_M, b_M)X_0]. \tag{18}$$

Arrange γ_1, γ_2, γ_3, and γ_4 in descending order with regard to their absolute values (or, in the case of complex numbers, modulus). Let the corresponding vectors be $V_1 = (v_{11}, v_{12})^{'}$, $V_2 = (v_{21}, v_{22})^{'}$, $V_3 = (v_{31}, v_{32})^{'}$, and $V_4 = (v_{41}, v_{42})^{'}$. Since one is an eigenvalue, we must have $|\gamma_1| \geq 1$.

For the following discussion, we will assume $R_1 = (V_1, V_2) \begin{pmatrix} \gamma_1, & 0 \\ 0, & \gamma_2 \end{pmatrix} (V_1, V_2)^{-1}$ and $R_2 = (V_3, V_4) \begin{pmatrix} \gamma_3, & 0 \\ 0, & \gamma_4 \end{pmatrix} (V_3, V_4)^{-1}$. Other cases are similar.

Now let us denote the coefficient matrices K_1 and K_2 by

$$K_1 = \begin{pmatrix} K_1(1,1), & K_1(1,2) \\ K_1(2,1), & K_1(2,2) \end{pmatrix}, \quad K_2 = \begin{pmatrix} K_2(1,1), & K_2(1,2) \\ K_2(2,1), & K_2(2,2) \end{pmatrix},$$

and

$$\alpha_1 = \frac{(K_1(1,1)v_{22} - K_1(2,1)v_{21})(v_{11} + v_{12})}{v_{11}v_{22} - v_{12}v_{21}}, \qquad \beta_1 = \frac{(K_1(1,2)v_{22} - K_1(2,2)v_{21})(v_{11} + v_{12})}{v_{11}v_{22} - v_{12}v_{21}},$$

$$\alpha_2 = \frac{(K_1(2,1)v_{11} - K_1(1,1)v_{12})(v_{21} + v_{22})}{v_{11}v_{22} - v_{12}v_{21}}, \qquad \beta_2 = \frac{(K_1(2,2)v_{11} - K_1(1,2)v_{12})(v_{21} + v_{22})}{v_{11}v_{22} - v_{12}v_{21}},$$

$$\alpha_3 = \frac{(K_2(1,1)v_{42} - K_2(2,1)v_{41})(v_{31}+v_{32})}{v_{31}v_{42}-v_{32}v_{41}}, \qquad \beta_3 = \frac{(K_2(1,2)v_{42} - K_2(2,2)v_{41})(v_{31}+v_{32})}{v_{31}v_{42}-v_{32}v_{41}},$$
$$\alpha_4 = \frac{(K_2(2,1)v_{31} - K_2(1,1)v_{32})(v_{41}+v_{42})}{v_{31}v_{42}-v_{32}v_{41}}, \qquad \beta_4 = \frac{(K_2(2,2)v_{31} - K_2(1,2)v_{32})(v_{41}+v_{42})}{v_{31}v_{42}-v_{32}v_{41}}.$$

Then

$$\begin{aligned}
(a_M, b_M) &= (1,1)\left[(\sum_{n=0}^{M} R_1^n)K_1 + (\sum_{n=0}^{M} R_2^n)K_2\right] \\
&= (1,1)\left[(V_1,V_2)\begin{pmatrix} \sum_{n=0}^{M}\gamma_1^n, & 0 \\ 0, & \sum_{n=0}^{M}\gamma_2^n \end{pmatrix}(V_1,V_2)^{-1}K_1\right. \\
&\qquad \left. +(V_3,V_4)\begin{pmatrix} \sum_{n=0}^{M}\gamma_3^n, & 0 \\ 0, & \sum_{n=0}^{M}\gamma_4^n \end{pmatrix}(V_3,V_4)^{-1}K_2\right] \\
&= \left(\sum_{i=1}^{4}\alpha_i E_{M,i}, \sum_{i=1}^{4}\beta_i E_{M,i}\right), \qquad (19)
\end{aligned}$$

where $E_{M,i} = \sum_{n=0}^{M}\gamma_i^n$, and α_i, β_i, $i = 1,2,3,4$, are constants as defined before.

Proposition 5 *If $\rho < 1$, then the Markov process is ergodic and there exists a positive probability vector X_0 such that equation (18) is satisfied. Moreover, either*

(i) (a_M, b_M) does not converge to finite (a,b) but the ratio a_M/b_M converges to a constant, K, and

$$\frac{P_{F,0}}{P_{S,0}} = -\lim_{M\to\infty}\frac{a_M}{b_M} = -K, \qquad (20)$$

(ii) or, (a_M, b_M) converges to finite vector (a,b) and

$$aP_{S,0} + bP_{F,0} = 1. \qquad (21)$$

Proof From (17), we know that $P_{S,0} + P_{F,0} > 0$ when $\rho < 1$. Suppose, by contradiction, that $P_{S,n}$ (or $P_{F,n}$) equals zero for some $n \geq 0$. Then from equations (1)-(4), $P_{S,n+1} = 0$ (or $P_{F,n+1} = 0$). Because $p_{SF}\cdot p_{FS} \neq 0$, it follows that $P_{F,n} = 0$ (or $P_{S,n} = 0$), and recursively $P_{S,k} = P_{F,k} = 0$ for all k. This contradicts $P_{S,0} + P_{F,0} > 0$. Therefore, all the probabilities $(P_{S,n},\ P_{F,n},\ \forall n \geq 0)$ are positive, and the Markov process is ergodic.

Because there might be identical γ's in $\gamma_1, \gamma_2, \gamma_3, \gamma_4$, we first collect terms in (19). Then we denote by γ_i the lowest ranking γ whose α and β coefficients are not both zero.

Suppose $|\gamma_i| \geq 1$, and without loss of generality, suppose $\alpha_i \neq 0$. Then since $\lim_{M\to\infty} |E_{M,i}| = \infty$ and $a_M = \sum_{i=1}^{4} \alpha_i E_{M,i}$, this means $\lim_{M\to\infty} |a_M| = \infty$. Because $\lim_{M\to\infty} (a_M, b_M)X_0 = 1$, this also implies that $\lim_{M\to\infty} |b_M| = \infty$. Otherwise we would have $P_{S,0} = 0$, contradicting the fact that the solution to (18) is positive. So $\beta_i \neq 0$ as well.

The coefficient of the γ_i^M term in $(a_M, b_M)X_0$ is $\alpha_i P_{S,0} + \beta_i P_{F,0}$. As $M \to \infty$, this coefficient must vanish. Therefore

$$\frac{P_{F,0}}{P_{S,0}} = -\lim_{M\to\infty} \frac{a_M}{b_M} = -\frac{\alpha_i}{\beta_i}. \tag{22}$$

This corresponds to the first case in the proposition statement.

