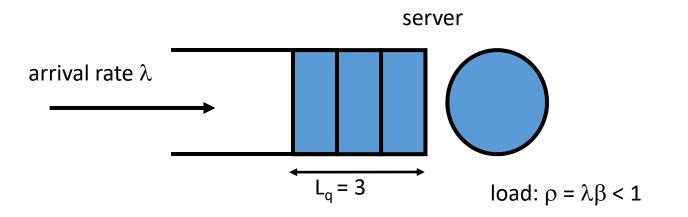
Algorithmic Methods in Queueing Theory (AlQT)



Thanks to: Ahmad Al Hanbali

CW

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Time schedule



Course	Teacher	Торісѕ	Date
1	Rob	Methods for equilibrium distributions for Markov chains	25/01/21
2	Rob	Markov processes and transient analysis	01/02/21
3	Rob	M/M/1-type models and matrix-geometric method	08/02/21
4	Rob	Buffer occupancy method	15/02/21
5	Rob	Descendant set approach	22/02/21

Wrap up of last two courses



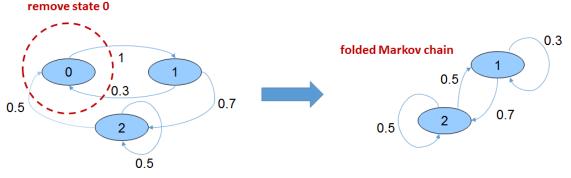
 Calculating equilbrium distributions for discretetime Markov chains

Direct methods

- 1. Gaussian elimination numerically unstable
- 2. GTH method (reduction of Markov chains via folding)
- Spectral decomposition theorem for matrix power Qⁿ
- Maximum eigenvalue (spectral radius) and second largest eigenvalues (sub-radius)

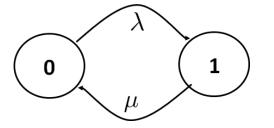
Indirect methods

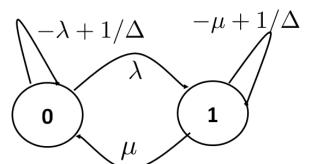
- 1. Matrix powers
- 2. Power method
- 3. Gauss-Seidel



Wrap up of last week

• Continuous-time Markov chains and transient analysis $\sqrt{-\lambda + 1/\Delta} = -\mu + \frac{1}{2}$





Continuous-time Markov chains

- 1. Generator matrix Q
- 2. Uniformization
- 3. Relation CTMC with discrete-time MC at jump moments

Transient analysis

- 1. Kolmogorov equations
- 2. Differential equation
- 3. Expression $P(t) = e^{Qt} = X \operatorname{diag} \left(e^{\lambda_i t} \right) Y^T = \sum_{i=1}^{N} e^{\lambda_i t} x_i y_i^T$
- 4. Mean occupancy time over (0,T)





Lecture 7:

Algorithmic methods for M/M/1type models

Lecture 7 overview



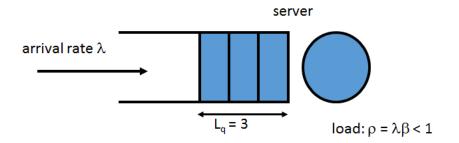
 This Lecture deals with continuous time Markov chains with infinite state space as opposed to finite space Markov chains in Lectures 5 and 6

Objective:

To find the equilibrium distribution of the Markov chain

Background (1): M/M/1 queue

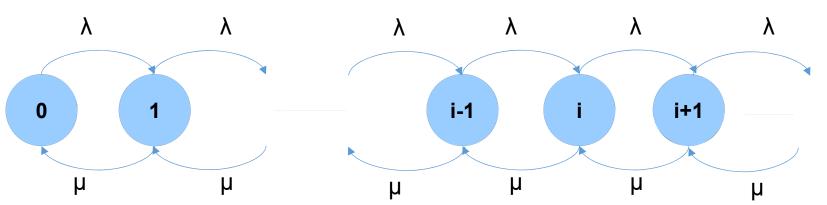




- □ Customers arrive according to **Poisson process** of rate λ , i.e., the inter-arrival times are iid exponential random variables (rv) with rate λ
- \Box Customers' service times are iid exponential rv with mean $1/\mu$
- □ Inter-arrival times and service times are independent
- Service discipline can be First-In-First-Out (FIFO), Last-In-First-Out (LIFO), or Processor Sharing (PS)

Under above assumptions, $\{N(t), t \ge 0\}$, the number of customers in M/M/1 queue at time t is continuous-time infinite space Markov chain

Background (2): M/M/1 queue



Let p_i denote equilibrium probability of state i, then

•
$$-\lambda p_0 + \mu p_1 = 0$$
,

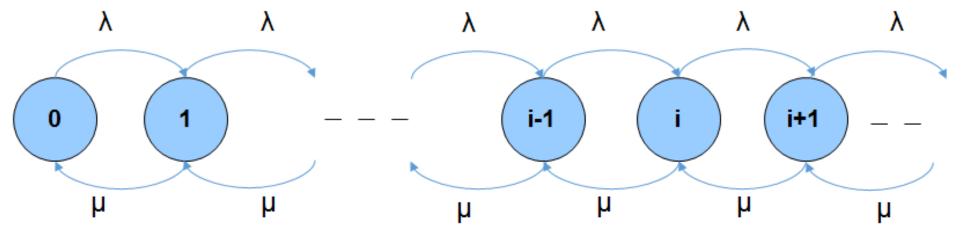
•
$$\lambda p_{i-1} - (\lambda + \mu)p_i + \mu p_{i+1} = 0$$
, $i = 1, 2, ...$
Solving equilibrium equations for $\rho = \lambda/\mu < 1$ (with $\sum_{i\geq 0} p_i = 1$) gives:

$$p_i = p_{i-1}\rho, \ p_0 = 1 - \rho \Rightarrow p_i = (1 - \rho)\rho^i, i \ge 0,$$

This means N is geometrically distributed with parameter ρ_{g} Lecture 7: M/M/1 type models

Background (3): M/M/1 queue





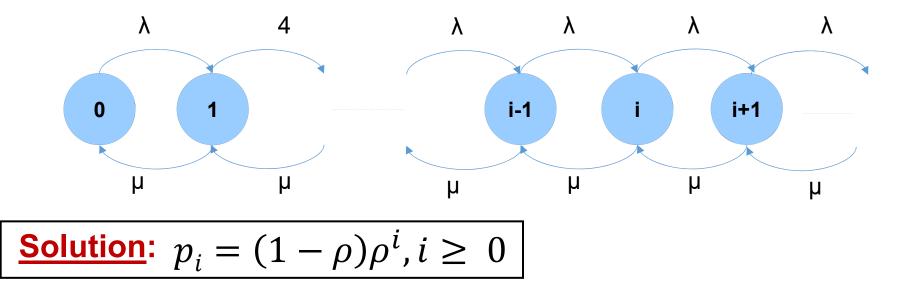
Solution: $p_i = (1 - \rho)\rho^i$, $i \ge 0$

