Maximum pressure policies for stochastic processing networks

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The 2011 Lunteren Conference

Outline

1. Stochastic processing network models
2. A motivating example arising from wafer fabrication lines
3. Maximum pressure policies
4. Throughput optimality
5. Asymptotic optimality under complete resource pooling (single bottleneck)
6. References
7. Appendix: Supplements and multiple bottlenecks diffusion limits

Stochastic Processing Network Models

A Stochastic Processing Network Model

Basic elements:

- $\mathbf{I+1}$ buffers
- $\mathbf{K}$ processors
- $\mathbf{J}$ activities

Indexes:

- $i \in \mathcal{I} \cup \{0\}$
- input and service processors $k \in \mathcal{K}$
- input and service activities $j \in \mathcal{J}$

Material consumption:

- μ_j: service rate for activity j;
- $B_{ij} = 1$ if activity j processes jobs in in buffer i and $B_{ij} = 0$ otherwise;
- $P^j_{ii'}$ is a fraction of buffer i jobs served by activity j that go next to buffer i';

Resource Allocation

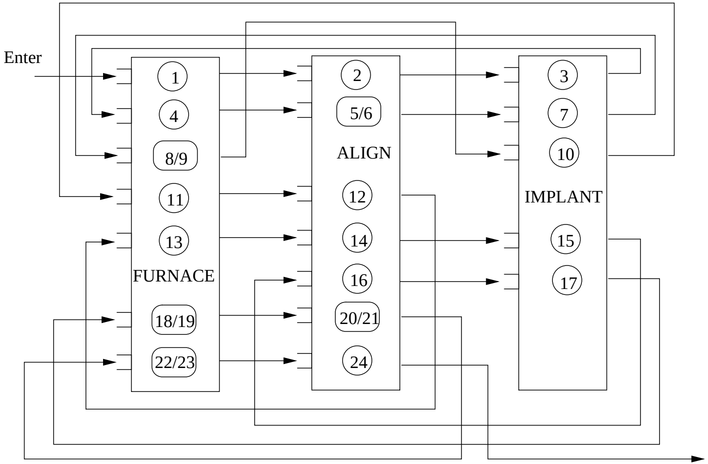
- $A_{kj} = 1$ if activity j requires processor k and 0 otherwise; multiple processors may be needed to activate an activity.
- Allocation space $\mathcal{A}$ is the set of allocations $a \in \mathbb{R}_+^{\mathbf{J}}$ satisfying

$$\sum_j A_{kj} a_j \le 1 \text{ for each service processor,}$$

$$\sum_j A_{kj} a_j = 1 \text{ for each input processor;}$$

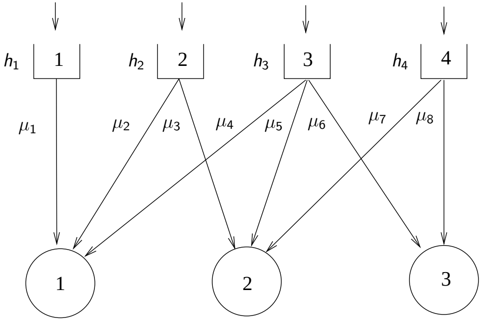
- a_j the level at which activity j is undertaken;
- more constraints on a can be added.

Multiclass Queueing Networks: A Re-Entrant Line



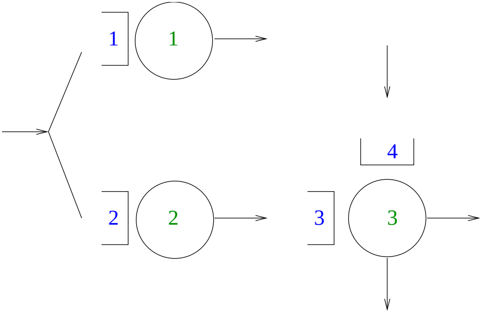
- one input processor, one input activity; the input processor never idles.
- three service processors

Skill-Based Routing



- four input processors, each processing one input activity
- three service processors

Queueing Networks with Alternate Routes



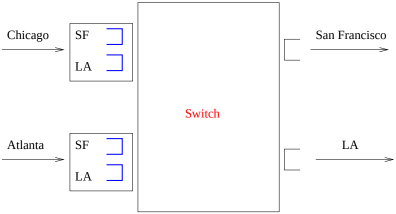
Laws and Louth (1990)

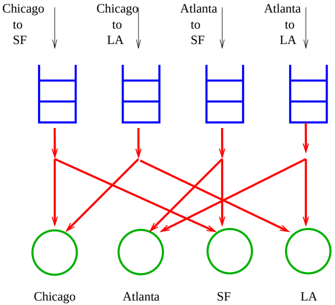
Kelly and Laws (1993)

Dai, Hasenbein and Kim (2007)

- two input processors; the left one processes two input activities and the right one processes one input activity.