Now suppose $|\gamma_i| < 1$. Since the eigenvalues with non-zero α and β coefficients all lie within the unit disk, we have, from (18), that $\lim_{M\to\infty} (a_M, b_M) = (a, b)$ for finite (a, b). Therefore, from (18), we have equation (21). This corresponds to the second case in the proposition statement.

△

In general, eigenvalues of the rate matrices are usually restricted to the inside of the unit disk. Lemma 1 shows that in our system, however, the spectral radii of the rate matrices could be no smaller than one. But the divergence of the powers of rate matrix provides us with equation (20) or (21), a simpler second equation than (18).

Remark 1 Note that the underlying CTMC steady-state probability distribution can be modeled in the following way. First, arrange the states as $(P_{S,0}, P_{F,0}, P_{S,1}, P_{F,1}, ...)$. Then the infinitesimal generator Q is

$$Q = \begin{vmatrix} -\lambda I & \lambda I & & & & \\ A^{'} & -B^{'} & \lambda I & & & \\ & A^{'} & -B^{'} & \lambda I & & \\ & & A^{'} & -B^{'} & \lambda I & \cdots \\ & & & A^{'} & -B^{'} & \cdots \\ & & & \cdot & \cdot & \cdot \\ & & & \cdot & \cdot & \cdot \\ & & & \cdot & \cdot & \cdot \end{vmatrix},$$

and the solution to the steady-state probability balance equation is as follows:

$$(X_0^{'}, X_1^{'}, ..., X_n^{'}, ...) = (X_0^{'}, X_1^{'}, ..., X_n^{'}, ...)Q.$$

This is an example of a "Quasi-Birth-and-Death Process". Theorem 3.1.1 in Neuts [5] states that the Markov process is positive recurrent if and only if the minimal nonnegative solution R to the matrix-quadratic equation (8) has all its eigenvalues inside the unit disk and the finite system of equations

$$(R - C)X_0 = 0 \tag{23}$$

$$(1, 1)(I - R)^{-1}X_0 = 1 \tag{24}$$

has a (unique) positive solution X_0. In this case,

$$X_n = R^n X_0. \tag{25}$$

It is not evident, however, that conditions (23)-(24) are always satisfied, and even if they are satisfied, they may be difficult to verify. Our algorithm, as described in Proposition 3, guarantees a solution as a superposition of two matrix-geometric series and the major computation requirement is the solution of a polynomial equation (11), and the solution of linear equations (12). Hence, our approach provides a numerically simple algorithm for all cases, including those in which (23)-(24) are satisfied and Neuts's results apply.

3.4 Average waiting time and queue length.

Once we know the complete distribution of the number in the system, we can compute all the important queueing measures - average number in the system, average queue length, average waiting time in the system, and average waiting time in queue. In fact we only need to compute any one of the four. The others follow easily from Little's Law and $W_s = W_q + 1/\mu$. We will focus on finding the average number in the system.

Because $X_n = (R_1^n K_1 + R_2^n K_2)X_0, \ \forall n$, if we let L denote the long-run average number in the system, then $L = (1, 1)\sum_{n=0}^{\infty} n(R_1^n K_1 + R_2^n K_2)X_0$.

We can find L from the following two equations. Let $G = \sum_{n=0}^{\infty} nP_{S,n}$ and $H = \sum_{n=0}^{\infty} nP_{F,n}$, then $L = G + H$. There are many ways to find G and H, including differentiation of the moment

generating functions. The following are just two examples.

$$(\mu_S - \lambda)G + (\mu_F - \lambda)H = \lambda \tag{26}$$

$$\mu_S p_{SF} G - \mu_F p_{FS} H = \frac{p_{FS}}{p_{SF} + p_{FS}} \cdot \frac{\lambda^2}{\mu_S} + \lambda P_{S,0} - \frac{\lambda p_{FS}}{(p_{SF} + p_{FS})} \tag{27}$$

We can also directly compute L from the matrices R_1, K_1, R_2, K_2 - which we have already obtained when determining X_0. This method will be particularly useful in the finite waiting space case. So we will defer the discussion till then.

Detailed derivation of (26) and (27) can be found in Appendix B.

4 $M/MMPP/1/N$ queueing system solution

In many applications, there is a physical limitation on the waiting space and the system loss probability is of primary concern. In the following analysis we will assume a limited capacity of N in the system. Any job that arrives when there are already N jobs in the system will be lost. We shall use the same $P_{S,n}$ and $P_{F,n}$ notation. The new balance equations are as follows:

$$\lambda P_{S,0} = \mu_S p_{SS} P_{S,1} + \mu_F p_{FS} P_{F,1}$$

$$\lambda P_{F,0} = \mu_S p_{SF} P_{S,1} + \mu_F p_{FF} P_{F,1},$$

$$(\mu_S + \lambda)P_{S,n} = \lambda P_{S,n-1} + \mu_S p_{SS} P_{S,n+1} + \mu_F p_{FS} P_{F,n+1} \tag{28}$$

$$(\mu_F + \lambda)P_{F,n} = \lambda P_{F,n-1} + \mu_S p_{SF} P_{S,n+1} + \mu_F p_{FF} P_{F,n+1}, \quad 1 \le n < N \tag{29}$$

$$\mu_S P_{S,N} = \lambda P_{S,N-1} \tag{30}$$

$$\mu_F P_{F,N} = \lambda P_{F,N-1}. \tag{31}$$

Again we need two equations to solve for $P_{S,0}$ and $P_{F,0}$. The first comes from solution of (28) and (29). As in the infinite waiting space case, we know that there exist R_1, R_2, K_1, and K_2 such that (8)-(10) are satisfied and for all n,

$$X_n = (R_1^n K_1 + R_2^n K_2) X_0. \tag{32}$$

In particular

$$X_{N-1} = (R_1^{N-1} K_1 + R_2^{N-1} K_2) X_0 \quad \text{and} \quad X_N = (R_1^N K_1 + R_2^N K_2) X_0. \tag{33}$$

This, together with (30) and (31), implies

$$\begin{pmatrix} \mu_S & 0 \\ 0 & \mu_F \end{pmatrix} (R_1^N K_1 + R_2^N K_2) X_0 = \lambda (R_1^{N-1} K_1 + R_2^{N-1} K_2) X_0$$
$$(R_1^N K_1 + R_2^N K_2) X_0 = J (R_1^{N-1} K_1 + R_2^{N-1} K_2) X_0$$

So

$$\left[(R_1 - J) R_1^{N-1} K_1 + (R_2 - J) R_2^{N-1} K_2 \right] X_0 = 0 \tag{34}$$

where $J = \begin{pmatrix} \lambda/\mu_S & 0 \\ 0 & \lambda/\mu_F \end{pmatrix}$ provides us with the first equation we need.