Feature: jumps only to neighbouring states

Idea of generalization to "M/M/1-type" queues:

- 1. State i replaced by **set of states** (called level i)
- 2. Load p replaced by rate matrix R

Background (4): M/M/1 queue



Tail probabilities:

conditioning w.r.t. number of customers upon arrival + PASTA

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$$\begin{split} P(W > t) &= \sum_{i=0}^{\infty} (1 - \rho) \rho^{i} \sum_{j=0}^{i-1} \frac{(\mu t)^{j}}{j!} e^{-\mu t} = \sum_{j=0}^{\infty} \frac{(\mu t)^{j}}{j!} e^{-\mu t} \sum_{i=j+1}^{\infty} (1 - \rho) \rho^{i} \\ &= \sum_{j=0}^{\infty} \frac{(\mu t)^{j}}{j!} e^{-\mu t} \rho^{j+1} \neq \rho e^{-\mu (1 - \rho) t}, \quad t \ge 0. \end{split}$$

given i customers upon arrival, waiting time Erlang-i distributed with mean i/ μ if Poisson process with rate μ , # arrivals in (0;t) is Poisson with mean μ t ¹⁰ Prob { time until i-th arrival > t) = Prob { # of arrivals in (0;t) } < i

Lecture 7: M/M/1 type models

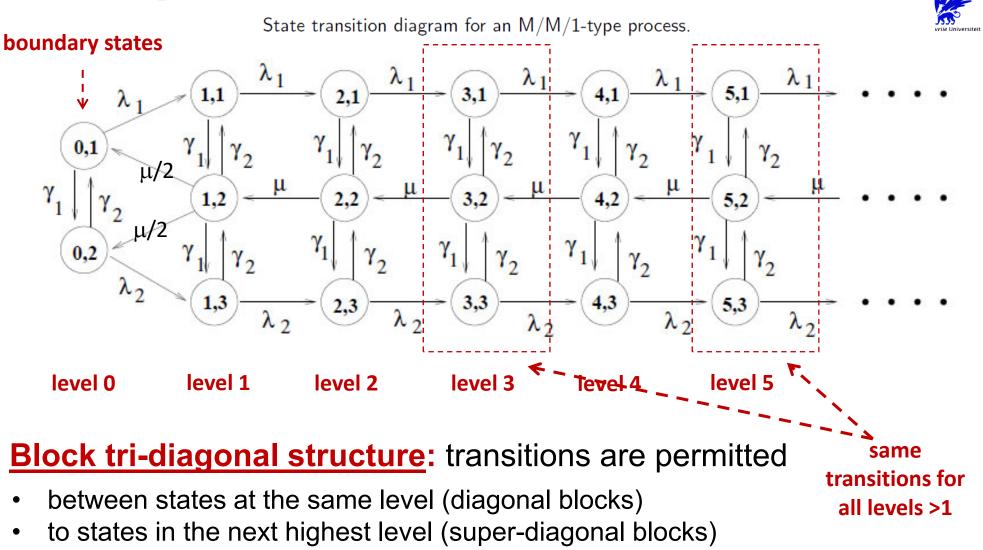
Background (5): M/M/1 queue

- Stability condition: expected queue length is finite, load
 ρ:= λ/μ < 1. This can be interpreted as drift to the right is smaller than drift to left
- In stable case, ρ is probability the M/M/1 system is non-empty, i.e. , $P(N = 0) = 1 \rho$
- Q, the generator of M/M/1 queue, is a tri-diagonal matrix, and has the form

$$Q = \begin{pmatrix} -\lambda & \lambda & 0 & \cdots \\ \mu & -\lambda - \mu & \lambda & \ddots \\ 0 & \mu & -\lambda - \mu & \ddots \\ \vdots & \ddots & \mu & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix}$$

Quasi Birth Death (QBD) process

- A two-dimensional irreducible continuous time Markov process with states (i, j), where $i = 0, ..., \infty$ and j = 0, ..., m 1
- □ Subset of state space with common *i* entry is called **level** *i* (*i* > 0) and denoted $l(i) = \{(i, 0), (i, 1), ..., (i, m - 1)\}$. $l(0) = \{(0,0), (0,1), ..., (i, n - 1)\}$. This means state space is $\bigcup_{i \ge 0} l(i)$
- Transition rate from (i, j) to (i', j') is equal to zero for $|i i'| \ge 2$
- For n > 1, transition rate between states in l(i) and between states in l(i) and $l(i \pm 1)$ is **independent of n**



and to states in the adjacent lower level (sub-triangular blocks) •

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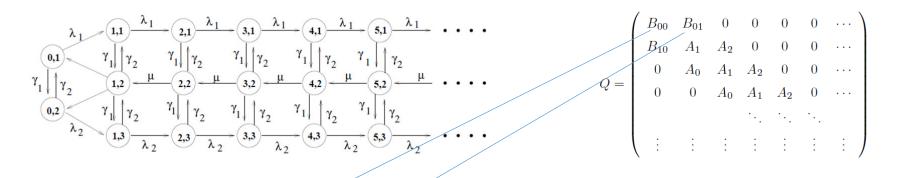


Order the states **lexicographically**, i.e., (0,0), ..., (0,n-1), (1,0), ..., (1,m-1), (2,0), ..., (2,m-1), ..., the *generator* of the QBD has the following form:

(B_{00})	B_{01}	0	0	0	0)	
B_{10}	A_1	A_2	0	0	0		
0	A_0	A_1	A_2				
0	0	A_0	A_1	A_2	0		
			÷.,	÷.,	÷.,		
:	:	:	:	:	:	:	
		$\begin{array}{ccc} B_{10} & A_1 \\ 0 & A_0 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} B_{10} & A_1 & A_2 \\ 0 & A_0 & A_1 \\ 0 & 0 & A_0 \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$

Note that row sums are 0:

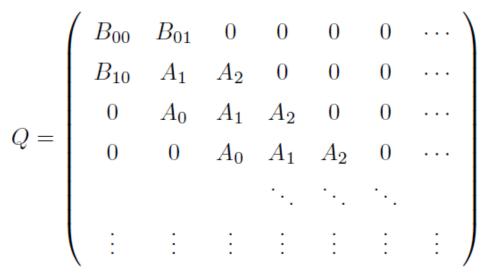
 $(B_{00} + B_{01})e = 0$, $(B_{10} + A_1 + A_2)e = 0$, and $(A_0 + A_1 + A_2)e = 0$