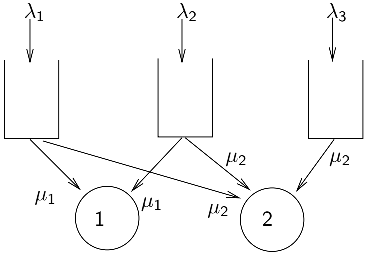
Input Queued Data Switches





- In each time slot, at most one packet is sent from each input port
- In each time slot, at most one packet is sent to each output port
- Multiple packets can be transferred in a single time slot
- A high speed switch needs to maintain thousands of flows

Operational policies



- $\mathcal{A} = \{a \in \mathbb{R}_+^{\mathbf{J}} : Aa \le e\}$
- $\mathcal{E} = \{a_1, ..., a_u\}$ – set extreme points of $\mathcal{A}$.
- $\mathcal{A}(t)$ – set of feasible allocations at time t.
- $\mathcal{E}(t) = \mathcal{A}(t) \cap \mathcal{E}$ – set of feasible, extreme allocations at time t.
- e.g. $a_1 = (1, 1, 1, 0, 0, 0, 0, 0)$, $a_2 = (1, 1, 1, 1, 0, 1, 0, 0)$

Performance Measures

First order ones:

- Throughput: rate at which entities leave a system
- Utilization

Second order ones:

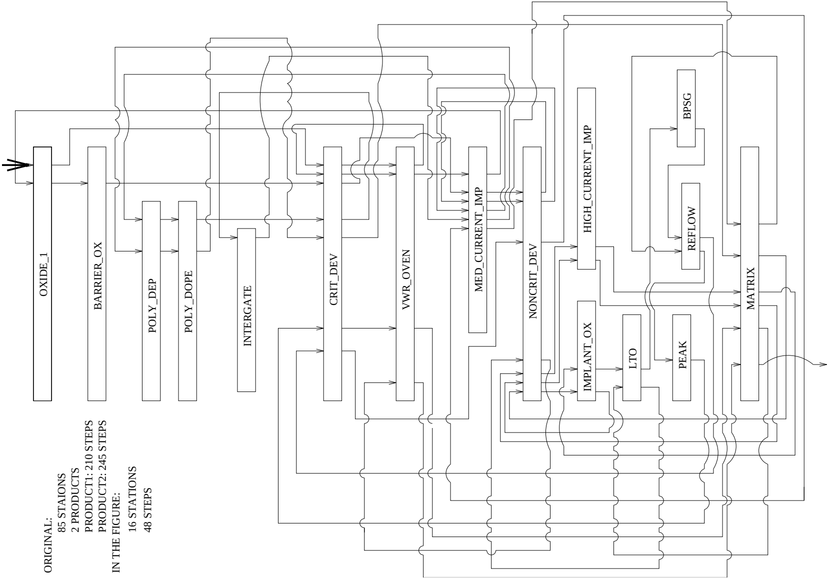
- Cycle time: processing times plus waiting time of an entity; average and variance of cycle time
- Long-run average cost

Operational policies can have a dramatic impact on key performance measures.

