



Lecture 7

Prof. Krishna R. Pattipati

**Dept. of Electrical and Computer Engineering
University of Connecticut**

Contact: krishna@engr.uconn.edu (860) 486-2890

EE 336

***Stochastic Models for the Analysis of Computer Systems
and Communication Networks***

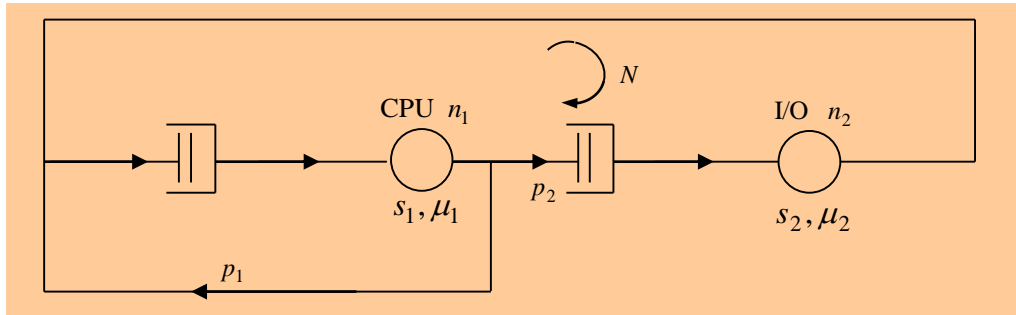


Overview

- ❑ Summary of Lecture 6
- ❑ Single-class Closed Queuing Networks
- ❑ Computational Algorithms
 - Convolution Algorithm
 - Mean Value Analysis
- ❑ Applications
 - Computer Systems
 - Flow Control in Communication Networks

Single-class Closed Queuing Networks -1

- Consider a two node network



$$n_1 + n_2 = N$$

- The visit ratio equations are

$$\left. \begin{aligned} v_1 &= p_1 v_1 + v_2 \\ v_2 &= p_2 v_1 \end{aligned} \right\} \text{ have infinite \# of solutions}$$

$v_i \sim$ Relative Throughput

- ⇒ Choices

$$1) v_1 = \frac{1}{p_1} \Rightarrow v_2 = \frac{p_2}{p_1}$$

visit interpretation

$$2) v_1 = \frac{\mu_1}{s_1} \Rightarrow v_2 = \frac{\mu_1 p_2}{s_2}$$

all utilizations will be scaled by CPU utilization (i.e., node 1)

$$3) v_1 = 1 \Rightarrow v_2 = p_2$$

CPU is the reference node

$$4) v_1 + v_2 = 1$$

Probability interpretation



Single-class Closed Queuing Networks -2

- The probability distributions has *product form*

$$p(n_1, n_2) = \frac{1}{G(N)} Y_1(n_1) Y_2(n_2)$$

$$\text{where } Y_i(n_i) = \left(\frac{v_i s_i}{\mu_i} \right)^{n_i} \quad i = 1, 2$$

- ⇒ $G(N)$ is the convolution of $Y_1(N)$ and $Y_2(N)$

$$G(N) = \sum_{n_1=0}^N Y_1(n_1) Y_2(N - n_1) = Y_1(N) * Y_2(N)$$

- ⇒ Throughput: $X(N) = \frac{G(N-1)}{G(N)}$

- Nodal throughput: $X_i(n) = v_i X(n) \Rightarrow \frac{X_i(n)}{X_j(n)} = \frac{v_i}{v_j}$

relative throughput

- Mean value analysis (MVA) equation

$$p_i(n/N) = \frac{v_i X(N) s_i}{\mu_i} p_i(n-1/N-1) \quad i = 1, 2; n = 1, 2, \dots, N$$

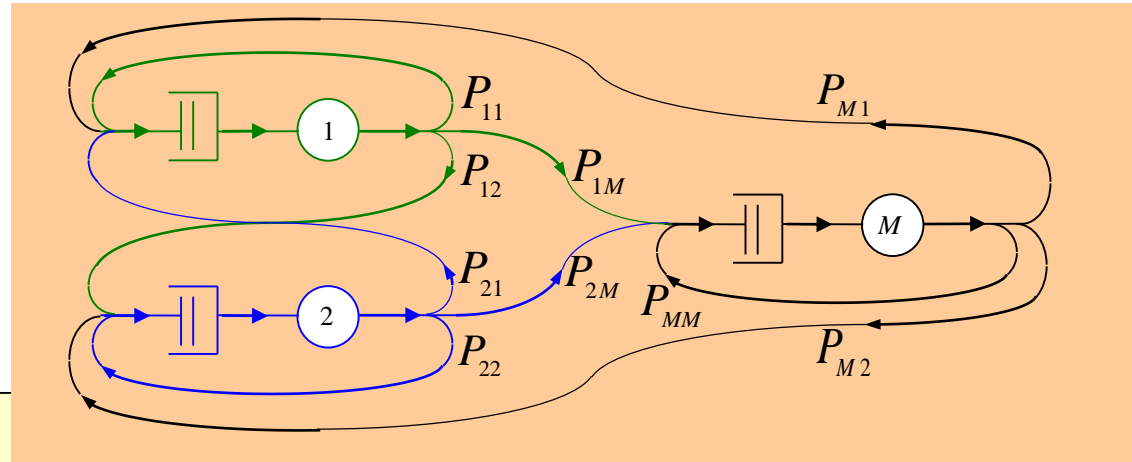
$p_i(n/N) \Rightarrow$ marginal probability that there are n customers at node i given N customers in the network

- ⇒ Response time equation for node i : $R_i(N) = \frac{v_i s_i}{\mu_i} [1 + Q_i(N-1)]$

- ❖ The results are valid for general networks as well with minor changes for various node types



General Structure of Closed Network - 1



Know

- The number of customers in the network is a constant, N
- Since the N customers are distributed among M nodes,

$$n_1 + n_2 + \dots + n_M = N$$
- The service demand at node i is exponentially distributed with mean S_i
- The node types can be of one of the four types

$$\mu_i(n) = \begin{cases} \mu_i & \text{Single-server} \\ n\mu_i & \text{Infinite-server} \\ \min(n, m_i)\mu_i & \text{Multi-server} \\ \{\mu_i(1), \dots, \mu_i(m_i)\} & \text{State-dependent node} \end{cases}$$