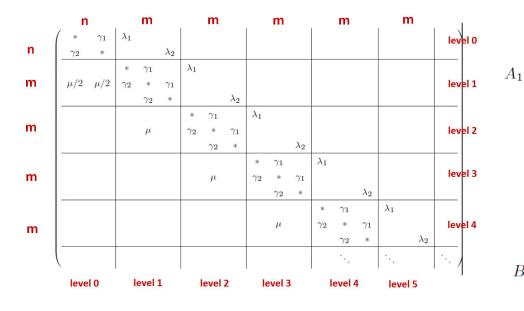


		n m			m	m m				m			m			r	ĩ		
_		(*	γ_1	λ_1														level	
n = 2	n	γ_2	*			λ_2													
				*	γ_1		λ_1												
- 2	m	$\mu/2$	$\mu/2$	γ_2	*	γ_1												level	
m = 3					γ_2	*			λ_2										
							*	γ_1		λ_1									
	m				μ		γ_2	*	γ_1									level	
								γ_2	*			λ_2							
										*	γ_1		λ_1					level	
	m							μ		γ_2	*	γ_1							
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	m										μ		γ_2	*	γ_1			level	
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Generator matrix





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Block matrices

departures: $i \rightarrow i-1$ arrivals: $i \rightarrow i+1$

$$A_{0} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \mu & 0 \\ 0 & 0 & 0 \end{pmatrix}, \quad A_{2} = \begin{pmatrix} \lambda_{1} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \lambda_{2} \end{pmatrix}$$
$$= \begin{pmatrix} -(\gamma_{1} + \lambda_{1}) & \gamma_{1} & 0 \\ \gamma_{2} & -(\mu + \gamma_{1} + \gamma_{2}) & \gamma_{1} \\ 0 & \gamma_{2} & -(\gamma_{2} + \lambda_{2}) \end{pmatrix}$$
generator of transitions within level

$$B_{00} = \begin{pmatrix} -(\gamma_1 + \lambda_1) & \gamma_1 \\ \gamma_2 & -(\gamma_2 + \lambda_2) \end{pmatrix},$$

$$B_{01} = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & 0 & \lambda_2 \end{pmatrix}, \quad B_{10} = \begin{pmatrix} 0 & 0 \\ \mu/2 & \mu/2 \\ 0 & 0 \end{pmatrix}.$$

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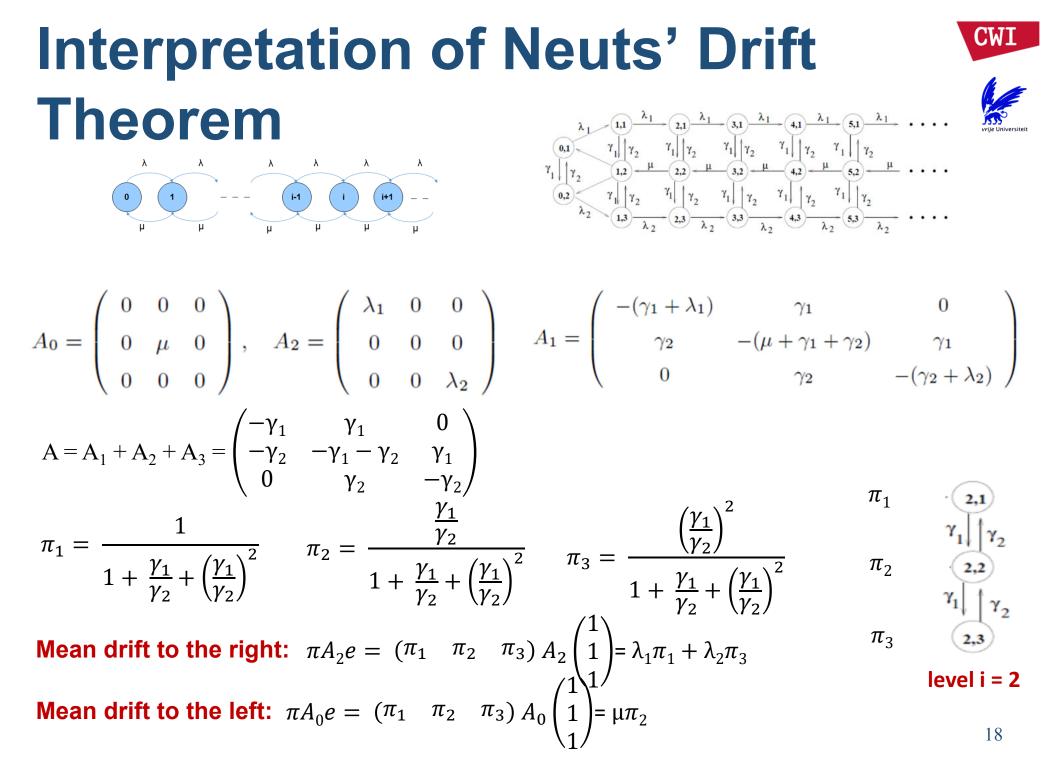
Theorem: The QBD is **ergodic** (i.e., mean recurrence time of the states is finite) iff

 $\pi A_2 e < \pi A_0 e$ (mean drift condition)

where *e* is the column vector of ones and π is the equilibrium distribution of the *irreducible* Markov chain with generator $A = A_0 + A_1 + A_2$, $\pi A = 0$, $\pi e = 1$

Interpretation: $\pi A_2 e$ is mean drift from level *i* to i + 1. $\pi A_0 e$ is mean drift from level *i* to i - 1 (Neuts' drift condition)

Generator A describes the behavior of QBD within level 17



Lecture 7: M/M/1 type models

Equilibrium distribution of QBDs



Let $p_n = (p(n, 0), \dots, p(n, m - 1))$ and $p = (p_0, p_1, \dots)$ Then <u>equilibrium equation</u> "pQ = 0" reads

- $p_{0B_{00}} + p_{1B_{10}} = 0$,
- $p_{0B_{01}} + p_{1A_1} + p_2A_0 = 0$

•
$$p_{n-1}A_2 + p_nA_1 + p_{n+1}A_0 = 0, n \ge 2$$

Q =

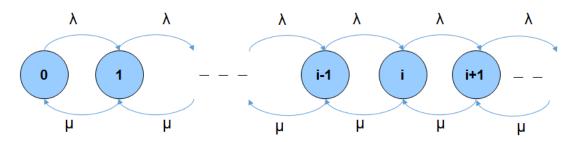
Theorem: if the QBD is positive recurrent, there exists a constant matrix R, such that

$$p_n = p_{n-1}R, n \ge 2 \rightarrow p_n = p_1R^{n-1}, n \ge 2$$

To do: find p_0 , p_1 , and R

Special case of QBD: M/M/1 queue





In that case, the "block matrices" simplify to: $B_{00} = (0), \quad B_{01} = (\lambda), \quad B_{10} = (0)$ $A_0 = (\mu), \quad A_1 = (-\lambda - \mu), \quad A_2 = (\lambda)$

Then the equilibrium probability of state *i*

$$\begin{aligned} &-\lambda p_0 + \mu p_1 = 0, \\ &\lambda p_{i-1} - (\lambda + \mu) p_i + \mu p_{i+1} = 0, \qquad i = 1, 2, ... \end{aligned}$$

Solving equilibrium equations for $\rho = \lambda/\mu < 1$ gives: $p_i = p_{i-1}\rho, \ p_0 = 1 - \rho \Rightarrow \ p_i = (1 - \rho)\rho^i, i \ge 0,$