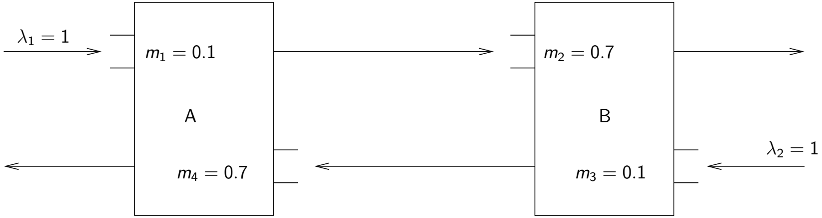
Part II

An example arising from wafer fabrication lines

Flow in a Wafer Fab



The Kumar-Seidman, Rybko-Stolyar Network

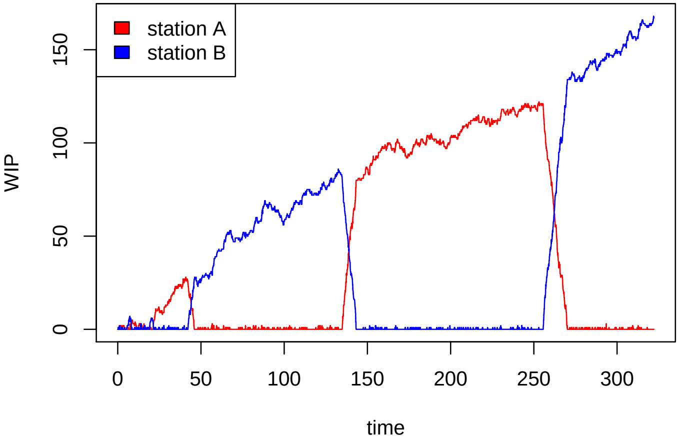


- Traffic intensity:

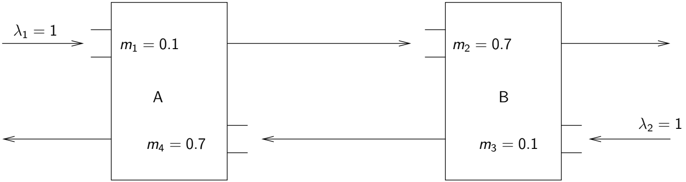
$$\rho_1 = \lambda_1 m_1 + \lambda_2 m_4 = 0.8 \text{ and } \rho_2 = \lambda_1 m_2 + \lambda_2 m_3 = 0.8.$$

- Pull policy – give priority to products closer to completion

WIP Levels at Two Stations



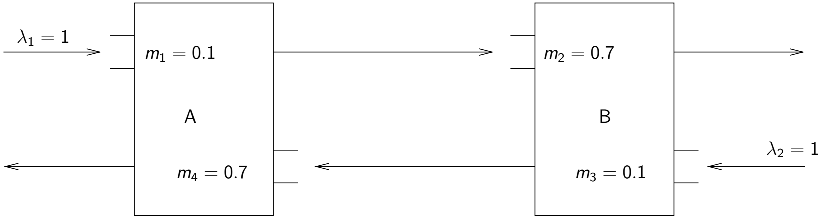
Utilization and Cycle Time



# departed	100	1,000	10,000	100,000
Average cycle time	13.68	99.87	927.96	7277.62
Utilization A	0.65	0.48	0.46	0.71
Utilization B	0.49	0.67	0.73	0.44
Overall Utilization	0.57	0.58	0.60	0.58

the throughput is about 0.7.

Maximum throughput



Under the pull policy, the system is "stable" if and only if

$$\rho_1 = \lambda_1 m_1 + \lambda_2 m_4) \le 1, \quad \Rightarrow \quad \lambda_1^* = \lambda_2^* = \frac{1}{.8} = 1.25,$$

$$\rho_2 = \lambda_1 m_2 + \lambda_2 m_3 \le 1,$$

$$\rho_v = \lambda_1 m_2 + \lambda_2 m_4 \le 1. \quad \Rightarrow \quad \lambda_1^* = \lambda_2^* = \frac{1}{1.4} = 0.714$$

Dai and Vande Vate, *Operations Research*, 721–744, 2000.

Inefficient Policies

- First-in-first-out (FIFO) (Bramson 1994, Seidman 1994)
- Static buffer priority (Lu-Kumar 1992)
- Shortest processing time first
- Shortest remaining processing time first
- Exhaustive service (Kumar-Seidman 1990)
- ...

Symptoms:

- WIP is high, and
- bottleneck machines are underutilized

Part III

Maximum pressure policies

Maximum Pressure Policies

- Fix an $\alpha = (\alpha_i) \in \mathbb{R}^{\mathbf{I}}_{+}$ with $\alpha_i > 0$.
- Pressure at time t for activity j,

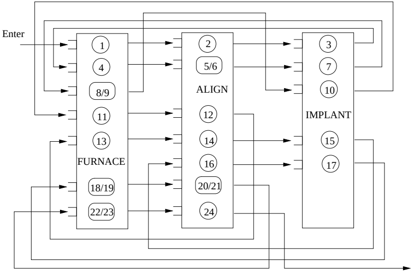
$$p_j(t) = \mu_j \left(\sum_{i \in \mathcal{I} \cup \{0\}} B_{ij} \Big(\alpha_i Z_i(t) - \sum_{i'} P^j_{ii'} \alpha_{i'} Z_{i'}(t) \Big) \right),$$

  where $Z_i(t)$ is the number of jobs in buffer i at time t.
- At any time t, choose an allocation a

$$a \in \operatorname*{argmax}_{a \in \mathcal{E}(t)} \sum_j a_j p_j(t).$$

- Tassiulas (1995): Adaptive back-pressure congestion control based on local information.