The second equation is obtained from the normalization condition that the probabilities sum to one. In this finite waiting space case, we do not have the problem of divergence. Therefore the second equation is quite straightforward:

$$(1,1) \sum_{n=0}^{N} X_n = 1 \qquad \Rightarrow \qquad (1,1) \sum_{n=0}^{N} (R_1^n K_1 + R_2^n K_2) X_0 = 1. \tag{35}$$

We will use the following algebraic identities to facilitate the computation of $\sum R^n$ and $\sum n R^n$.

Let

$$f_1(x,N) = \sum_{n=0}^{N} x^n = \frac{1 - x^{N+1}}{1-x},$$

$$f_2(x,N) = \sum_{n=0}^{N} n x^n = \frac{x - x^{N+1}(1 + N - Nx)}{(1-x)^2},$$

$$g_1(x,N) = \sum_{n=1}^{N} n x^{n-1} = \frac{1 - x^N (1 + N - Nx)}{(1-x)^2},$$

and

$$g_2(x,N) = \sum_{n=1}^{N} n^2 x^{n-1} = \frac{1 + x - x^N (1 + 2N + N^2 + x - 2Nx - 2N^2 x + N^2 x^2)}{(1-x)^3},$$

then

- if $R = (V_1, V_2) \begin{pmatrix} \gamma_1 & 0 \\ 0 & \gamma_2 \end{pmatrix} (V_1, V_2)^{-1}$, then $R^n = (V_1, V_2) \begin{pmatrix} \gamma_1^n & 0 \\ 0 & \gamma_2^n \end{pmatrix} (V_1, V_2)^{-1}$,

$$\sum_{n=0}^{N} R^n = (V_1, V_2) \begin{pmatrix} f_1(\gamma_1, N) & 0 \\ 0 & f_1(\gamma_2, N) \end{pmatrix} (V_1, V_2)^{-1},$$

and

$$\sum_{n=0}^{N} nR^n = (V_1, V_2) \begin{pmatrix} f_2(\gamma_1, N) & 0 \\ 0 & f_2(\gamma_2, N) \end{pmatrix} (V_1, V_2)^{-1};$$

- if $R = (V_1, U_1) \begin{pmatrix} \gamma & 1 \\ 0 & \gamma \end{pmatrix} (V_1, U_1)^{-1}$, then $R^n = (V_1, U_1) \begin{pmatrix} \gamma^n & n\gamma^{n-1} \\ 0 & \gamma^n \end{pmatrix} (V_1, U_1)^{-1}$,

$$\sum_{n=0}^{N} R^n = (V_1, U_1) \begin{pmatrix} f_1(\gamma, N) & g_1(\gamma, N) \\ 0 & f_1(\gamma, N) \end{pmatrix} (V_1, U_1)^{-1},$$

and

$$\sum_{n=0}^{N} nR^n = (V_1, U_1) \begin{pmatrix} f_2(\gamma, N) & g_2(\gamma, N) \\ 0 & f_2(\gamma, N) \end{pmatrix} (V_1, U_1)^{-1}.$$

Note that all the γ_i's and V_i's have already been obtained in the process of computing R_1 and R_2. So the above computations are straightforward. Using these identities, we can simplify (34) and (35) and quickly compute X_0. After that, we can calculate X_n for all n via (32). The other queueing measures follow from straightforward computation and will not be presented here. Again, we will take advantage of the fact that we have already obtained all the eigenvalues and eigenvectors in computing X_0 to facilitate these computations. For example, to find the long-run average number-in-system, we directly compute $L = \sum_{n=0}^{N} nX_n$, using the identities above concerning $\sum nR^n$.

Because arrivals are Poisson, the PASTA property for continuous-time Markov chains (see Wolff [8] for example) implies that the loss probability equals the probability that there are N in the system: $P_{S,N} + P_{F,N} = (1, 1)X_N$.

Remark 2 Naoumov [4] proves that, in finite QBD systems, the steady-state distribution of the number-in-system may be described as the superposition of two matrix-geometric series: $X_n = R^n a + S^{N-n} b$. Here a and b are vectors that satisfy certain boundary conditions. While this solution form holds for $m \geq 3$, the calculation of the two matrices, R and S, necessitates the computation of two infinite series of (recursively defined) matrices. In particular,

$$R = \lim_{k \to \infty} R_k, \qquad \text{where} \qquad R_0 = 0, \qquad R_{k+1} = R_k^2 - (D - I)R_k + C$$
$$S = \lim_{k \to \infty} S_k, \qquad \text{where} \qquad S_0 = 0, \qquad S_{k+1} = CS_k^2 - (D - I)S_k + I$$

Therefore in the case of a 2-state $M/MMPP/1$ system, we extend his results by providing more properties of the rate matrices and by providing a more computationally efficient procedure.

5 Numerical analysis

In this section, we study the performance difference between the $M/MMPP/1$ system and an analogous $M/G/1$ system in which service times have the same first two moments as those in the $M/MMPP/1$ system but are *i.i.d.*

5.1 Infinite waiting space: the $M/MMPP/1$ system.

We first consider the case of systems with infinite waiting spaces. The Pollaczek-Khintchine formula implies that the average queue length of an $M/G/1$ system depends on the service time distribution only through the first two moments (for example, see Wolff [8, page 385]). Therefore, without loss of generality, when calculating queueing measures such as the average queue length, we can assume that the $M/G/1$ system has *i.i.d.* hyper-exponential (H_2) service times, with $p_{FS}/(p_{SF}+p_{FS})$ fraction of the services being slow and $p_{SF}/(p_{SF}+p_{FS})$ fraction being fast.

The cases we study include a wide variety of scenarios: high/low system utilization, high/medium/low switching probabilities, and combinations of these. In Table 1 we report the average queue length in these systems, and we observe two interesting phenomena from these results.

First, when $\mu_S < \lambda$ and p_{SF} is very small (at the same time p_{FS} cannot be very large as otherwise the system may be unstable), the expected queue length in the $M/MMPP/1$ system is much larger than that in the $M/H_2/1$ system. This is not surprising: when p_{SF} is small, once the server becomes slow it tends to stay slow for a long time; if at the same time $\mu_S < \lambda$, then the queue length grows very quickly. In the corresponding $M/H_2/1$ system, however, the *i.i.d.* service times prevent this from happening, and the system backlog fluctuates less. Neuts [5, page 266, Example 2] observes similar numerical phenomenon as well.

Second, when $p_{SF}+p_{FS} > 1$, the expected backlog in the $M/H_2/1$ queue actually exceeds that for the $M/MMPP/1$ system. This phenomenon is somewhat unexpected because one would normally think that the serial correlations among the modulated service times would cause the $M/MMPP/1$ system to have a worse performance than the $M/H_2/1$ system.