General Structure of Closed Network - 2

- The routing of a customer is governed by a Discrete-time Markov chain
- Any work conserving queuing discipline at each node
 - ⇒ when a customer is present, the server will not turn him away or become idle

■ Want to determine

Q_i = Mean number of customers at node i (queue length)

R_i = Response time

U_i = Utilization of node i

$X(n)$ = Network (system) throughput

$X_i(n)$ = Nodal throughput at node i

$p_i(n/N)$ = Marginal prob. that there are n customers at node i



General Structure of Closed Network - 3

Method

– Visits computed from

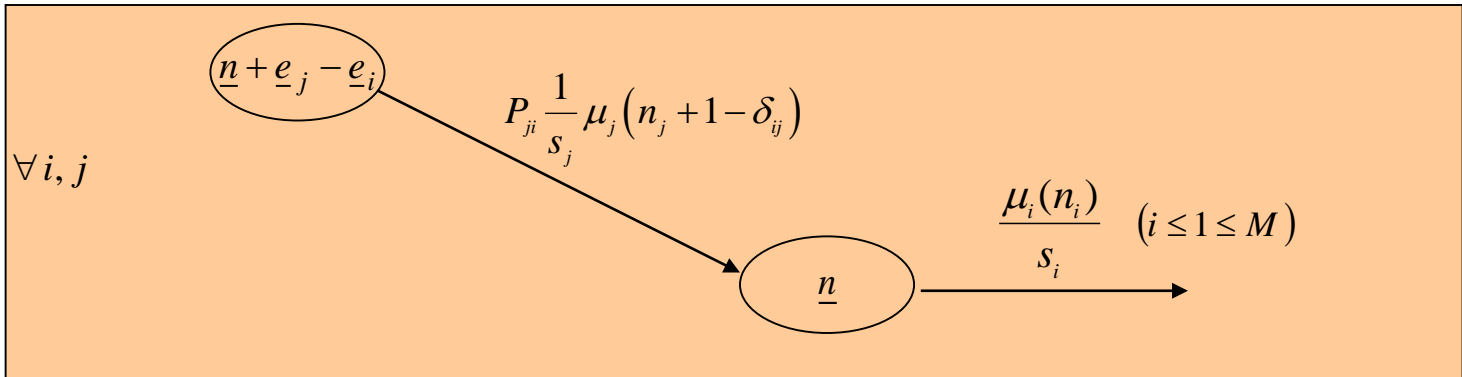
$$v_i = \sum_{j=1}^M P_{ji} v_j \quad \text{or} \quad 1 = \sum_{j=1}^M P_{ji} \frac{v_j}{v_i} \quad \forall i = 1, 2, \dots, M \quad \dots \dots \dots (1)$$

state $(n_1, n_2, \dots, n_M) \ni n_1 + n_2 + \dots + n_M = N$

➤ Number of possible states: **Distribution of N objects among M Nodes**

$$\binom{N + M - 1}{M - 1}$$

Homework problem





Global and Local Balance Equations

Global balance equations

$$\sum_{i=1}^M \sum_{j=1}^M P_{ji} \frac{\mu_j(n_j + 1 - \delta_{ij})}{s_j} p(\underline{n} + \underline{e}_j - \underline{e}_i) = \sum_{i=1}^M \frac{\mu_i(n_i)}{s_i} p(\underline{n})$$

(or)
$$\sum_{i=1}^M \sum_{j=1}^M P_{ji} \left[\frac{\mu_j(n_j + 1 - \delta_{ij})}{s_j} p(\underline{n} + \underline{e}_j - \underline{e}_i) - \frac{\mu_i(n_i)v_j}{s_i v_i} p(\underline{n}) \right] = 0$$
 use (1) here

Local balance equations

$$\frac{\mu_j(n_j + 1 - \delta_{ij})}{s_j v_j} p(\underline{n} + \underline{e}_j - \underline{e}_i) = \frac{\mu_i(n_i)}{s_i v_i} p(\underline{n})$$

$$\Rightarrow p(\underline{n}) = \frac{1}{G_M(N)} \prod_{i=1}^M Y_i(n_i) \quad \Rightarrow Y_i(n_i) = \frac{(v_i s_i)^{n_i}}{\prod_{k=1}^{n_i} \mu_i(k)}$$

$G_M(N) \rightarrow$ Normalization constant



Specialization to Each Node Type

Special Cases

- Single-server nodes: $Y_i(n_i) = \left(\frac{v_i s_i}{\mu_i} \right)^{n_i}$

- Infinite-server nodes: $Y_i(n_i) = \left(\frac{v_i s_i}{\mu_i} \right)^{n_i} \frac{1}{n_i!}$

- Multi-server case:
$$Y_i(n_i) = \begin{cases} \left(\frac{v_i s_i}{\mu_i} \right)^{n_i} \frac{1}{n_i!}; & n_i \leq m_i \\ \left(\frac{v_i s_i}{\mu_i} \right)^{m_i} \frac{1}{m_i!} \left(\frac{v_i s_i}{m_i \mu_i} \right)^{n_i - m_i}; & n_i > m_i \end{cases}$$

- State-dependent node case:
$$Y_i(n_i) = \begin{cases} \frac{(v_i s_i)^{n_i}}{\prod_{k=1}^{n_i} \mu_i(k)}; & n_i \leq m_i \\ \frac{(v_i s_i)^{n_i}}{\prod_{k=1}^{n_i} \mu_i(k)} \frac{1}{[\mu_i(m_i)]^{n_i - m_i}}; & n_i > m_i \end{cases}$$



Properties of Normalization Constant - 1

□ Properties

$$G_M(N) = \sum_{n_1=0}^N \sum_{n_2=0}^{N-n_1} \sum_{n_3=0}^{N-n_1-n_2} \cdots \sum_{n_{M-1}=0}^{N-\sum_{i=1}^{M-2} n_i} Y_1(n_1)Y_2(n_2)\cdots Y_{M-1}(n_{M-1})Y_M\left(N - \sum_{i=1}^{M-1} n_i\right)$$

$$= Y_1(N) * Y_2(N) * \cdots * Y_M(N) \quad \text{Convolution of } Y_i \text{'s}$$