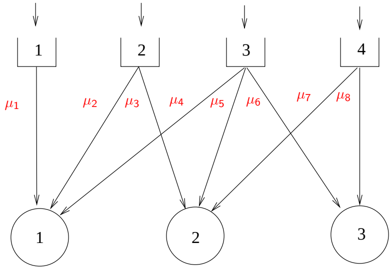
Maximum Pressure Policies for Multiclass Queueing Networks



- Server k chooses to work on a buffer that has the highest pressure.
- The pressure at buffer i is

$$p_i(t) = \mu_i \Big(Z_i(t) - Z_{i+1}(t) \Big).$$

- If all $p_i(t) \le 0$, idle the server.
- Generalization: change $Z_i(t)$ to $\alpha_i Z_i(t)$

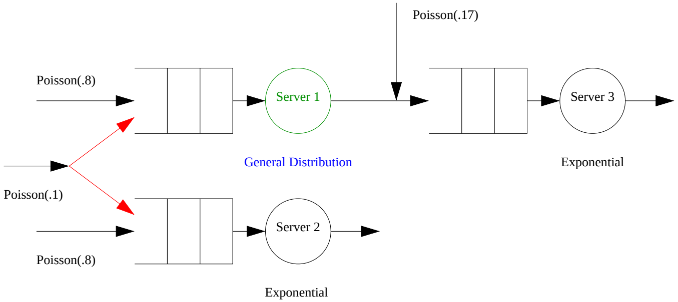


For example, processor 1 chooses to work on buffer i that attains

$$\max\{\mu_1 Z_1(t), \mu_2 Z_2(t), \mu_4 Z_3(t)\}.$$

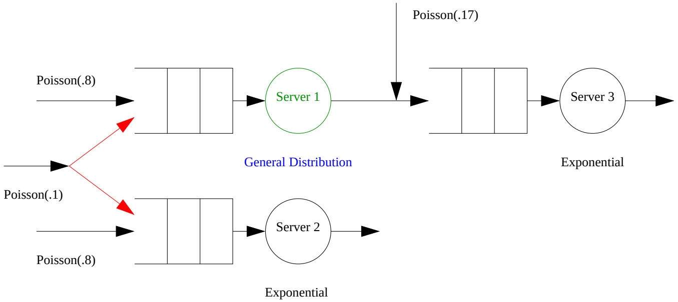
- Mandelbaum-Stolyar (04): generalized $c\mu$-rule; van Mieghem (95)
- Stolyar (04): MaxWeight policies

Maximum Pressure Policies: Alternate Routing



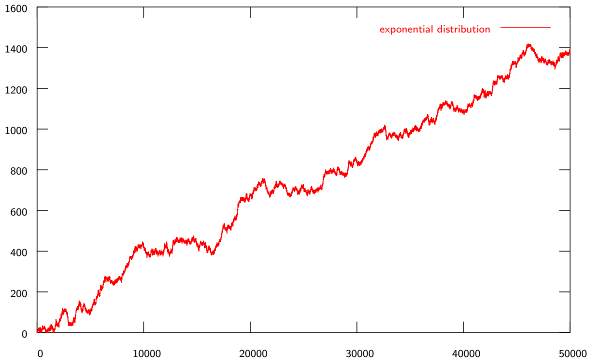
- An MPP translates into: Join-the-shortest-queue and server 1 idles when $Z_3(t) > Z_1(t)$.

Maximum Pressure Policies: Alternate Routing



- An MPP translates into: Join-the-shortest-queue and server 1 idles when $Z_3(t) > Z_1(t)$.
- MPPs can be idling policies.

Non-Idling Server 1



Number of jobs in queue 3

Features of Maximum Pressure Policies

- They are simple.
- They are semi-local.
- They are throughput optimal.
- They are asymptotically optimal in workload and certain holding cost structure.