R-matrix

for any other non-negative solution S, we have $R \le S$



Lemma: The matrix *R* is the minimal nonnegative solution to the matrix equation

$$A_2 + RA_1 + R^2 A_0 = 0$$

Proof: Substituting $p_n = p_1 R^{n-1}$, $n \ge 2$ into the balance equations $p_{n-1}A_2 + p_n A_1 + p_{n+1}A_0 = 0, n \ge 2$ implies that $p_1 R^{n-2} (A_2 + RA_1 + R^2A_0) = 0$

- *R* is called the **rate matrix** of the Markov process Q
- *R* has spectral radius < 1, and thus, *I-R* is invertible



Lemma: The matrix *R* is the minimal nonnegative solution to the matrix equation

$$A_2 + RA_1 + R^2 A_0 = 0$$

$$B_{00} = (0), \quad B_{01} = (\lambda), \quad B_{10} = (0), \quad e = (1)$$

$$A_0 = (\mu), \quad A_1 = (-\lambda - \mu), \quad A_2 = (\lambda), \quad R = (\rho)$$

In M/M/1-case, the matrix R = (r) and the above equation is:

$$\lambda + r(-\lambda - \mu) + r^2\mu = 0 \rightarrow r = 1 \text{ or } r = \rho$$

smallest nonnegative solution

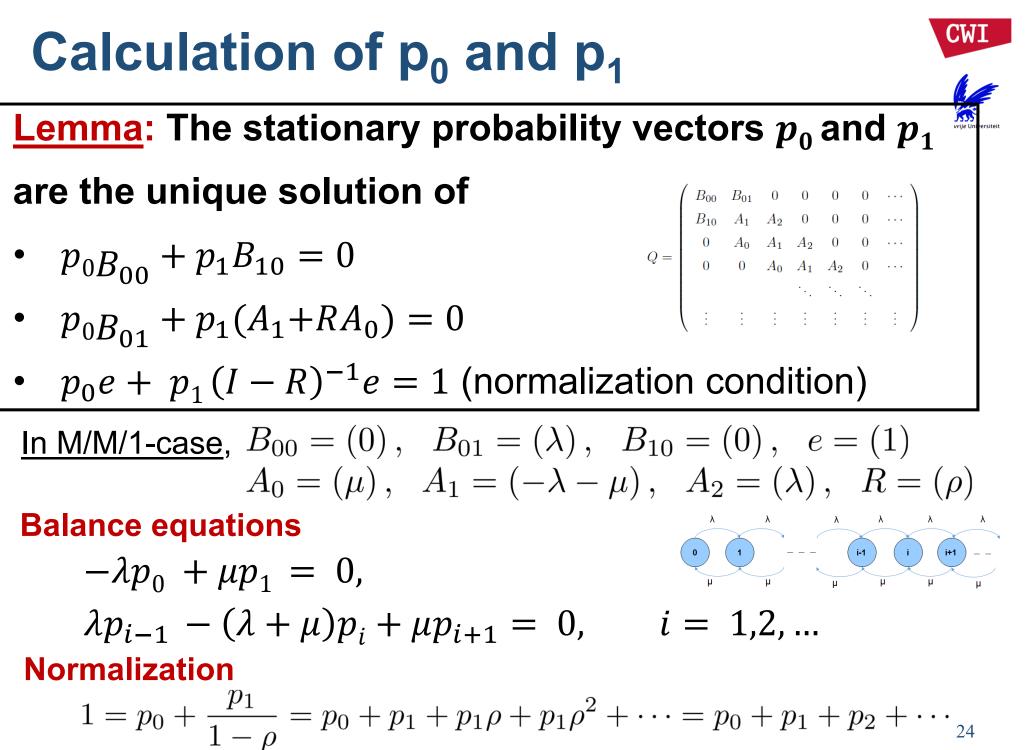


Lemma: The matrix *R* satisfies the following equation

 $A_2 + RA_1 + R^2A_0 = 0$

Iterative solution to compute R Lemma implies: $A_2A_1^{-1} + R + R^2A_0A_1^{-1} = 0$ Hence: $R = -A_2A_1^{-1} - R^2A_0A_1^{-1} = -V - R^2W$ Iteration: $R_{(0)} = 0$; $R_{(k+1)} = -V - R_{(k)}^2W$, k = 1, 2, ...

The iteration can be shown to converge to R (fixed point equation), since spectral radius < 1



Lecture 7: M/M/1 type models

Matrix geometric method



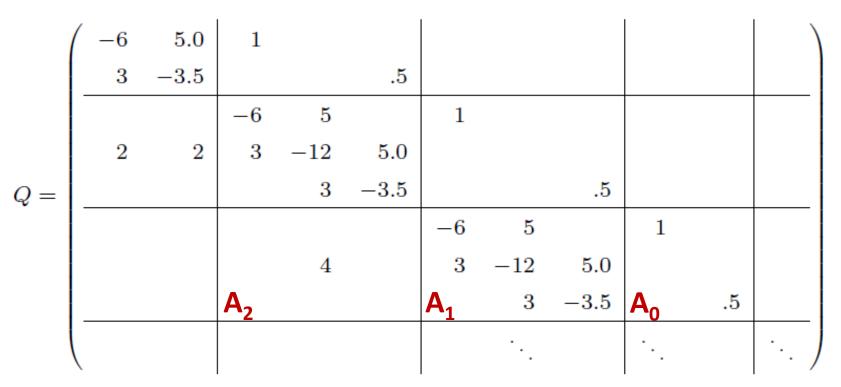
- **<u>Step 1</u>**: Verify that the matrix satisfies requirements of QBD structure
- Step 2: Verify that stability condition is satisfied
- **<u>Step 3</u>**: Use recursion to compute the R-matrix
- **<u>Step 4</u>**: Solve the set of equations to calculate p_0 and p_1
- **<u>Step 5</u>**: Use recursion $p_n = p_{n-1}R$ to find all other p_n vectors

Example of Matrix Geometric method

Take the following parameter values for the example QBD process on page 13:

$$\lambda_1 = 1, \ \lambda_2 = .5, \ \mu = 4, \ \gamma_1 = 5, \ \gamma_2 = 3.$$

The infinitesimal generator is then given by



Step 1. The matrix obviously has the correct QBD structure.