In z-domain

$$G_M(z) = \prod_{i=1}^M Y_i(z) = G_{M-1}(z)Y_M(z)$$

If we let

$$G_l(z) = \prod_{i=1}^l Y_i(z)$$

$$G_l(z) = G_{l-1}(z)Y_l(z), \quad G_0(z) = 1, \quad G_0(n) = \delta_{n0} = \begin{cases} 1 & n = 0 \\ 0 & \text{else} \end{cases}$$

$$G_l(n) = \sum_{k=0}^n G_{l-1}(n-k)Y_l(k)$$

Basis of convolution algorithm
[G_l(0) = 1, G_o(0) = 1]

In particular,

$$G_M(n) = G_{M-\{i\}}(n) * Y_i(n) \quad \forall i = 1, 2, \dots, M$$



Properties of Normalization Constant -2

Special Cases

1. Single-server case

$$G_l(n) = \sum_{k=0}^n G_{l-1}(n-k) \left(\frac{v_l s_l}{\mu_l} \right)^k \Rightarrow G_l(z) = G_{l-1}(z) Y_l(z); \quad Y_l(z) = \left(1 - \frac{v_l s_l}{\mu_l} z \right)^{-1}$$

$$\Rightarrow G_l(z) - \frac{v_l s_l}{\mu_l} z G_l(z) = G_{l-1}(z)$$

(or) $G_l(n) = G_{l-1}(n) + \frac{v_l s_l}{\mu_l} G_l(n-1)$

2. Infinite-server case

$$Y_i(z) = \sum_{n_i=0}^{\infty} \left(\frac{v_i s_i}{\mu_i} \right)^{n_i} \frac{z^{n_i}}{n_i!} = e^{\left(\frac{v_i s_i}{\mu_i} \right) z}$$

$$G_{l+M_l-1}(n) = \sum_{k=0}^n G_{l-1}(n-k) G_{M_l}(k)$$

Suppose, had M_l infinite server nodes. Then

$$G_{M_l}(z) = \exp \left(\left[\sum_{i=1}^{M_l} \frac{v_i s_i}{\mu_i} \right] z \right)$$



Can combine infinite server nodes into a 'single equivalent node'

$$G_{M_l}(n) = \frac{1}{n!} \left(\sum_{i=1}^{M_l} \frac{v_i s_i}{\mu_i} \right)^{n_i} \quad \text{(or)} \quad G_{M_l}(n) = \frac{1}{n} \left(\sum_{i=1}^{M_l} \frac{v_i s_i}{\mu_i} \right) G_{M_l}(n-1); \quad G_{M_l}(0) = 1$$



Properties of Normalization Constant -3

3. Multi-server case

$$G_l(n) = \sum_{k=0}^n G_{l-1}(n-k)Y_l(k)$$

$$Y_l(k) = \begin{cases} \left(\frac{v_l s_l}{k \mu_l} \right) Y_l(k-1); Y_l(0) = 1; & k \leq m_l \\ \left(\frac{v_l s_l}{m_l \mu_l} \right) Y_l(k-1); & k > m_l \end{cases}$$

2. State-dependent server case

$$G_l(n) = \sum_{k=0}^n G_{l-1}(n-k)Y_l(k)$$

$$Y_l(k) = \begin{cases} \left(\frac{v_l s_l}{\mu_l(k)} \right) Y_l(k-1); Y_l(0) = 1; & k \leq m_l \\ \left(\frac{v_l s_l}{\mu_l(m_l)} \right) Y_l(k-1); & k > m_l \end{cases}$$

Can we get a better
Recursion like the way
We did for M|M|m and
S-D queues?....YES



New Recursion for Multi-server and SD Nodes -1

$$G_l(n) = \sum_{k=0}^n G_{l-1}(n-k)Y_l(k) \Rightarrow G_l(z) = Y_l(z)G_{l-1}(z) = \left[\sum_{k=0}^{\infty} Y_l(k)z^k \right] G_{l-1}(z)$$

$$\begin{aligned} G_l(z) \cdot \left(1 - \frac{v_l s_l}{\mu_l(m_l)} z \right) &= \sum_{k=0}^{\infty} \left[Y_l(k)z^k - Y_l(k) \frac{v_l s_l}{\mu_l(m_l)} z^{k+1} \right] G_{l-1}(z) \\ &= \left[\sum_{k=0}^{m_l-1} Y_l(k)z^k - \sum_{k=0}^{m_l-2} Y_l(k) \frac{v_l s_l}{\mu_l(m_l)} z^{k+1} \right] G_{l-1}(z) \\ &= G_{l-1}(z) + \sum_{k=1}^{m_l-1} \left[Y_l(k) - Y_l(k-1) \frac{v_l s_l}{\mu_l(m_l)} \right] z^k G_{l-1}(z) \\ &= G_{l-1}(z) + \sum_{k=1}^{m_l-1} \frac{(v_l s_l)^k}{\prod_{q=1}^{k-1} \mu_l(q)} \left[\frac{1}{\mu_l(k)} - \frac{1}{\mu_l(m_l)} \right] z^k G_{l-1}(z) \end{aligned}$$

$$G_l(n) = G_{l-1}(n) + \frac{v_l s_l}{\mu_l(m_l)} G_l(n-1) + \underbrace{\sum_{k=1}^{\min(m_l-1, n)} \frac{(v_l s_l)^k}{\prod_{q=1}^{k-1} \mu_l(q)} \left[\frac{1}{\mu_l(k)} - \frac{1}{\mu_l(m_l)} \right] G_{l-1}(n-k)}_{\sum_{k=1}^{\min(m_l-1, n)} Y_l(k) \left[1 - \frac{\mu_l(k)}{\mu_l(m_l)} \right] G_{l-1}(n-k)}$$

$$\sum_{k=1}^{\min(m_l-1, n)} Y_l(k) \left[1 - \frac{\mu_l(k)}{\mu_l(m_l)} \right] G_{l-1}(n-k)$$