Part IV

Throughput optimality

Stability

Recall that $Z_i(t)$ is the buffer level at time t in buffer i.

Rate stability

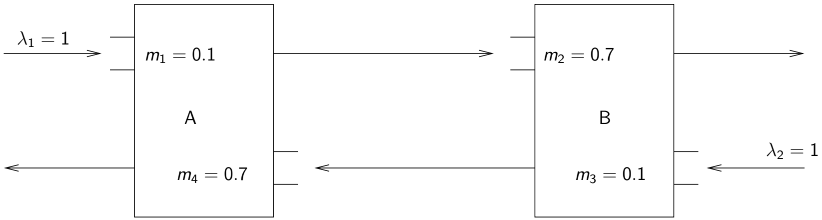
With probability one,

$$\lim_{t\to\infty} Z_i(t)/t = 0, \text{ for each buffer } i$$

which is equivalent to that departure rate is equal to arrival rate.

Positive Harris recurrence

Traffic Intensity



Define $\rho = \max(\rho_1, \rho_2)$, where

$$\rho_1 = \lambda_1 m_1 + \lambda_2 m_4) \leq 1,$$
$$\rho_2 = \lambda_1 m_2 + \lambda_2 m_3 \leq 1.$$

Static Planing Problem

The static planning problem (Harrison 00):

$$
\begin{aligned}
\text{minimize} \quad & \rho \\
\text{subject to} \quad & Rx = 0 \\
& \sum_j A_{kj} x_j = 1 \text{ for each input processor } k \\
& \sum_j A_{kj} x_j \le \rho \text{ for each service processor } k \\
& x \ge 0
\end{aligned}
$$

- $R_{ij} = \mu_j (B_{ij} - \sum_{i'} B_{i'j} P^j_{i'i})$
- A: capacity consumption matrix
- x_j: fraction of time for activity j;
- ρ: utilization of bottleneck servers.

Stability Result

Theorem (Dai-Lin 05)

If the stochastic processing network operating under any operational policy is rate stable, the static planning LP has a feasible solution with $\rho \leq 1$.

Theorem (Dai-Lin 05)

Conversely, suppose that Assumption 1 in the appendix is satisfied. If the static planning LP has a feasible solution with $\rho \leq 1$, the stochastic processing network operating under a maximum pressure policy is rate stable.

Proof: Fluid Model Approach

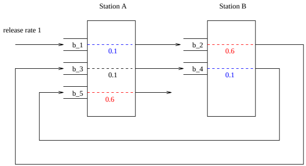
Theorem (Dai-Lin 05)

A stochastic processing network is rate stable if the corresponding continuous, deterministic fluid model is weakly stable.

Theorem (Dai 95)

A multiclass queueing network is positive Harris recurrent if the corresponding continuous, deterministic fluid model is stable.

Fluid Model Equations



Let $T_k(t)$ be the cumulative time that class k jobs have received in $[0, t]$.

$$Z_1(t) = Z_1(0) + \lambda t - \mu_1 T_1(t),$$
$$Z_k(t) = Z_k(0) + \mu_{k-1} T_{k-1}(t) - \mu_k T_k(t),$$
$$T_k(0) = 0 \text{ and } T_k(\cdot) \text{ is nondecreasing},$$
$$(T_1(t) + T_3(t) + T_5(t)) - (T_1(s) + T_3(s) + T_5(s)) \le (t - s)$$
$$(T_2(t) + T_4(t)) - (T_2(s) + T_4(s)) \le (t - s)$$

Fluid Model under MPP

$$\sum_{i=1}^{5} \dot{\bar{T}}_i(t) p_i(t) = \max\Big\{ \sum_i a_i p_i(t) : a_1 + a_3 + a_5 \le 1, a_2 + a_4 \le 1. \Big\}, \quad (1)$$

where , the buffer i pressure $p_i(t) = \mu_i(\bar{Z}_i(t) - \bar{Z}_{i+1}(t))$.

- The drift of the quadratic function $f(t) = \sum_i \bar{Z}_i^2(t)/2$ is given by $\dot{f}(t) = \lambda Z_1(t) - \sum_i \dot{\bar{T}}_i(t) p_i(t)$.
- Under a maximum pressure policy, $\dot{f}(t)$ is minimized among all policies.

Weak Stability of Fluid Model

Definition (Weak Stability)

A fluid model is said to be weakly stable if for every fluid model solution with $\bar{Z}(0) = 0$, $\bar{Z}(t) = 0$ for $t \geq 0$.