As we noted before Theorem 1, however, the $M/H_2/1$ system is in fact an $M/MMPP/1$ system with switching probabilities $(p'_{SF}, p'_{FS}) = \frac{1}{p_{SF}+p_{FS}}(p_{SF}, p_{FS})$ where $p'_{SF} + p'_{FS} = 1$. So, the comparison in Table 1 is equivalent to the comparison between an $M/MMPP/1$ system with switching probabilities (p_{SF}, p_{FS}) and an $M/MMPP/1$ system with switching probabilities (p'_{SF}, p'_{FS}).

Table 1: $M/MMPP/1/\infty$ vs $M/G/1/\infty$

λ	μ_S	μ_F	p_{SF}	p_{FS}	ρ	$Q_{M/MMPP/1}$	$Q_{M/H_2/1}$	Diff.%
10	8	50	0.6	0.3	0.550	1.262	1.217	-3.60%
			0.3	0.6	0.900	10.803	10.550	-2.34%
			0.9	0.15	0.350	0.389	0.396	1.77%
			0.15	0.9	1.100		unstable	
			0.15	0.15	0.725	4.596	2.914	-36.61%
			0.55	0.55	0.725	2.836	2.914	2.73%
			0.9	0.9	0.725	2.518	2.914	15.74%
10	12.5	50	0.6	0.3	0.400	0.409	0.400	-2.20%
			0.3	0.6	0.600	1.115	1.100	-1.39%
			0.9	0.15	0.286	0.174	0.176	1.00%
			0.15	0.9	0.714	1.934	1.940	0.30%
			0.15	0.15	0.500	0.867	0.680	-21.56%
			0.55	0.55	0.500	0.669	0.680	1.67%
			0.9	0.9	0.500	0.619	0.680	9.82%

When $p_{SF} + p_{FS} > 1$, $p'_{SF} < p_{SF}$ and $p'_{FS} < p_{FS}$. From the intuition obtained in the first observation, we conjecture that because the $M/MMPP/1$ system representing the $M/G/1$ analogue has smaller switching probabilities, the underlying Markov Chain tends to stay in both states longer and therefore the system performance is actually worse than the original $M/MMPP/1$ system. Conversely, when $p_{SF} + p_{FS} < 1$, the $M/G/1$ system performs better.

Conjecture 1 *The long-run average queue length of the $M/MMPP/1$ system is smaller than that of its $M/G/1$ analogue when $p_{SF} + p_{FS} > 1$, larger when $p_{SF} + p_{FS} < 1$, and the same when $p_{SF} + p_{FS} = 1$.*

We will not attempt to prove the conjecture in this paper. The numerical results in Table 1, however, show that this conjecture holds for a wide variety of examples.

Most significantly, we find concrete examples to show that the system performance (average queue length, average number in the system, average waiting time in queue, and average waiting time in the system) of the $M/MMPP/1$ system is not necessarily worse or better than its analogous $M/G/1$ system. As the conjecture states, the difference appears to depend on the switching probabilities.

5.2 The $M/MMPP/1/N$ System.

We next compare results for systems with finite waiting spaces. Table 2 reports results that are computed for the same set of parameters as those in Table 1. The difference here is that there is an $N = 7$ limit on the waiting space. In addition, we also compare the loss probabilities here.

Note that Conjecture 1 not only holds in this finite-waiting-space for the expected queue length, it also holds for the loss probabilities. The intuition provided in the previous section also appears to apply here.

Note also that the relative difference in loss probabilities between the $M/MMPP/1$ system and its $M/H_2/1$ analogue is magnitudes higher than the difference in expected queue length in all the cases. This suggests that while an $M/G/1$ approximation may perform well in terms of the expected queue length, it may not be a good approximation in terms of real loss probability.

Table 2: $M/MMPP/1/N$ vs $M/M/1/N$ when $N = 7$

λ	μ_S	μ_F	p_{SF}	p_{FS}	Q Diff.%	$P_{M/MMPP/1/7}\{\text{Loss}\}$	$P_{M/H_2/1/7}\{\text{Loss}\}$	$P\{\text{Loss}\}$ Diff. %
10	8	50	0.6	0.3	-1.93%	3.11%	2.93%	-5.76%
			0.3	0.6	-0.44%	11.05%	10.85%	-1.79%
			0.9	0.15	1.28%	0.78%	0.82%	4.49%
			0.15	0.9	0.01%	17.92%	17.96%	0.22%
			0.15	0.15	-13.35%	9.08%	6.13%	-32.49%
			0.55	0.55	0.98%	5.93%	6.13%	3.28%
			0.9	0.9	5.50%	5.06%	6.13%	21.00%
10	12.5	50	0.6	0.3	-1.76%	0.52%	0.49%	-6.28%
			0.3	0.6	-0.86%	1.91%	1.86%	-2.70%
			0.9	0.15	0.86%	0.14%	0.14%	4.15%
			0.15	0.9	0.14%	3.37%	3.39%	0.47%
			0.15	0.15	-14.82%	1.63%	1.02%	-37.67%
			0.55	0.55	1.20%	0.98%	1.02%	4.17%
			0.9	0.9	7.13%	0.79%	1.02%	27.98%

6 Conclusion

Our analysis and procedures should also hold in more general cases in which the Markov chain that modulates service times has $m \geq 3$ states. Because of the birth-and-death nature of the system - in which the number of jobs in the system can only move up or down by one at a time - the state balance equations can be represented as quadratic difference equations even when $m \geq 3$. Therefore the matrix-geometric type solutions should still hold. We argue as follows.

Since the state transition equations can be represented by (5) (where the matrices D and C are of dimension $m \geq 3$ now), the eigenvalues and eigenvectors of the rate matrices should still satisfy (11) and (12). Therefore we will follow the same procedure to solve (11) and (12) first and get $2m$ γ's and v's. Then we will follow Propositions 1 and 2 to generate m rate matrices. Finally we will

find m coefficient matrices, K, such that boundary conditions such as (6) are satisfied. As a result, X_n could be represented as $X_n = \sum_{i=1}^{m} R_i^n K_i X_0$.

Unlike the case $m = 2$, however, it is difficult to prove that $m \geq 3$ rate matrices can be generated from the $2m$ solutions of (11) and (12) such that boundary conditions can be satisfied. Other difficulties may include the fact that there is no closed-form solution to high degree polynomial equation (11), as well as the fact that, once the dimension grows big, it may become difficult to invert the matrices. However, there are numerical procedures for finding roots to polynomial equations and, with the fast-increasing available computing power, even large matrices can be inverted relatively quickly.