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Step 2: Check stability

2. We check that the system is stable by verifying Equation (8). The infinitesimal generator matrix

$$A = A_0 + A_1 + A_2 = \begin{pmatrix} -5 & 5 & 0\\ 3 & -8 & 5\\ 0 & 3 & -3 \end{pmatrix}$$

has stationary probability vector

 $\pi_A = (.1837, .3061, .5102)$

and

$$.4388 = \pi_A A_2 e < \pi_A A_0 e = 1.2245$$



Lecture 7: M/M/1 type models

Example of MGM

Recall that

$$R = -A_2 A_1^{-1} - R^2 A_0 A_1^{-1} = -V - R^2 W$$



Step 3: Recursion for R-matrix

3. We now initiate the iterative procedure to compute the rate matrix

R. The inverse of A_1 is

$$A_1^{-1} = \left(\begin{array}{ccc} -.2466 & -.1598 & -.2283 \\ -.0959 & -.1918 & -.2740 \\ -.0822 & -.1644 & -.5205 \end{array}\right)$$

which allows us to compute

$$V = A_2 A_1^{-1} = \begin{pmatrix} -.2466 & -.1598 & -.2283 \\ 0 & 0 & 0 \\ -.0411 & -.0822 & -.2603 \end{pmatrix}$$
$$W = A_0 A_1^{-1} = \begin{pmatrix} 0 & 0 & 0 \\ -.3836 & -.7671 & -1.0959 \\ 0 & 0 & 0 \end{pmatrix}$$

Example of MGM Recursion $R_{(0)} = 0; \quad R_{(k+1)} = -V - R_{(k)}^2 W, \quad k = 1, 2, ...$

$$R_{(k+1)} = \begin{pmatrix} .2466 & .1598 & .2283 \\ 0 & 0 & 0 \\ .0411 & .0822 & .2603 \end{pmatrix} + R_{(k)}^2 \begin{pmatrix} 0 & 0 & 0 \\ .3836 & .7671 & 1.0959 \\ 0 & 0 & 0 \end{pmatrix}$$

and iterating successively, beginning with $R_{\left(0\right)}=0,$ we find

$$R_{(1)} = \begin{pmatrix} .2466 & .1598 & .2283 \\ 0 & 0 & 0 \\ .0411 & .0822 & .2603 \end{pmatrix}, R_{(2)} = \begin{pmatrix} .2689 & .2044 & .2921 \\ 0 & 0 & 0 \\ .0518 & .1036 & .2909 \end{pmatrix},$$
$$R_{(3)} = \begin{pmatrix} .2793 & .2252 & .2921 \\ 0 & 0 & 0 \\ .0567 & .1134 & .3049 \end{pmatrix}, \cdots$$

After 48 iterations, successive differences are less than 10^{-12} , at which point

$$R_{(48)} = \left(\begin{array}{ccc} .2917 & .2500 & .3571 \\ 0 & 0 & 0 \\ .0625 & .1250 & .3214 \end{array}\right).$$



Equations for p₀ and p₁

CWI

- $p_{0B_{00}} + p_1 B_{10} = 0$
- $p_{0B_{01}} + p_1(A_1 + RA_0) = 0$
- $p_0 e + p_1 (I R)^{-1} e = 1$ (normalization condition)

Step 4: calculation of p₀ and p₁

$$(p_0, p_1) \begin{pmatrix} B_{00} & B_{01} \\ B_{10} & A_1 + RA_0 \end{pmatrix} = (p_0, p_1) \begin{pmatrix} -6 & 5.0 & 1 & 0 & 0 \\ 3 & -3.5 & 0 & 0 & .5 \\ \hline 0 & 0 & -6 & 6.0 & 0 \\ 2 & 2 & 3 & -12.0 & 5.0 \\ 0 & 0 & 0 & 3.5 & -3.5 \end{pmatrix} = (0, 0)$$

Solution:

 $(\pi_0, \pi_1) = (1.0, 1.6923, | .3974, .4615, .9011)$

Next step: normalization

Equations for p_0 and p_1

CWI

- $p_{0B_{00}} + p_1B_{10} = 0$
- $p_{0B_{01}} + p_1(A_1 + RA_0) = 0$
- $p_0 e + p_1 (I R)^{-1} e = 1$ (normalization condition)

<u>Step 4</u>: normalization of p_0 and p_1

Normalization constant equals

$$\alpha = \pi_0 e + \pi_1 \left(I - R \right)^{-1} e$$

$$= (1.0, \ 1.6923) e + (.3974, \ .4615, \ .9011) \begin{pmatrix} 1.4805 & .4675 & .7792 \\ 0 & 1 & 0 \\ .1364 & .2273 & .15455 \end{pmatrix} e$$

$$= 2.6923 + 3.2657 = 5.9580$$

which allows us to compute

$$\pi_0/\alpha = (.1678, .2840)$$

and

$$\pi_1/\alpha = (.0667, .0775, .1512)$$

Lecture 7: M/M/1 type models

Step 5: subcomponents of stationary distribution

$$\pi_2 = \pi_1 R = (.0667, .0775, .1512) \begin{pmatrix} .2917 & .2500 & .3571 \\ 0 & 0 & 0 \\ .0625 & .1250 & .3214 \end{pmatrix}$$
$$= (.0289, .0356, .0724)$$

and

$$\pi_3 = \pi_2 R = (.0289, .0356, .0724) \begin{pmatrix} .2917 & .2500 & .3571 \\ 0 & 0 & 0 \\ .0625 & .1250 & .3214 \end{pmatrix}$$
$$= (.0130, .0356, .0336)$$

and so on.



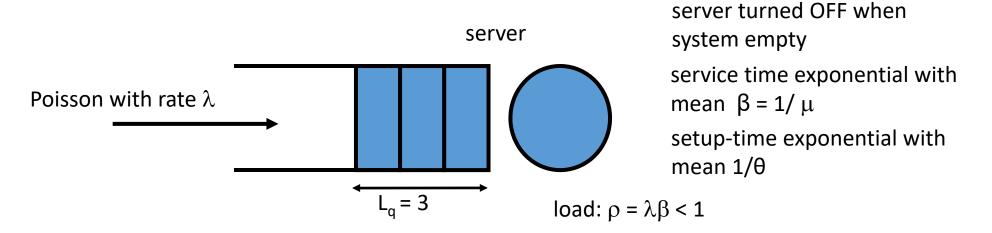


Applications of three M/M/1-type models

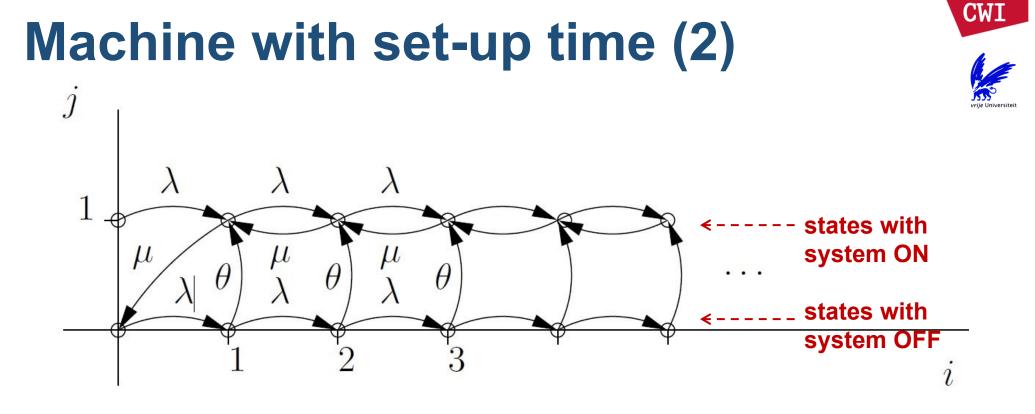
- 1. Machine with set-up times
- 2. Unreliable machine
- 3. M/E_r/1 model