- Consider the quadratic function $f(t) = \sum_i \bar{Z}_i^2(t)/2$.
- Under a maximum pressure policy, $\dot{f}(t) \leq 0$. Therefore, $\bar{Z}(t) = 0$ for all t if $\bar{Z}(0) = 0$; the fluid model is weakly stable.

Fluid Limits

- Fluid model equations are justified through a fluid limit procedure.
- A function $(\bar{Z}, \bar{T})$ is said to be a fluid limit if

$$\frac{1}{r_n}(Z(r_n t, \omega), T(r_n t, \omega)) \to (\bar{Z}(t), \bar{T}(t))$$

as $r_n \to \infty$ for some sample path ω

Part V

Asymptotic optimality under complete resource pooling (CRP) or single bottleneck assumption

Quadratic Holding Cost

- Each buffer i, the holding cost rate is $h_i\big(Z_i(t)\big)^2$.
- The network cost rate is

$$h(Z(t)) = \sum_i h_i\big(Z_i(t)\big)^2.$$

- Under a policy π, the expected total discounted holding cost

$$J_\pi \equiv \mathbb{E}\left(\int_0^\infty e^{-\gamma t} h\big(Z^\pi(t)\big)dt\right).$$

Asymptotic Optimality on Quadratic Holding Cost

- Consider a sequence of networks indexed by r in heavy traffic,

$$\lim_{r\to\infty} R^r = R. \tag{2}$$

- Diffusion Scaling: $\widehat{Z}^r(t) = Z^r(rt)/\sqrt{r}$ and

$$\widehat{J}^r_\pi \equiv \mathbb{E}\left(\int_0^\infty e^{-\gamma t} h(\widehat{Z}^r(t))dt\right).$$

Theorem (Dai-Lin 08)

For a sequence of networks that satisfies a heavy traffic condition and a complete resource pooling condition, the maximum pressure policy with $\alpha = h$ is asymptotically optimal to minimize the quadratic holding cost, i.e.,

$$\lim_{r\to\infty} \widehat{J}^r_{\mathrm{MPP}} \le \liminf_{r\to\infty} \widehat{J}^r_\pi \quad \textit{for any policy } \pi.$$

References: Stochastic Processing Networks

- Harrison, J. M. (2000). Brownian models of open processing networks: canonical representation of workload. *Annals of Applied Probability*, **10** 75–103. Correction: **13**, 390–393 (2003).
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- Harrison, J. M. (2003). A broader view of Brownian networks. *Annals of Applied Probability*, **13** 1119–1150.

References: Maximum Pressure Policies

- Dai, J. G. and Lin, W. (2005). Maximum pressure policies in stochastic processing networks. *Operations Research*, **53** 197–218.
- Dai, J. G. and Lin, W. (2008). Asymptotic optimality of maximum pressure policies in stochastic processing networks. *Annals of Applied Probability*, **18** 2239–2299.
- Ata, B. and Lin, W. (2008). Heavy traffic analysis of maximum pressure policies for stochastic processing networks with multiple bottlenecks. *Queueing Systems*, **59** 191–235.

References on Unstable Queueing Networks

- Dai, Hasenbein and VandeVate, Stability and instability of a two-station queueing network, *Annals of Applied Probability*, 2004.
- Dai, Hasenbein and VandeVate, Stability of a Three-Station Fluid Network, *Queueing Systems*, 1999
- Bramson, A Stable Queueing network with unstable fluid network, *Annals of Applied Probability*, 1999.

Part V

An Appendix

- Assumption 1.
- The heavy traffic assumption
- The complete resource pooling assumption
- State space collapse and semimartingale reflecting Brownian motions (SRBMs) as diffusion limits
- Extension of maximum pressure policies

Assumption 1

Assumption

For any vector $z \in \mathbb{R}^{\mathbf{I}}_{+}$, there exists an $a \in \arg\max_{a \in \mathcal{E}} \sum_i v(a,i) z_i$ such that $v(a,i) = 0$ if $z_i = 0$, where $v(a,i) = \sum_j a_j R_{ij}$ is the consumption rate of buffer i under allocation a.

The assumption holds when each activity is associated with one buffer (in Leontief networks).