A Proofs of the results in 3.2

Proof of Proposition 2 We prove that the required vector, U, can be found via the following equation,

$$(\hat{\gamma}^2 I - D\hat{\gamma} + C)U = -(2\hat{\gamma}I - D)V, \tag{36}$$

and that it always exists. To do this, we note that

$$2\gamma I - D = \frac{d}{d\gamma}(\gamma^2 I - D\gamma + C).$$

Therefore if we denote $\gamma^2 I - D\gamma + C$ by $\begin{pmatrix} w_1(\gamma), & w_2(\gamma) \\ w_3(\gamma), & w_4(\gamma) \end{pmatrix}$, then $-(2\gamma I - D) = \begin{pmatrix} -w_1^{'}(\gamma), & -w_2^{'}(\gamma) \\ -w_3^{'}(\gamma), & -w_4^{'}(\gamma) \end{pmatrix}$.

Furthermore, $\det(\gamma^2 I - D\gamma + C) = w_1(\gamma)w_4(\gamma) - w_2(\gamma)w_3(\gamma)$. $\hat{\gamma}$ being a multiple solution to (11) implies that:

$$\det(\gamma^2 I - D\gamma + C)|_{\gamma=\hat{\gamma}} = w_1(\hat{\gamma})w_4(\hat{\gamma}) - w_2(\hat{\gamma})w_3(\hat{\gamma}) = 0, \tag{37}$$

and

$$\left.\frac{d\det(\gamma^2 I - D\gamma + C)}{d\gamma}\right|_{\gamma=\hat{\gamma}} = w_1^{'}(\hat{\gamma})w_4(\hat{\gamma}) + w_1(\hat{\gamma})w_4^{'}(\hat{\gamma}) - w_2^{'}(\hat{\gamma})w_3(\hat{\gamma}) - w_2(\hat{\gamma})w_3^{'}(\hat{\gamma}) = 0. \tag{38}$$

Moreover, V being a solution to (12) means $(\hat{\gamma}^2 - D\hat{\gamma} + C)V = 0$; i.e. if we denote $V = (v_1, v_2)^{'}$, then

$$\begin{pmatrix} w_1(\hat{\gamma}), & w_2(\hat{\gamma}) \\ w_3(\hat{\gamma}), & w_4(\hat{\gamma}) \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = 0. \tag{39}$$

Without loss of generality, from (39) we can assume that

$$w_3(\hat{\gamma}) = cw_1(\hat{\gamma}), \quad w_4(\hat{\gamma}) = cw_2(\hat{\gamma}), \quad v_1 = -w_2(\hat{\gamma}), \quad v_2 = w_1(\hat{\gamma}),$$

where c is a constant.

Then (38) reduces to:

$$\begin{aligned} 0 &= w_1^{'}(\hat{\gamma})w_4(\hat{\gamma}) + w_1(\hat{\gamma})w_4^{'}(\hat{\gamma}) - w_2^{'}(\hat{\gamma})w_3(\hat{\gamma}) - w_2(\hat{\gamma})w_3^{'}(\hat{\gamma}) \\ &= w_1^{'}(\hat{\gamma})(-cv_1) + v_2 w_4^{'}(\hat{\gamma}) - w_2^{'}(\hat{\gamma})(cv_2) - (-v_1)w_3^{'}(\hat{\gamma}). \end{aligned}$$

Hence

$$w_3^{'}(\hat{\gamma})v_1 + w_4^{'}(\hat{\gamma})v_2 = c(w_1^{'}(\hat{\gamma})v_1 + w_2^{'}(\hat{\gamma})v_2), \tag{40}$$

and (36) becomes:

$$\begin{pmatrix} w_1(\hat{\gamma}), & w_2(\hat{\gamma}) \\ cw_1(\hat{\gamma}), & cw_2(\hat{\gamma}) \end{pmatrix} U = \begin{pmatrix} -(w_1^{'}(\hat{\gamma})v_1 + w_2^{'}(\hat{\gamma})v_2) \\ -c(w_1^{'}(\hat{\gamma})v_1 + w_2^{'}(\hat{\gamma})v_2) \end{pmatrix}. \tag{41}$$

Since these two equations are linearly dependent, a non-trivial solution U always exists for (36).

Now suppose, by contradiction, that U and V are linearly dependent. Then $U = c_0 V$ for some constant c_0. From (39) this means that if we denote U by $(u_1, u_2)^{'}$, then

$$w_1(\hat{\gamma})u_1 + w_2(\hat{\gamma})u_2 = 0, \quad w_3(\hat{\gamma})u_1 + w_4(\hat{\gamma})u_2 = 0,$$

and therefore from (41)

$$w_1^{'}(\hat{\gamma})u_1 + w_2^{'}(\hat{\gamma})u_2 = 0, \quad w_3^{'}(\hat{\gamma})u_1 + w_4^{'}(\hat{\gamma})u_2 = 0.$$

That is, $(\hat{\gamma}^2 I - D\hat{\gamma} + C)U = 0$ and $(2\hat{\gamma}I - D)U = 0$. Pre-multiplying both equations by A we get $(A\hat{\gamma}^2 - B\hat{\gamma} + \lambda I)U = 0$ and $\left.\frac{d \det(A\gamma^2 - B\gamma + \lambda I)}{d\gamma}\right|_{\gamma=\hat{\gamma}} U = 0$. Because

$$(A\gamma^2 - B\gamma + \lambda I) = \begin{pmatrix} \mu_S p_{SS}\gamma^2 - (\lambda + \mu_S)\gamma + \lambda, & \mu_F p_{FS}\gamma^2 \\ \mu_S p_{SF}\gamma^2, & \mu_F p_{FF}\gamma^2 - (\lambda + \mu_F)\gamma + \lambda \end{pmatrix},$$

this would imply $(\mu_S p_{SS}\hat{\gamma}^2 - (\lambda + \mu_S)\hat{\gamma} + \lambda)u_1 + \mu_F p_{FS}\hat{\gamma}^2 u_2 = 0$ and $(2\mu_S p_{SS}\hat{\gamma} - \lambda - \mu_S)u_1 + 2\mu_F p_{FS}\hat{\gamma}u_2 = 0$. This means $\hat{\gamma} = \frac{2\lambda}{\lambda + \mu_F}$. Similarly we can show $\hat{\gamma} = \frac{2\lambda}{\lambda + \mu_S}$, and, in turn, that $\mu_S = \mu_F$, which contradicts the assumption $\mu_S < \mu_F$.