New Recursion for Multi-server and SD Nodes -2

1. Single-server case ($m_l = 1$)

$$G_l(n) = G_{l-1}(n) + \frac{v_l s_l}{\mu_l(m_l)} G_l(n-1)$$

2. Infinite-server case ($m_l = \infty$)

$$G_l(n) = G_{l-1}(n) + \sum_{k=1}^n Y_l(k) G_{l-1}(n-k) = \sum_{k=0}^n Y_l(k) G_{l-1}(n-k); Y_l(k) = \frac{1}{k} \frac{v_l s_l}{\mu_l} Y_l(k-1); Y_l(0) = 1$$

3. Multi-server case

$$G_l(n) = G_{l-1}(n) + \frac{v_l s_l}{\mu_l(m_l)} G_l(n-1) + \sum_{k=1}^{\min(m_l-1, n)} Y_l(k) \left[1 - \frac{k}{m_l} \right] G_{l-1}(n-k)$$

$$Y_l(k) = \begin{cases} \left(\frac{v_l s_l}{k \mu_l} \right) Y_l(k-1); Y_l(0) = 1; & k \leq m_l \\ \left(\frac{v_l s_l}{m_l \mu_l} \right) Y_l(k-1); & k > m_l \end{cases}$$



Computation of Normalization Constant

□ Algorithm

$$G_0(0) = 1$$

$$G_l(0) = 1 \quad \forall l = 1, 2, \dots, M$$

Do $n = 1, 2, \dots, N$

 Do $l = 1, 2, \dots, M$

 Evaluate Convolution Sum

 End Do

End Do

Key: It turns out that all performance measures Q_i, U_i, R_i , etc. are functions of $G(N)$



Performance Measures from $G(N)$ -1

1. Marginal Probabilities at each node i

k at node $i \Rightarrow N-k$ at all other nodes

Know

$$G_M(N) = \sum_{k=0}^N G_{M-\{i\}}(N-k)Y_i(k)$$

$$1 = \sum_{k=0}^N \frac{G_{M-\{i\}}(N-k)Y_i(k)}{G_M(N)} = \sum_{k=0}^N p_i(k/N)$$

$$\Rightarrow p_i(k/N) = \frac{G_{M-\{i\}}(N-k)Y_i(k)}{G_M(N)}$$

For single-server nodes the result simplifies to:


$$p_i(k/N) = \left[\frac{G_M(N-k) - \frac{v_i s_i}{\mu_i} G_M(N-k-1)}{G_M(N)} \right] \left(\frac{v_i s_i}{\mu_i} \right)^k$$



Performance Measures from $G(N)$ -2

2. Throughput of node i

$$\begin{aligned} X_i(N) &= \sum_{k=1}^N p_i(k/N) \frac{\mu_i(k)}{s_i} \\ &= \sum_{k=1}^N \frac{G_{M-\{i\}}(N-k) Y_i(k)}{G_M(N)} \frac{\mu_i(k)}{s_i} \\ &= v_i \sum_{k=1}^N \frac{G_{M-\{i\}}(N-k) Y_i(k-1)}{G_M(N)} = v_i \frac{\sum_{n=0}^{N-1} G_{M-\{i\}}(N-1-n) Y_i(n)}{G_M(N)} \\ &= v_i \frac{G_M(N-1)}{G_M(N)} \\ &= v_i X(N) \end{aligned}$$

 **Network Throughput**

Performance Measures from $G(N)$ -3

3. Queue length

$$Q_i(N) = \sum_{k=1}^N k p_i(k/N)$$

For single-server nodes

$$\begin{aligned} Q_i(N) &= \sum_{k=1}^N k p_i(k/N) = \sum_{k=1}^N k \left[\frac{G_M(N-k)Y_i(k) - G_M(N-k-1)Y_i(k+1)}{G_M(N)} \right] \\ &= \sum_{k=1}^N \frac{G_M(N-k)Y_i(k)}{G_M(N)} \\ &= \sum_{k=1}^N \left[\left(\prod_{l=1}^k \frac{G_M(N-l)}{G_M(N-l+1)} \right) \frac{v_i s_i}{\mu_i} \right] = \sum_{k=1}^N \prod_{l=0}^{k-1} \left(X(N-l) \frac{v_i s_i}{\mu_i} \right) \\ &= \sum_{k=1}^N \left[\prod_{l=0}^{k-1} U_i(N-l) \right] = \sum_{k=1}^N \prod_{l=k}^N U_i(l) \end{aligned}$$

As $N \rightarrow \infty$ $Q_i(N) \rightarrow \frac{U_i}{1-U_i}$

Like in M/M/1 queue

4. Response time

$$R_i(N) = \frac{Q_i(n)}{X(n)} \quad \text{Over all visits}$$

Mean Value Analysis Recursion

Marginal probabilities,
$$p_i(k/N) = \frac{G_{M-\{i\}}(N-k)Y_i(k)}{G_M(N)}$$

$$p_i(k-1/N-1) = \frac{G_{M-\{i\}}(N-k)Y_i(k-1)}{G_M(N-1)}$$

$$\Rightarrow p_i(k/N) = \frac{Y_i(k)}{Y_i(k-1)} \frac{G_M(N-1)}{G_M(N)} p_i(k-1/N-1)$$

$$\Rightarrow p_i(k/N) = \frac{X(N)v_i s_i}{\mu_i(k)} p_i(k-1/N-1) \quad k = 0,1,2,\dots,N$$

- Probability distribution at node i with N customers is related to the probability distribution at the same node with $(N-1)$ customers