The Heavy Traffic Assumption

Consider a sequence of stochastic processing networks that satisfies assumption (2). The static planning problem (Harrison 00):

$$
\begin{aligned}
\text{minimize} \quad & \rho \\
\text{subject to} \quad & Rx = 0 \\
& \sum_j A_{kj} x_j = 1 \text{ for each input processor } k \\
& \sum_j A_{kj} x_j \leq \rho \text{ for each service processor } k \\
& x \geq 0
\end{aligned}
$$

- x_j: fraction of time for activity j is employed;
- ρ: utilization of bottleneck servers.

Assumption

The optimal solution (ρ^*, x^*) is unique and $\rho^* = 1$.

The Complete Resource Pooling (CRP) Assumption

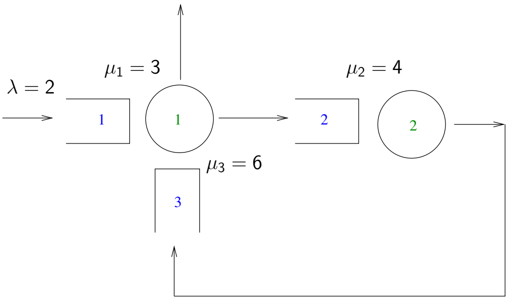
The dual LP:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{k\in\mathcal{K}_I} z_k \\
\text{subject to} \quad & \sum_{i\in\mathcal{I}} y_i R_{ij} \le -\sum_{k\in\mathcal{K}_I} z_k A_{kj} \text{ for each input activity } j \\
& \sum_{i\in\mathcal{I}} y_i R_{ij} \le \sum_{k\in\mathcal{K}_S} z_k A_{kj} \text{ for each service activity } j \\
& \sum_{k\in\mathcal{K}_S} z_k = 1, \\
& z_k \ge 0
\end{aligned}
$$

Assumption

The dual LP has a nonnegative, unique optimal solution (y^*, z^*).

An Example of CRP: Multiclass queueing networks

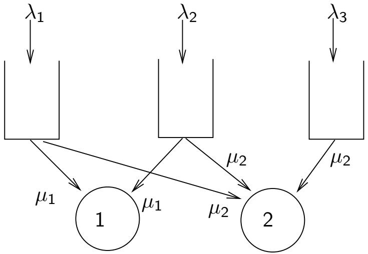


Unique solution (ρ^*, x^*)

- $x_j^* = \lambda m_j$, $j = 1, 2, 3$
- $\rho_1 = x_1^* + x_3^*$,
  $\rho_2 = x_2^*$
- $\rho^* = \max(\rho_1, \rho_2)$.

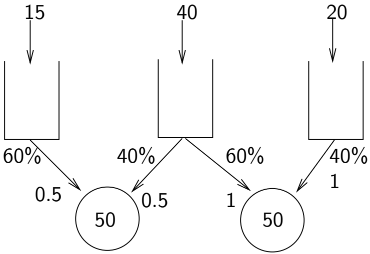
- Heavy traffic assumption: $\rho^* = 1$
- Complete resource pooling condition: either $\rho_1^* = 1$ and $\rho_2^* < 1$ or $\rho_1^* < 1$ and $\rho_2^* = 1$.
- In the former case, $y^* = (m_1 + m_3, m_3, m_3)$; in the latter case, $y^* = (m_2, m_2, 0)$.
- Ata-Kumar (05) does not cover this class of networks

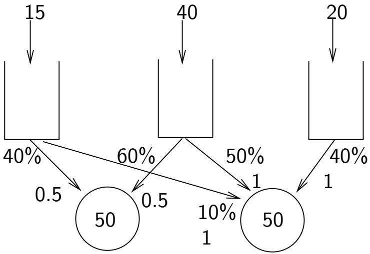
An Example of CRP: Parallel server queues



- Assume $\rho^* = 1$ and x^* is unique.
- Complete resource pooling: all servers communicate through basic activities.
- Harrison-Lopez (99), and Bell-Williams (05)

An Example of multiple LP Solutions





- $\rho^* = 1$, but x^* is not unique

- Assume the complete resource pooling condition and (y, z) is the unique solution to the dual LP.
- Let $W(t) = y \cdot Z(t)$ and $\widehat{W}^r(t) = W(rt)/\sqrt{r} = y \cdot \widehat{Z}^r(t)$.