Machine with set-up times (1)



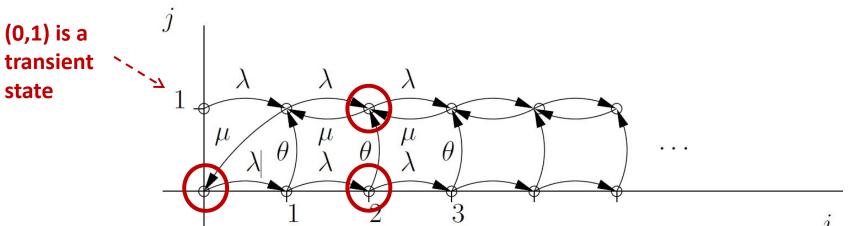


- In addition to assumptions on the M/M/1 system, further assume that the system is turned off when it is empty
- System is turned on again when a new customer arrives
- The set-up time is exponentially distributed with mean $1/\theta$



- Number of customers in system is not a Markov process: evolution depends on whether ON or OFF
- Two-dimensional process of state (i, j) where *i* is number of customers and *j* is system state (j = 0 if system is off, j = 0 if system is on) is Markov process

Machine with set-up time (3)



□ p(i,j) is equilibrium probability of state $(i,j), i \ge 0, j = 0, 1$

Balance equations:

1.
$$p(0,0)\lambda = p(1,1)\mu$$

2. $p(i,0)(\lambda + \theta) = p(i - 1,0)\lambda$ $(i \ge 1)$
3. $p(i,1)(\lambda + \mu) = p(i,0)\theta + p(i + 1,1)\mu + p(i - 1,1)\lambda$ $(i \ge 1)$

CW

Machine with set-up time (4)

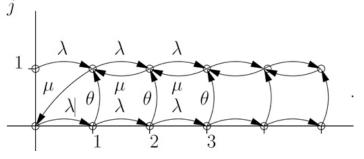


Let $p_i = (p(i, 0), p(i, 1))$, then **balance equations** read

$$p_0B_1 + p_1B_2 = 0,$$

$$p_{i-1}A_0 + p_iA_1 + p_{i+1}A_2 = 0, i \ge 1$$

where



$$A_{0} = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix}, A_{2} = \begin{pmatrix} 0 & 0 \\ 0 & \mu \end{pmatrix}, A_{1} = \begin{pmatrix} -(\lambda + \theta) & \theta \\ 0 & -(\lambda + \mu) \end{pmatrix},$$
$$B_{1} = \begin{pmatrix} -\lambda & 0 \\ 0 & -\lambda \end{pmatrix}, B_{2} = \begin{pmatrix} 0 & 0 \\ \mu & 0 \end{pmatrix}$$

We use the Matrix-Geometric Method (MGM) to the find the equilibrium probability distribution

Machine with set-up time (5)



Let $p_i = (p(i, 0), p(i, 1))$, then balance equations read $p_0B_1 + p_1B_2 = 0$, $p_{i-1}A_0 + p_iA_1 + p_{i+1}A_2 = 0, i \ge 1$

Generator matrix (block structure)

$$Q = \begin{pmatrix} B_1 & A_0 & 0 & \cdots \\ B_2 & A_1 & A_0 & \ddots \\ 0 & A_2 & A_1 & \ddots \\ \vdots & \ddots & A_2 & \ddots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix} \qquad A_0 = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix}, A_2 = \begin{pmatrix} 0 & 0 \\ 0 & \mu \end{pmatrix}, A_1 = \begin{pmatrix} -(\lambda + \theta) & \theta \\ 0 & -(\lambda + \mu) \end{pmatrix}$$
$$B_1 = \begin{pmatrix} -\lambda & 0 \\ 0 & -\lambda \end{pmatrix}, B_2 = \begin{pmatrix} 0 & 0 \\ \mu & 0 \end{pmatrix}$$

We use the Matrix-Geometric Method (MGM) to the find the equilibrium probability distribution

Lecture 7: M/M/1 type models

Matrix Geometric method (1)

Balance principle: Global balance equations are given by equating flow from level i to i + 1 with flow from i + 1 to i which gives,

$$(p(i, 0) + p(i, 1))\lambda = p(i + 1, 1)\mu, i \ge 1$$

In matrix notation, this gives

$$p_{i+1}A_2 = p_iA_3$$
, where $A_3 = \begin{pmatrix} \lambda & 0 \\ \lambda & 0 \end{pmatrix}$

Recall that (balance equation)

Elimination of p_{i+1} gives, for $i \ge 1$, $p_{i-1}A_0 + p_iA_1 + p_{i+1}A_2 = 0, i \ge 1$ $p_{i-1}A_0 + p_i(A_1 + A_3) = 0 \Rightarrow p_i = -p_{i-1}A_0(A_1 + A_3)^{-1}$ $\Rightarrow R = -A_0(A_1 + A_3)^{-1} = \begin{pmatrix} \lambda / (\lambda + \theta) & \lambda / \mu \\ 0 & \lambda / \mu \end{pmatrix}$ Explicit expression for R

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Matrix Geometric method (2)

 <u>Stability condition</u>: absolute values of eigenvalues of R should be strictly smaller than 1

 $\lambda < \mu \text{ and } \theta > 0$ (0,1) is a transient state

Normalization condition gives

 $p_0(I+R+R^2+\cdots)e=1 \Rightarrow p_0(I-R)^{-1}e=1$

- Note that (0,1) is a transient state, thus p(0,1) = 0. Normalization gives that $p(0,0) = \frac{\theta}{\theta + \lambda} \left(1 - \frac{\lambda}{\mu}\right)$
- Mean number of customers

$$E[L] = \sum_{i \ge 1} i p_i e = p_0 R(I - R)^{-2} e$$

Observations:

if $\theta \rightarrow$ infinity, then regular M/M/1, and p(0,0)= 1 – λ/μ

if
$$\lambda/\mu \rightarrow 1$$
, then $p(0,0) \rightarrow 0$



Explicit solutions in special cases

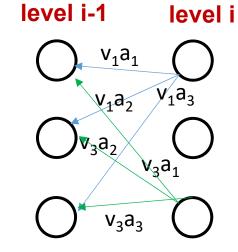


<u>Property</u>: In case $A_2 = v \cdot \alpha$ is a product of two vectors where v is column vector and α is row vector with $\sum_{j=0}^{m} \alpha_j = 1$, the rate matrix reads, with e is a column vector of ones,