- More Generally,

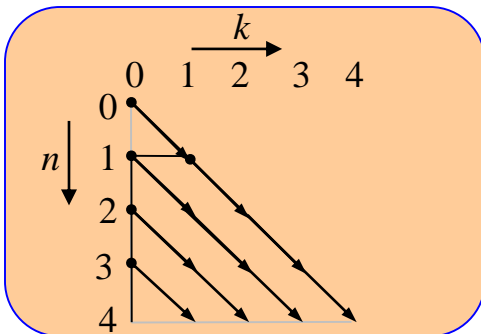
$$p_i(k/n) = \frac{X(n)v_i s_i}{\mu_i(k)} p_i(k-1/n-1); \quad k = 0,1,2,\dots,n$$

$$n = 0,1,2,\dots,N$$

$$p_i(0/0) = 1$$

$$p_i(0/n) = 1 - \sum_{k=1}^n p_i(k/n)$$

Often results in negative probabilities



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MVA Equations for Response Time -1

$$\begin{aligned}
Q_i(n) &= \sum_{k=1}^n k p_i(k/n) \\
&= \sum_{k=1}^n \frac{kv_i s_i}{\mu_i(k)} X(n) p_i(k-1/n-1) \\
&= v_i s_i X(n) \left[\sum_{k=1}^{m_i-1} \frac{k}{\mu_i(k)} p_i(k-1/n-1) + \sum_{k=m_i}^n \frac{k}{\mu_i(m_i)} p_i(k-1/n-1) \right] \\
&= \frac{v_i s_i X(n)}{\mu_i(m_i)} \left[\underbrace{\sum_{k=1}^{m_i-1} k \left[\frac{\mu_i(m_i)}{\mu_i(k)} - 1 \right]}_{\gamma_i(n-1)} p_i(k-1/n-1) + 1 + Q_i(n-1) \right]
\end{aligned}$$

$$\frac{\mu_i(m_i)}{\mu_i(k)} = \frac{m_i}{k} \text{ for multi-server node}$$

$$Q_i(n) = \frac{v_i s_i X(n)}{\mu_i(m_i)} [1 + \gamma_i(n-1) + Q_i(n-1)]$$

(or)

$$R_i(n) = \frac{v_i s_i}{\mu_i(m_i)} [1 + \gamma_i(n-1) + Q_i(n-1)]$$

Note: $Q_i(0) = 0$



MVA Equations for Response Time -2

□ Special cases

1. Single-server case

$$R_i(n) = \frac{v_i s_i}{\mu_i} [1 + Q_i(n-1)]$$

2. Infinite-server case

$$\begin{aligned} R_i(n) &= \lim_{m_i \rightarrow \infty} \frac{v_i s_i}{\mu_i} \left[\sum_{k=1}^{m_i-1} \left(1 - \frac{k}{m_i} \right) p_i(k-1/n-1) + \frac{1}{m_i} + \frac{Q_i(n-1)}{m_i} \right] \\ &= \frac{v_i s_i}{\mu_i} \end{aligned}$$

■ Expected network response time: $\sum_{i=1}^M R_i(n) = R(n)$

■ Throughput: $\frac{n}{R(n)} = X(n)$

■ Queue length: $Q_i(n) = X(n)R_i(n)$



MVA Equations for Response Time -3

- Probability distribution at state-dependent nodes

$$p_i(k/n) = \frac{v_i s_i X(n)}{\mu_i(k)} p_i(k-1/n-1); \quad k = 1, 2, \dots, n_i; \quad n_i = \min(m_i - 1, n)$$

$$p_i(\geq m_i/n) = \frac{v_i s_i X(n)}{\mu_i(m_i)} p_i(\geq m_i - 1/n - 1)$$

$$p_i(0/n) = 1 - \sum_{k=1}^{m_i-1} p_i(k/n) - p_i(\geq m_i/n)$$

- Utilization of each node (needs to be computed for final population only)

$$U_i(N) = 0$$

Infinite-server nodes

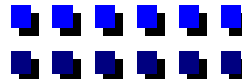
$$U_i(N) = \frac{X(N)v_i s_i}{\mu_i}$$

Single-server nodes

$$U_i(N) = \frac{X(N)v_i s_i}{\mu_i(m_i)}$$

Multi-server & state-dependent nodes

Throughput
max. Service Capacity





MVA Equations for Response Time -4

□ Computation of *queue length* and *utilization at each node*

■ Algorithm

$$Q_i(0) = 0$$

$$p_i(0/0) = 1$$

Do $n = 1, 2, \dots, N$

Do $i = 1, 2, \dots, M$

Update response time $R_i(n)$

End Do

$$X(n) = n / \sum_{i=1}^M R_i(n)$$

Do $i = 1, 2, \dots, M$

Compute $Q_i(n)$

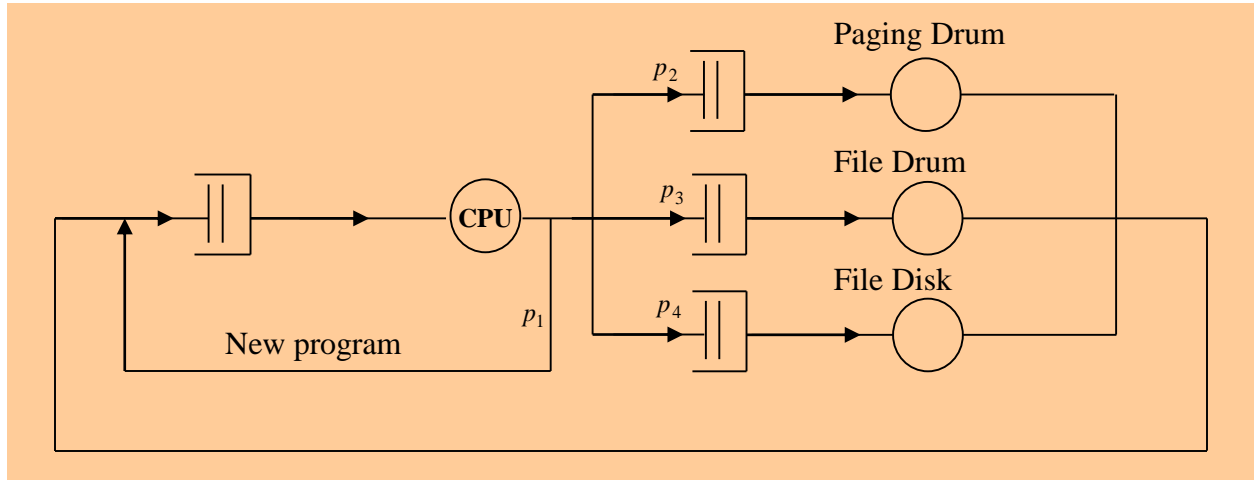
End Do

Compute $p_i(k/n)$ at multi-server & state-dependent nodes

End Do

Compute $U_i(N) \quad i = 1, 2, \dots, M$

Application Example: “what if studies” - 1



Number of visits: $v_1 = \frac{1}{p_1}$, $v_2 = \frac{p_2}{p_1}$, $v_3 = \frac{p_3}{p_1}$ & $v_4 = \frac{p_4}{p_1}$