Theorem (Workload Optimality (Dai-Lin 08))

For a sequence of networks that satisfies the heavy traffic condition and the complete resource pooling condition, any the maximum pressure policy is asymptotically optimal for workload in that for each $t \geq 0$ and $w > 0$,

$$\mathbb{P}\Big(\lim_{r\to\infty} \widehat{W}^r_{\mathrm{MPP}}(t) > w\Big) \leq \mathbb{P}\Big(\liminf_{r\to\infty} \widehat{W}^r_{\pi}(t) > w\Big).$$

Proof: A Lower Bound on Workload Process

We can write $\widehat{W}^r(t)$ as

$$\widehat{W}^r(t) = \widehat{X}^r(t) + \widehat{Y}^r(t),$$

where $\widehat{Y}^r(t) \geq 0$ and nondecreasing. This implies

$$\widehat{W}^r(t) \geq \widehat{W}^{*,r}(t) \equiv \widehat{X}^r(t) - \inf_{0 \leq s \leq t} \widehat{X}^r(s).$$

Letting $\widehat{W}^*(t) \equiv \widehat{X}^*(t) - \inf_{0 \leq s \leq t} \widehat{X}^*(s)$,

$$\mathbb{P}\Big(\liminf_{r \to \infty} \widehat{W}^r(t) > w\Big) \geq \mathbb{P}\Big(\widehat{W}^*(t) > w\Big).$$

Proof: A Heavy Traffic Limit Theorem

Theorem

For a sequence of networks that satisfies the heavy traffic condition and a complete resource pooling condition, under the maximum pressure policy with $\alpha = e$,

$$(\widehat{W}^r, \widehat{Z}^r) \Rightarrow (\widehat{W}^*, \widehat{Z}^*),$$

where $\widehat{Z}^* = y\widehat{W}^*/\|y\|^2$.

- A key to the proof of this theorem is to show a state space collapse result:

$$\sup_{0 \le t \le T} \left| \widehat{Z}^r(t) - \frac{y\widehat{W}^r(t}{\|y\|^2} \right| \to 0 \text{ in probability as } r \to \infty.$$

- Use framework of Bramson (98)
- Unlike Chen and Mandelbaum (90), non-bottleneck stations do not disappear.

Asymptotic Optimality Proof (for $h = e$)

Consider the optimization problem

$$\begin{aligned} \min \quad & \sum_{i=1}^{3} q_i^2 \\ s.t. \quad & y \cdot q = w \\ & q \geq 0. \end{aligned}$$

- The optimal solution is given by $q^* = yw/\|y\|^2$.
- For any given w, it is optimal to distribute the workload to the buffers in proportion to y.
- MPP not only minimizes the workload process $W(t)$, but also distributes it in the optimal way.

Extension: Linear holding cost

- Dai-Lin (08): for each $\epsilon > 0$, one can find an MPP policy with parameter α that is asymptotically ϵ-optimal; choice of α is data heavy.
- Ata and Kumar (05) uses Harrison's BIGSTEP method; rules out multiclass networks
- Bell and Williams (05) parallel-server queues; Ghamami and Ward (09)
- Lin (09): β-Maximum Pressure Policies in Stochastic Processing Networks: Heavy Traffic Analysis. Fix a $\beta > 0$ and $(\alpha_i) > 0$

$$p_i(t) = \mu_i\Big(\alpha_i(Z_i(t))^\beta - \alpha_{i+1}(Z_{i+1}(t))^\beta\Big)$$

Extension: More than one bottleneck

- Let $\{(y^\ell, z^\ell) : \ell = 1, \ldots, L\}$ denote the set of basic optimal solutions to the dual LP.
- Let $\hat{W}^r_\ell(t) = y^\ell \cdot \hat{Z}^r(t)$.

Theorem (Ata-Lin 08)

Consider a sequence of networks that satisfies the heavy traffic condition. Assume that $y^\ell \geq 0$ for each ℓ and $y^1, \ldots, y^L$ are linearly independent. Under a maximum pressure policy with parameter α,

$$(\widehat{W}^r, \widehat{Z}^r) \Rightarrow (\widehat{W}^*, \widehat{Z}^*),$$

where $\widehat{W}$ is an L-dimensional SRBM, and $\widehat{Z}^* = \Delta \widehat{W}^*$.

Other extensions

- Rajagopalan, Shah and Shin (09): random-access algorithm to approximate a maximum pressure policy for single-hop networks
- Shah and Wischik (09): optimal scheduling algorithms for switched networks under light load, critical load, and overload; performance of MaxWeight policies in overloaded fluid networks.