Thus U and V are linearly independent. If we let $R = (V,U)\begin{pmatrix} \hat{\gamma} & 1 \\ 0 & \hat{\gamma} \end{pmatrix}(V,U)^{-1}$, then (13) and (14) hold. Moreover,

$$\begin{aligned}(R^2 - DR + C)(V,U) &= R(\hat{\gamma}V, V + \hat{\gamma}U) - D(\hat{\gamma}V, V + \hat{\gamma}U) + C(V,U) \\ &= (\hat{\gamma}^2 V, 2\hat{\gamma}V + \hat{\gamma}^2 U) - D(\hat{\gamma}V, V + \hat{\gamma}U) + C(V,U) \\ &= ((\hat{\gamma}^2 I - D\hat{\gamma} + C)V, (\hat{\gamma}^2 I - D\hat{\gamma} + C)U + (2\hat{\gamma}I - D)V) \\ &= \mathbf{0}.\end{aligned}$$

Therefore $(R^2 - DR + C) = 0$, as (V,U) is invertible.

△

Proof of part 1 of Lemma 2 Once we substitute $\gamma = 1$ into (11), it is straightforward to verify that the determinant of the resulting matrix is zero.

As a result, (11), or equivalently, $\det(A\gamma^2 - B\gamma + \lambda I) = 0$ can be simplified to

$$\begin{aligned}0 &= (\mu_S\mu_F(p_{SS}p_{FF} - p_{SF}p_{FS}))\gamma^4 - ((\lambda + \mu_S)\mu_F p_{FF} + (\lambda + \mu_F)\mu_S p_{SS})\gamma^3 \\ &\quad +(\lambda(\mu_S p_{SS} + \mu_F p_{FF}) + (\lambda + \mu_S)(\lambda + \mu_F))\gamma^2 - (2\lambda^2 - \lambda\mu_S - \lambda\mu_F)\gamma + \lambda^2 \\ &= (\gamma - 1)[\mu_S\mu_F(p_{SS} + p_{FF} - 1)\gamma^3 - (\lambda\mu_S p_{SS} + \lambda\mu_F p_{FF} + \mu_S\mu_F)\gamma^2 \\ &\qquad +\lambda(\lambda + \mu_S + \mu_F)\gamma - \lambda^2].\end{aligned}$$

Obviously 0 cannot be a root because $\lambda^2 \neq 0$. Now suppose we have another root that is 1. Then we would have

$$\mu_S\mu_F(p_{SS} + p_{FF} - 1) - (\lambda\mu_S p_{SS} + \lambda\mu_F p_{FF} + \mu_S\mu_F) + \lambda(\lambda + \mu_S + \mu_F) - \lambda^2 = 0, \tag{42}$$

which amounts to

$$1 = \lambda\frac{\mu_S p_{SF} + \mu_F p_{FS}}{\mu_S\mu_F(p_{SF} + p_{FS})}, \tag{43}$$

i.e. $\rho = 1$, a contradiction.

Now suppose the other three eigenvalues are the same, γ'. Then

$$3\gamma' = \frac{\lambda\mu_S p_{SS} + \lambda\mu_F p_{FF} + \mu_S\mu_F}{\mu_S\mu_F(p_{SS} + p_{FF} - 1)}, \tag{44}$$

$$3\gamma'^2 = \frac{\lambda(\lambda + \mu_S + \mu_F)}{\mu_S\mu_F(p_{SS} + p_{FF} - 1)}, \tag{45}$$

$$\gamma'^3 = \frac{\lambda^2}{\mu_S\mu_F(p_{SS}+p_{FF}-1)}.$$

(44) and (45) imply

$$(\lambda\mu_S p_{SS}+\lambda\mu_F p_{FF}+\mu_S\mu_F)^2 = 3\lambda(\lambda+\mu_S+\mu_F)\mu_S\mu_F(p_{SS}+p_{FF}-1)$$

i.e.

$$\begin{aligned} 0 &= \lambda^2[\mu_S^2p_{SS}^2+\mu_F^2p_{FF}^2+2\mu_S\mu_Fp_{SS}p_{FF}-3\mu_S\mu_F(p_{SS}+p_{FF}-1)] \\ &+ \lambda[2\mu_S^2\mu_Fp_{SS}+2\mu_S\mu_F^2p_{FF}-3(\mu_S+\mu_F)\mu_S\mu_F(p_{SS}+p_{FF}-1)]+\mu_S^2\mu_F^2. \end{aligned} \tag{46}$$

To show contradiction, we now prove that (46), as a quadratic equation of λ, has no real roots. That is, the discriminant is negative:

$$\begin{aligned} 0 &> [2\mu_S^2\mu_Fp_{SS}+2\mu_S\mu_F^2p_{FF}-3(\mu_S+\mu_F)\mu_S\mu_F(p_{SS}+p_{FF}-1)]^2 \\ &\quad -4[\mu_S^2p_{SS}^2+\mu_F^2p_{FF}^2+2\mu_S\mu_Fp_{SS}p_{FF}-3\mu_S\mu_F(p_{SS}+p_{FF}-1)]\mu_S^2\mu_F^2 \\ &= 3(p_{SS}+p_{FF}-1)\mu_S^2\mu_F^2\{\mu_S^2[-3p_{FS}-p_{SS}]+\mu_F^2[-3p_{SF}-p_{FF}]+\mu_S\mu_F[2(p_{SS}+p_{FF}-1)]\} \end{aligned}$$

But $(p_{SS}+p_{FF}-1)>0$, due to (45), and the coefficients of the quadratic terms in the parenthesis are negative. Thus we, again, only need to prove that the discriminant is negative:

$$\begin{aligned} 0 &> 4(p_{SS}+p_{FF}-1)^2-4(-3p_{FS}-p_{SS})(-3p_{SF}-p_{FF}) \\ &= -16p_{SF}p_{SS}-16p_{FS}p_{FF}-32p_{SF}p_{FS}, \end{aligned}$$

which is clear. Therefore, we have proved that (44) and (45) are contradictory. As a result, the other three eigenvalues cannot all be the same.

△

Proof of part 2 of Lemma 2 If we let $\gamma=1$, it is straightforward to verify that $(\mu_Fp_{FS},\mu_Sp_{SF})'$ is a solution to (12). Moreover, if we fix $V=(\mu_Fp_{FS},\mu_Sp_{SF})'$ in (12), then we get the following two equations:

$$\begin{aligned} \mu_S\mu_Fp_{FS}\gamma^2-(\lambda+\mu_S)\mu_Fp_{FS}\gamma+\lambda\mu_Fp_{FS} &= 0 \\ \mu_S\mu_Fp_{SF}\gamma^2-(\lambda+\mu_F)\mu_Sp_{SF}\gamma+\lambda\mu_Sp_{SF} &= 0 \end{aligned}$$

The first equation has two roots: 1 and λ/μ_S, and the second equation has two roots: 1 and λ/μ_F. Because $\mu_S < \mu_F$, 1 is then the only solution.