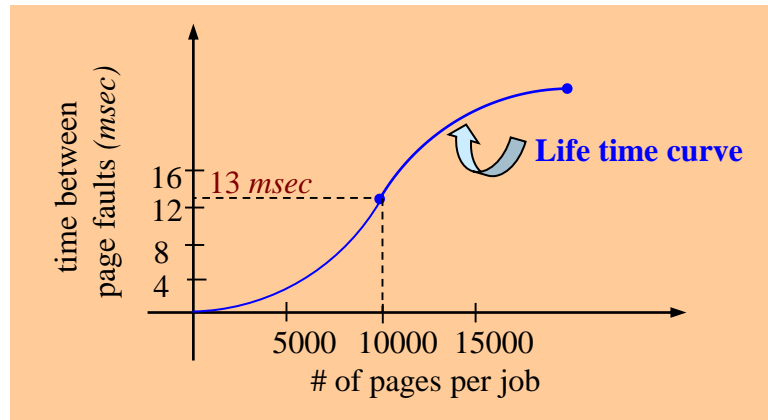
$$v_1 = 1 + v_2 + v_3 + v_4$$

- Each program requires 2.1 billion instructions to be executed: $v_1 s_1 = 2.1 \times 10^9$ Ins
 - CPU speed is 700 MIPS $\mu_1 = 0.7 \times 10^9$ Ins/sec
 - CPU time per program $\frac{v_1 s_1}{\mu_1} = 3$ sec/job
- (Over all visits)

Application Example: “what if studies” - 2

- ⇒ Given that 150 file drum accesses & 250 file disk accesses : $v_3 = 150$, $v_4 = 250$
- ⇒ To get v_2 , following information is given
 - Limited main memory of 30000 pages, divided equally among N jobs
Per job we have $30000/N$ pages
Larger the # of jobs \Rightarrow Smaller memory partition per job
 \Rightarrow More often CPU has to interrupt to get the next segment of the program from the page drum

If $N = 3 \Rightarrow$ Allotted 10000 pages per program



Average time between page faults = 13 msec

of page faults = # of visits to page drum, $v_2 = \frac{3}{13} \times 10^3 \cong 230$ visits



Application Example: “what if studies” - 3

- Paging drum has revolution speed of 3600 rpm = 60 rps

Transfers at $4\mu\text{s}/\text{word}$ (each page size is 1024 words)

$$\Rightarrow s_2 = 1, \quad \mu_2 = \left(\frac{1}{2 \times 60} + 1024 \times 4 \times 10^{-6} \right)^{-1} = 80 \text{ pages/sec}$$

$$v_2 = 230$$

$$v_1 = v_2 + v_3 + v_4 + 1 = 1 + 230 + 150 + 250 = 631$$

- File drum

$$s_3 = 1, \quad \mu_3 = 80 \text{ pages/sec}, \quad v_3 = 150$$

- File disk: 2400 rpm, $t_{seek} = 11\text{ms}$, transfer time = $6\mu\text{s}$

$$s_4 = 1, \quad \mu_4 = \left(\frac{1}{2 \times 40} + t_{seek} + 1024 \times 6 \times 10^{-6} \right)^{-1} = 33.7 \text{ pages/sec}, \quad v_4 = 250$$

- CPU $\frac{v_1 s_1}{\mu_1} = 3 \Rightarrow s_1 = \frac{2.1 \times 10^9}{631}; \quad v_1 = 630, \quad \mu_1 = 7 \times 10^8 \text{ Ins/sec}$

	CPU (1)	Paging Drum (2)	File Drum (3)	File Disk (4)
v_i	631	230	150	250
s_i	3.17×10^6	1page	1page	1page
μ_i	$7 \times 10^8 \text{ Ins/sec}$	80 pages/sec	80 pages/sec	33.7 pages/sec
$v_i s_i / \mu_i$	3	2.86	1.86	7.5

7.5

Bottleneck

Application Example: “*what if studies*” - 4

□ Using MVA or convolution algorithm, one can explore, for example, the following

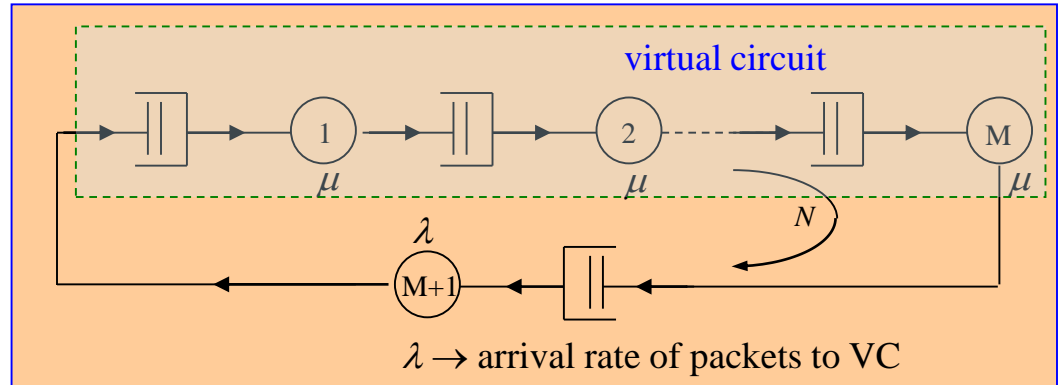
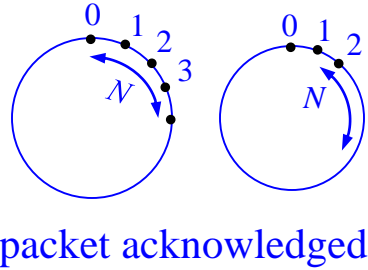
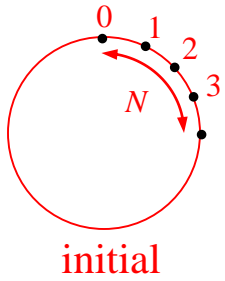
1. Performance measures
2. What if CPU is replaced by one that is 25% faster?
3. Replace file drum with one having 4500 rpm
4. Faster paging drum 4500 rpm
5. Balance utilization to file and disk drums

$$\Rightarrow \frac{v_3 s_3}{\mu_3} = \frac{v_4 s_4}{\mu_4} \quad \ni v_3 + v_4 = 400$$