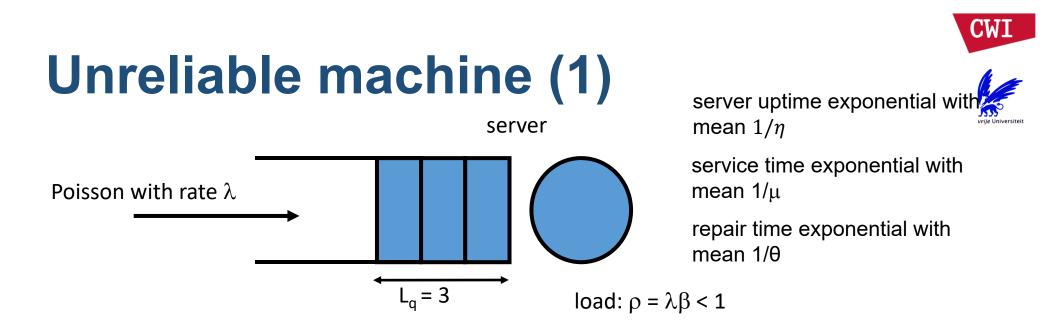
 $R = -A_0 (A_1 + A_0 e\alpha)^{-1},$

Interpretation of the assumption

When the process Q jumps from level i to level i-1, the probability of jumping to state (i-1, j) is <u>independent</u> of the starting state at level i



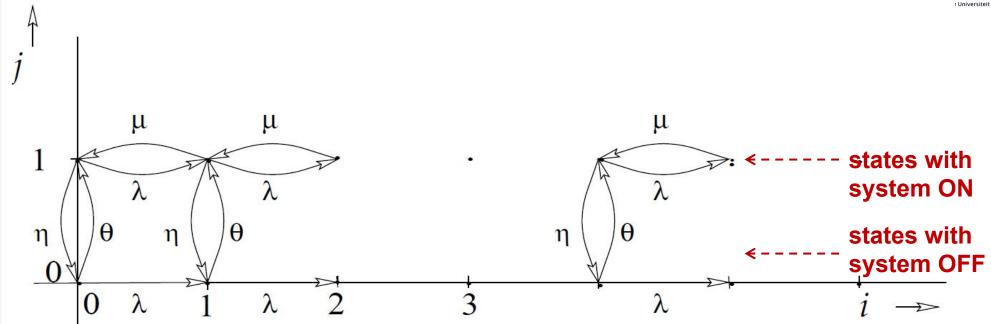
(see lecture notes for more details and special cases)



- Customers arrive according to Poisson process with rate λ
- Service times is exponentially distributed of mean $1/\mu$
- Uptime of the machine is exponentially distributed with mean $1/\eta$
- Repair time is exponentially distributed with mean $1/\theta$
- **Stability condition**: load is smaller than capacity of the machine: $\lambda/\mu < P(\text{machine is up}) = \theta/(\theta + \eta)$

Unreliable machine (2)

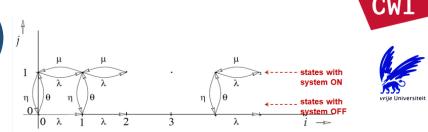




The **two-dimensional process** of state (i, j), where *i* number of customers, *j* the state of machine (j = 1 machine up, j = 0 machine down) is a Markov chain

• Note that
$$A_2 = \begin{pmatrix} 00\\ 0\mu \end{pmatrix} = \begin{pmatrix} 0\\ \mu \end{pmatrix} (0 \quad 1) = v\alpha$$
, with $v = \begin{pmatrix} 0\\ \mu \end{pmatrix}$ and $\alpha = (0 \quad 1)$.

Unreliable machine (3) $\int_{1}^{\frac{1}{2}} \int_{1}^{\frac{\mu}{2}} \int_{1}$



 $\frac{\lambda}{\mu} < \rho_U$ with $\rho_U = \frac{1/\eta}{1/\eta + 1/\theta}$ (=fraction of time that system is up)

Balance equations:

 $p(i,0)(\lambda + \theta) = p(i-1,0)\lambda + p(i,1)\eta, \quad i = 1, 2, \dots$ $p(i,1)(\lambda + \eta + \mu) = p(i,0)\theta + p(i+1,1)\mu + p(i-1,1)\lambda, \quad i = 1, 2, \dots$

Matrix notation:

 $p_0 B_1 + p_1 A_2 = 0,$ $p_{i-1}A_0 + p_iA_1 + p_{i+1}A_2 = 0, \qquad i = 1, 2, \dots,$ Level probabilities:

 $p_i = (p(i, 0), p(i, 1))$

$$A_{0} = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix}, \quad A_{1} = \begin{pmatrix} -(\lambda + \theta) & \theta \\ \eta & -(\lambda + \mu + \eta) \end{pmatrix}, \quad A_{2} = \begin{pmatrix} 0 & 0 \\ 0 & \mu \end{pmatrix}$$
$$B_{1} = \begin{pmatrix} -(\lambda + \theta) & \theta \\ \eta & -(\lambda + \eta) \end{pmatrix}.$$

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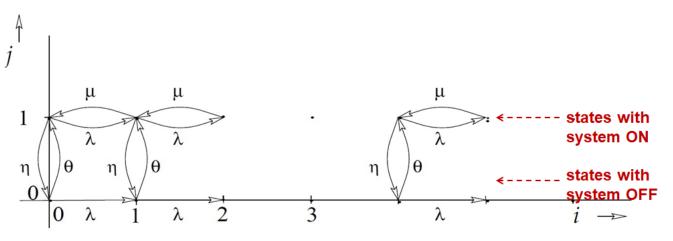
Unreliable machine (3)

Stability:

 $\frac{\lambda}{\mu} < \rho_{U} \text{ with } \rho_{U} = \frac{1/\eta}{1/\eta + 1/\theta} \text{ (=fraction of time that system is up)}$ $\pi_{0} = \frac{\eta}{\eta + \theta} \qquad \pi_{1} = \frac{\theta}{\eta + \theta}$ machine down machine up
(solution to MC within a level) $\int_{0}^{j} \frac{\mu}{\lambda + 1/\theta} = \frac{\mu}{\lambda + 1/\theta}$

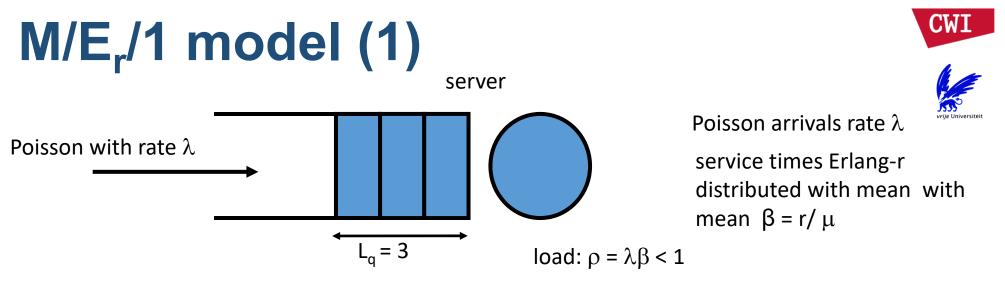
Mean drift to the left: $\pi A_2 e = (\pi_0 \quad \pi_1) \begin{pmatrix} 0 & 0 \\ 0 & \mu \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \mu \pi_1$ Mean drift to the right: $\pi A_0 e = (\pi_0 \quad \pi_1) \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \lambda$ Neuts' drift condition: $\lambda < \mu \pi_1 = \frac{\mu \theta}{n+\theta}$