$\triangle$

Proof of part 3 of Lemma 2 By contradiction, suppose $\gamma_i = \gamma_j = \gamma$ and V_i and V_j are linearly independent. Then due to Proposition 1, the matrix $R = (V_i, V_j) \begin{pmatrix} \gamma & 0 \\ 0 & \gamma \end{pmatrix} (V_i, V_j)^{-1}$ is a solution to (8). Note, however, that here $R = \gamma I$. But this is impossible because there exists no γ such that $\gamma^2 I - \gamma D + C = \mathbf{0}$.

$\triangle$

Proof of part 4 of Lemma 2 If V_i and V_j are linearly dependent then $V_i = cV_j$ where c is a constant. Therefore we have

$$(\gamma_i^2 I - D\gamma_i + C)V_i = 0 \tag{47}$$

$$(\gamma_j^2 I - D\gamma_j + C)V_j = 0 \Longleftrightarrow (\gamma_j^2 I - D\gamma_j + C)V_i = 0 \tag{48}$$

Multiplying (47) by γ_j and (48) by γ_i and taking the difference, we have

$$\begin{aligned} (\gamma_i\gamma_j(\gamma_i - \gamma_j)I + (\gamma_j - \gamma_i)C)V_i &= 0 \\ (\gamma_i\gamma_j I - C)V_i &= 0, \end{aligned}$$

since $\gamma_i \neq \gamma_j$. Therefore $\gamma_i\gamma_j$ is an eigenvalue of C.

$\triangle$

Proof of part (5) of Lemma 2 Suppose, by contradiction, that γ_i, γ_j, and γ_k are distinct. Then from Lemma 4, $\gamma_i\gamma_j$, $\gamma_i\gamma_k$ and $\gamma_j\gamma_k$ are all eigenvalues of C. Furthermore, if γ_i, γ_j, and γ_k are distinct and non-zero, then these three eigenvalues are distinct as well. But C has at most two distinct eigenvalues, a contradiction.

$\triangle$

The following two lemmas are used in the proof of part 3 of Proposition 3:

Lemma 3 *Let R be a 2×2 matrix with distinct eigenvalues γ_1 and γ_2 and corresponding eigenvectors V_1 and V_2. Then for any vector $V \neq \mathbf{0}$, if $R^2V = cV$ for a non-zero constant c, then $c = \gamma_i^2$ ($i = 1$ or 2), and $RV = \gamma_i V$ for the same i.*

Proof Since γ_1 and γ_2 are distinct, V_1 and V_2 are linearly independent, and V can be expressed as a linear combination of V_1 and V_2: $V = c_1V_1 + c_2V_2$. Then $R^2V = cV$ implies $c_1\gamma_1^2V_1 + c_2\gamma_2^2V_2 = c(c_1V_1 + c_2V_2)$, $i = 1$ or 2.

Again, since V_1 and V_2 are linearly independent, this implies $c_1\gamma_1^2 = c_1c$ and $c_2\gamma_2^2 = c_2c$. Because c_1 and c_2 cannot both be 0, if $c_1 \neq 0$, then $c = \gamma_1^2$, $c_2 = 0$, and $V = c_1V_1$; else if $c_2 \neq 0$, then $c = \gamma_2^2$, $c_1 = 0$, and $V = c_2V_2$.

△

Lemma 4 *$R_1 - R_2$ is invertible.*

Proof Suppose, by contradiction, that $R_1 - R_2$ is non-invertible. Then there exists $V \neq \mathbf{0}$ such that $R_1V = R_2V$. This, together with (8), implies that $R_1^2V = R_2^2V$, and hence $R_1R_2V = R_2R_1V$.

Now from (8), we have:

$$\begin{aligned}
[R_1^2 - DR_1 + C]R_2V - [R_2^2 - DR_2 + C]R_1V &= \mathbf{0} \\
R_1(R_1R_2)V - R_2(R_2R_1)V &= \mathbf{0} \\
(R_1 - R_2)(R_1R_2V) &= \mathbf{0}.
\end{aligned}$$

Since $R_1 \neq R_2$, the dimension of solution space of $(R_1 - R_2)X = \mathbf{0}$ is at most one. Because V and R_1R_2V are both solutions, we have $R_1R_2V = c_1V$ for some constant c_1. Moreover $R_1V = R_2V$ and $R_1R_2V = c_1V$ imply $R_1^2V = c_1V$, and hence $R_2^2V = c_1V$. Without loss of generality, let R_1 be the one-matrix solution of (8) with one as its eigenvalue. Then from Lemma 1, R_1 has two distinct eigenvalues. Since c_1 is an eigenvalue of R_1^2 and V its corresponding eigenvector, Lemma 3 implies that V is an eigenvector of R_1: $R_1V = \gamma V$. This implies $R_2V = \gamma V$ as well. But R_1 and R_2 do not have common eigenvalues according to part 2 of Proposition 3. This is a contradiction.

△

Proof of part 3 of Proposition 3 From (9) and (10), $(R_1 - R_2)K_1 = C - R_2$ and $(R_1 - R_2)K_2 = R_1 - C$. Then by Lemma 4, $K_1 = (R_1 - R_2)^{-1}(C - R_2), K_2 = (R_1 - R_2)^{-1}(R_1 - C)$

is a solution to (8), (9), and (10).

△

B Derivation of L in the infinite waiting space case

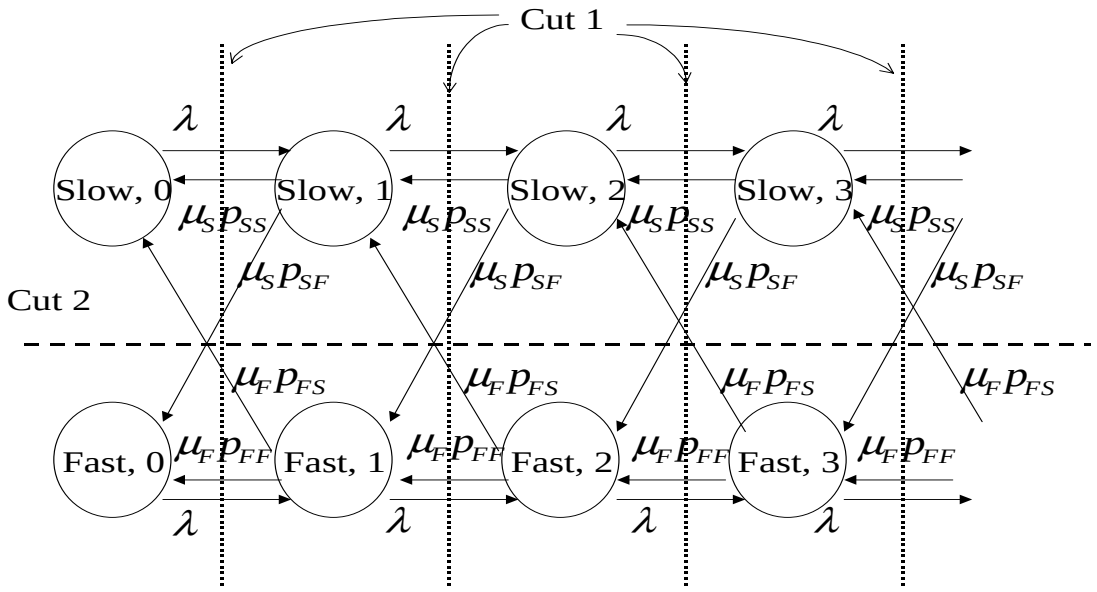

Figure 2: Two cuts in the state-transition diagram

To derive (26), we first balance flows across cuts 1 in the state-transition diagram (Figure 2). As a result we obtain the following equations:

$$\lambda(P_{S,n} + P_{F,n}) = \mu_S P_{S,n+1} + \mu_F P_{F,n+1} \quad \forall n \tag{49}$$

If we let $G = \sum_{n=0}^{\infty} nP_{S,n}$, $H = \sum_{n=0}^{\infty} nP_{F,n}$, multiply both sides of (49) by $n+1$, and sum over all n, then we obtain

$$\lambda \sum_{n=0}^{\infty} ((n+1)P_{S,n} + (n+1)P_{F,n}) \quad = \quad \mu_S \sum_{n=0}^{\infty} (n+1)P_{S,n+1} + \mu_F \sum_{n=0}^{\infty} (n+1)P_{F,n+1}$$

$$\lambda(G+H)+\lambda \;=\; \mu_S G+\mu_F H.$$

This is (26), the first equation needed.

Next we rewrite (5):

$$\begin{aligned} X_{n+2}-DX_{n+1}+CX_n &= 0, \qquad\qquad \forall n\geq 0 \\ X_1 &= CX_0. \end{aligned} \tag{50}$$

Again, we multiply (50) by $n+1$ and sum over n from 0 to ∞, to obtain:

$$\begin{aligned} \sum_{n=0}^{\infty}(n+2)X_{n+2}-\sum_{n=0}^{\infty}X_{n+2} &= D\sum_{n=0}^{\infty}(n+1)X_{n+1}-C\sum_{n=0}^{\infty}nX_n-C\sum_{n=0}^{\infty}X_n \\ \sum_{n=2}^{\infty}nX_n-\sum_{n=2}^{\infty}X_n &= D\sum_{n=1}^{\infty}nX_n-C\sum_{n=0}^{\infty}nX_n-C\sum_{n=0}^{\infty}X_n \\ \sum_{n=0}^{\infty}nX_n-X_1-\sum_{n=2}^{\infty}X_n &= D\sum_{n=0}^{\infty}nX_n-C\sum_{n=0}^{\infty}nX_n-C\sum_{n=0}^{\infty}X_n \\ (I-D+C)\sum_{n=0}^{\infty}nX_n &= \sum_{n=1}^{\infty}X_n-C\sum_{n=0}^{\infty}X_n. \end{aligned} \tag{51}$$

Now if we balance the flow across cut 2 in Figure 2, then we obtain $p_{SF}\mu_S\sum_{n=1}^{\infty}P_{S,n} = p_{FS}\mu_F\sum_{n=1}^{\infty}P_{F,n}$. Moreover, $\sum_{n=1}^{\infty}(P_{S,n}+P_{F,n})=\rho$. Therefore, $\sum_{n=1}^{\infty}P_{S,n} = \frac{p_{FS}}{p_{SF}+p_{FS}}\cdot\frac{\lambda}{\mu_S}$ and $\sum_{n=1}^{\infty}P_{F,n}=\frac{p_{SF}}{p_{SF}+p_{FS}}\cdot\frac{\lambda}{\mu_F}$, so (51) becomes:

$$\begin{pmatrix} -\mu_S P_{SF} & \mu_F P_{FS} \\ \mu_S P_{SF} & -\mu_F P_{FS} \end{pmatrix}\begin{pmatrix} G \\ H \end{pmatrix} = \begin{pmatrix} \frac{P_{FS}\lambda}{P_{SF}+P_{FS}} \\ \frac{P_{SF}\lambda}{P_{SF}+P_{FS}} \end{pmatrix} - \begin{pmatrix} \frac{p_{FS}}{p_{SF}+p_{FS}}\cdot\frac{\lambda}{\mu_S}+P_{S,0} \\ \frac{p_{SF}}{p_{SF}+p_{FS}}\cdot\frac{\lambda}{\mu_F}+P_{F,0} \end{pmatrix},$$

out of which we obtain (only) one independent equation, equation (27).

References

[1] Leonard Kleinrock. *Queueing Systems*, volume 1: Theory. John Wiley & Sons, 1975.

[2] R.M. Loynes. The stability of a queue with non-independent inter-arrival and service times. *Mathematical Proceedings of the Cambridge Philosophical Society*, 58(3):497–520, 1965.

[3] Douglas J. Morrice, Ravindra S. Gajulapalli, and Sridhar R. Tayur. A single server queue with cyclically indexed arrival and service rates. *Queueing Systems: Theory and Applications*, 15:165–198, 1994.

[4] Valeri Naoumov. Matrix-multiplicative approach to quasi-birth-and-death processes analysis. In Srinivas R. Chakravarthy and Attahiru S. Alfa, editors, *Matrix-Analytic Methods in Stochastic Models*, pages 87–106, New York, 1996. Marcel Dekker Inc.

[5] Marcel F. Neuts. *Matrix-Geometric Solutions in Stochastic Models : An Algorithmic Approach.* Number 2 in Johns Hopkins Series in the Mathematical Sciences. Johns Hopkins University Press, Baltimore, MD, 1981.

[6] N.U. Prabhu. *Stochastic Storage Processes: Queues, Insurance Risk, Dams, and Data Communication.* Springer-Verlag New York, Inc, second edition, 1997.

[7] L. D. Servi. Algorithmic solutions to recursively tradiagonal linear equations with application to multi-dimensional birth-death processes. Working paper, GTE Laboratories Incorporated, Waltham, MA 02254 USA, 1999.

[8] Ronald W. Wolff. *Stochastic Modeling and the Theory of Queues.* Prentice-Hall Inc., Englewood Cliffs, New Jersey 07632, 1989.

[9] Yixin Zhu and Huan Li. The MacLaurin expansion for a $G/G/1$ queue with Markov-modulated arrivals and services. *Queueing Systems: Theory and Applications*, 14:125–134, 1993.