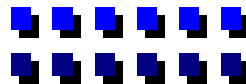
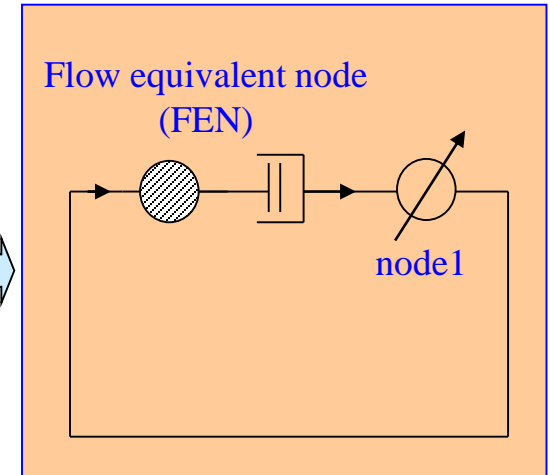
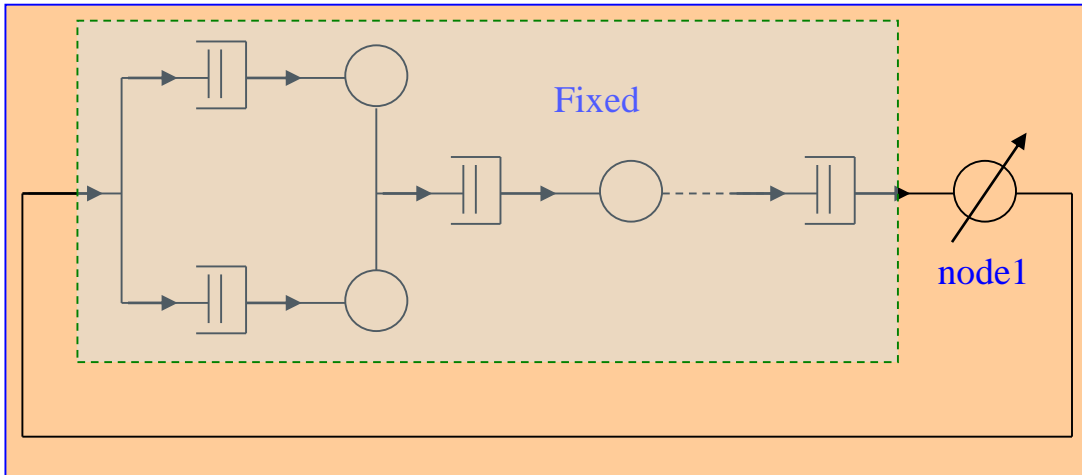
6. Increase memory size from 30000-40000 pages
 \Rightarrow time per page fault = 15ms



Application Example: "sliding window flow control" - 1



- Norton's theorem (or) Chandy-Herzog-Woo's theorem





Application Example: “sliding window flow control” - 2

- Know

$$p_1(k/N) = \frac{G_{M-\{1\}}(N-k)Y_1(k)}{G_M(N)}$$

$$G_M(N) = \sum_{k=0}^N G_{M-\{1\}}(N-k)Y_1(k)$$

- The network is equivalent to a ‘two node network’, if

$$G_{M-\{1\}}(n) = Y_{eq}(n) = \left(\prod_{k=1}^n \mu_{eq}(k) \right) \quad s_{eq} = 1, \quad v_{eq}=1$$

- Know

$$X_{eq}(n) = \frac{G_{M-\{1\}}(n-1)}{G_{M-\{1\}}(n)} = \frac{Y_{eq}(n-1)}{Y_{eq}(n)} = \mu_{eq}(n)$$

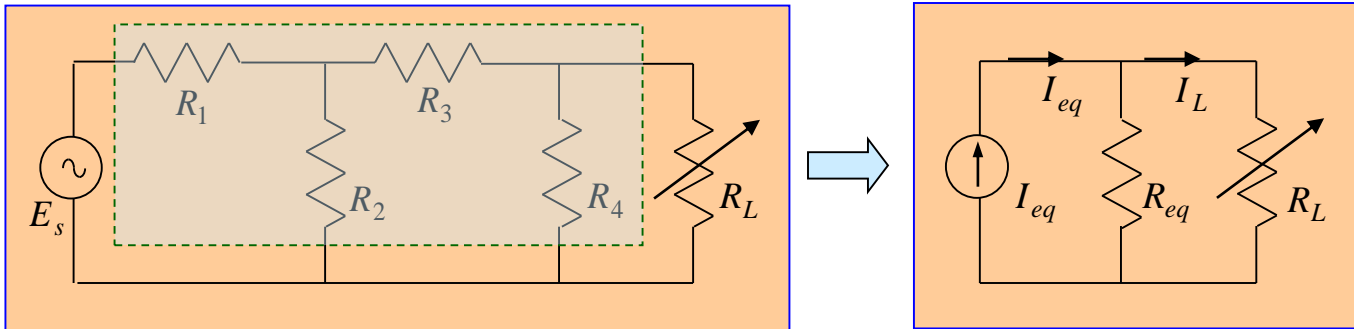
The service rate of flow eqv. node= Throughput of the boxed network

- $X_{eq}(n)$ can be found by “shorting” node 1
 - This is similar to Norton’s theorem of electrical circuits



Application Example: “sliding window flow control” - 3

- **Norton’s theorem:** Replace all sources by an equivalent current source and equivalent resistance (or impedance)



- Similarly, we short node 1 (subsystem of interest)
- Found throughput of the remaining network for all $n = 1, 2, \dots, N$
- Set service rate of flow equivalent node = $\mu_{eq}(n)$, $n = 1, 2, \dots, N$