Unreliable machine (4)



Since $A_2 = v\alpha$, the matrix-geometric method gives $p_i = p_{0R}i, i \ge 1$, with $R = -A_0(A_1 + A_0e\alpha)^{-1} = \frac{\lambda}{\mu} \begin{pmatrix} \frac{\eta+\mu}{\lambda+\theta} & 1\\ \frac{\eta}{\lambda+\theta} & 1 \end{pmatrix}$

- □ Note in this case we have that $p_0(I R)^{-1} = (1 p_u \quad p_u)$, where p_u is probability that the machine is up $\theta/(\eta + \theta)$.
- We find $p_0 = (1 p_u \quad p_u)(I R) = \left(p_u \frac{\lambda}{\mu}\right) \left(\frac{\eta}{\lambda + \theta} \quad 1\right)$



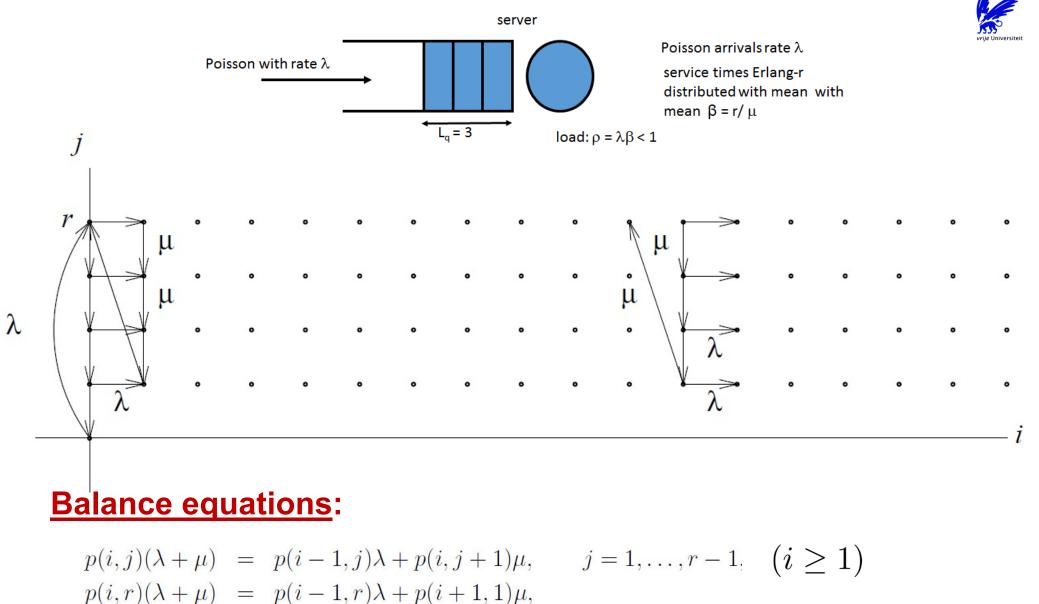
 \square Poisson arrivals with rate λ

- Service times is Erlang distributed of r phases each of mean 1/µ,
 i.e., is sum r exponentially distributed random variable, each of rate µ
- Stability if offered load is smaller than 1:

 $\rho = \lambda r/\mu < 1$

Two dimensional process of state (i,j) where i is number of customers in the system (excluding the customer in service) and j remaining phases of customer in service is Markov process
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M/E_r/1 model (2)



CW

M/E_r/1 model (2)

λ

State diagram:



Balance equations:

$$p(i,j)(\lambda + \mu) = p(i-1,j)\lambda + p(i,j+1)\mu, \qquad j = 1, \dots, r-1,$$

$$p(i,r)(\lambda + \mu) = p(i-1,r)\lambda + p(i+1,1)\mu, \qquad (i \ge 1)$$

<u>Matrix notation</u>: $p_{i-1}A_0 + p_iA_1 + p_{i+1}A_2 = 0, \quad i \ge 1$ where $p_i = (p(i, 1), \dots, p(i, r))$

μ

μ

$$A_{0} = \lambda I, A_{2} = \begin{pmatrix} 0 & \cdots & 0 & \mu \\ \vdots & & 0 & 0 \\ \vdots & & & \vdots \\ 0 & \cdots & \cdots & 0 \end{pmatrix}, A_{1} = \mu \begin{pmatrix} -1 & 0 & \cdots & 0 \\ 1 & -1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 1 & -1 \end{pmatrix} - \lambda I$$

Matrix Geometric method

Balance principle: Global balance equations are given by equating flow from level *i* to i + 1 with flow from i + 1 to *i* which gives,

$$(p(i, 1) + \dots + p(i, r))\lambda = p(i + 1, 1)\mu, i \ge 1$$

In matrix notation this gives

$$p_i A_3 = p_{i+1} A_2$$
, where $A_3 = \begin{pmatrix} 0 & \cdots & 0 \lambda \\ \vdots & \vdots & \vdots \lambda \\ 0 & \cdots & 0 \lambda \end{pmatrix}$

□ Elimination of p_{i+1} gives, for $i \ge 1$,

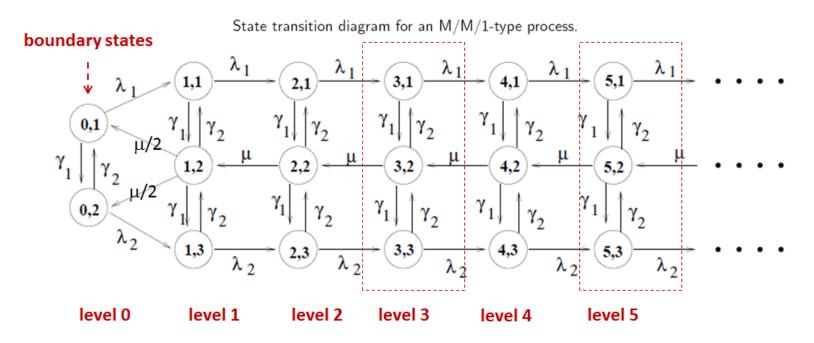
$$p_{i-1}A_0 + p_i(A_1 + A_3) = 0 \Rightarrow p_i = -p_{i-1}A_0(A_1 + A_3)^{-1}$$
$$\Rightarrow R = -A_0(A_1 + A_3)^{-1}$$



Wrap up



- Continuous-time Markov chains on a strip
- M/M/1-type structure, QBD-processes



- Equilibrium solution of the form $p_i = p_1 R^{i-1}$ (i = 1, 2,...)
- Matrix geometric methods
 - Powerful numerical method
 - Closed-form expressions in special cases

References



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