- **For the sliding window flow control problem:**

- Short node $M+1$, all nodes have same service rate
- Know $v = 1, s = 1$

$$R_i(n) = \frac{1}{\mu} [1 + Q_i(n-1)]$$

Since the network is balanced,

$$Q_i(n-1) = \frac{n-1}{M} \quad i = 1, 2, \dots, M$$




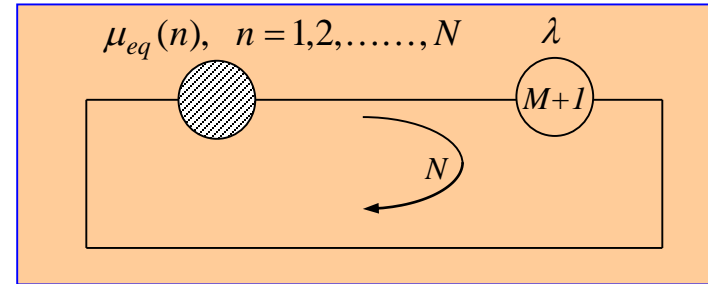
Application Example: “sliding window flow control” - 4

$$\Rightarrow R_i(n) = \frac{1}{\mu} \left[\frac{n+M-1}{M} \right]$$

$$R(n) = \sum_{i=1}^M R_i(n) = \frac{n+M-1}{\mu}$$

$$X_{eq}(n) = \frac{n\mu}{n+M-1} = \mu_{eq}(n)$$

So, the equivalent network is 



✳ Yes, can solve via MVA!!

□ Special Cases

■ Case 1

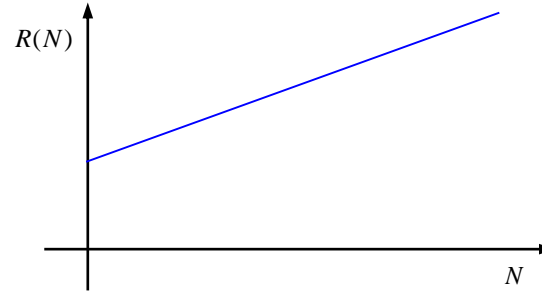
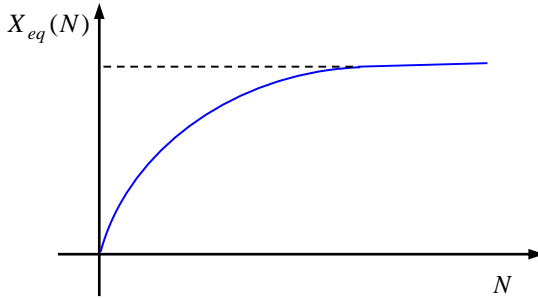
As $\lambda \rightarrow \infty$, all N packets will be at the equivalent network

$$\text{Throughput} = X_{eq}(N) = \frac{N\mu}{N+M-1}$$

$$\& R(N) = \left[\frac{N+M-1}{\mu} \right] = \frac{M-1}{\mu - X_{eq}(N)} \text{ because } \mu - X_{eq}(N) = \mu \frac{M-1}{N+M-1}$$



Application Example: "sliding window flow control" - 5



Case 2:

$$\lambda = \mu \Rightarrow X_{eq}(N) = \frac{N\mu}{(N+M)}$$

$$R_{eq}(N) = \frac{N+M}{\mu} \frac{M}{M+1}$$

"Maxwell Demon"

– What should we choose as N , the window length?

$$N \approx M$$

– How to optimally control λ as a function of n ?

See Lazar, IEEE T-AC, 1983, pp 1001-1009

"Bang Bang Control"

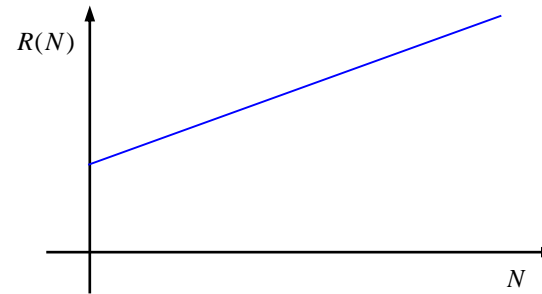
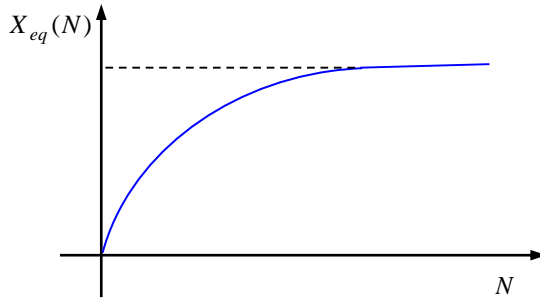
$$R(N) = \frac{M-1}{\mu - X_{eq}} \quad \text{as } \lambda \rightarrow \infty$$

$$\frac{X_{eq}}{R(N)} = \frac{X_{eq}(\mu - X_{eq})}{M-1} \Rightarrow \max \quad \text{at } X_{eq} = \mu/2 \quad N = M - 1$$

Power

$$\text{at } X_{eq} = 0, \quad R(N) = \frac{M-1}{\mu}$$

Application Example: “sliding window flow control” - 6



$$R(N) = \frac{M-1}{\mu - X_{eq}} \quad \text{as } \lambda \rightarrow \infty$$

$$\mu R(N) = \frac{M-1}{1 - \frac{X_{eq}}{\mu}} \Rightarrow \text{Normalized Delay} = \frac{M-1}{1 - \text{Normalized Throughput}}$$

$$\text{Find } X_{eq} \ni \mu R(N) = \frac{d(\mu R(N))}{dX_{eq}} X_{eq}$$

$$\Rightarrow X_{eq} = \frac{\mu}{2} \Rightarrow N = M-1 \text{ \& } \mu R(N) = 2(M-1)$$



Summary

- ❑ Single-class Closed Queuing Networks
- ❑ Computational Algorithms
 - Convolution Algorithm
 - Mean Value Analysis
- ❑ Applications
 - Computer Systems
 - Flow Control in Communication Networks