

# Free Boundary Problems and Asymptotically Optimal Control for Stochastic Networks.

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based on joint works with X.Liu and S.Saha

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Reflected Brownian Motions, Stochastic Networks, and their  
Applications.

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# A Problem.

- Let  $(\Omega, \mathcal{F}, \mathbb{P}, \{\mathcal{F}_t\})$  be a filtered probability space.
- Let  $B$  be a two dimensional  $\{\mathcal{F}_t\}$ -Brownian motion with drift  $\theta$  and covariance  $\Sigma$ .
- **Control Problem.**

$$\inf_Y \mathbb{E} \int_0^{\infty} e^{-t} h(X_t) dt$$

Subject to:

$$X_t = B_t + Y_t$$

$$Y_t \geq 0, Y \text{ is RCLL, adapted, non decreasing}$$

$$X_t \geq 0.$$

$$h(x) = (2x_1 - x_2)1_{x_1 \geq x_2} + (2x_2 - x_1)1_{x_2 \geq x_1}.$$

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- **Question:** Optimal Control?

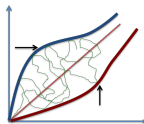
# Conjecture.

(See Martins, Shreve and Soner (1996).)

- Solution is a two dimensional reflected Brownian motion in a domain:
- There are functions  $\Psi_i : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ ,  $i = 1, 2$  such that  $\Psi_i$  are nondecreasing, 1-Lipschitz,  $\Psi_i(0) = 0$ ,  $\Psi_i(u) \rightarrow \infty$  as  $u \rightarrow \infty$ , and an optimal state process  $X^*$  is the unique solution of

$$X_1^*(t) = B_1(t) + \sup_{0 \leq s \leq t} [B_1(s) - \Psi_1(X_2^*(s))]^-$$

$$X_2^*(t) = B_2(t) + \sup_{0 \leq s \leq t} [B_2(s) - \Psi_2(X_1^*(s))]^-$$



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- In such singular control problems the goal is to find an optimal control of the following form: There is an open set  $\mathcal{O}$  in the state space – the *continuation region*, such that:
  - Starting within  $\mathcal{O}$  no control is applied until the boundary of  $\mathcal{O}$  is reached.
  - If the initial condition is in  $(\bar{\mathcal{O}})^c$  (*action region*), an instantaneous control in a pre-specified direction is applied to bring the state to  $\partial\mathcal{O}$ .
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- In terms of the associated HJB equation, in  $\mathcal{O}$  the value function satisfies a linear elliptic PDE while in  $\mathcal{O}^c$  a nonlinear first order PDE is satisfied.
- The boundary  $\partial\mathcal{O}$  separating these two regions is referred to as the *free boundary* for the system of PDE and determining this boundary is the *free boundary problem*.

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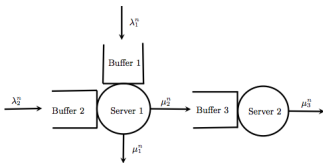
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- Arise in the control of SPN.



# A SPN Control Problem.

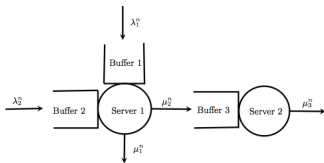
- 3 classes of jobs, 2 Servers.



- Class 1 jobs arrive at rate  $\lambda_1$  and exit the system after service (at rate  $\mu_1$ ).
- Class 2 jobs arrive at rate  $\lambda_2$ , after processing by server 1 (at rate  $\mu_2$ ) proceed for processing by server 2 (at rate  $\mu_3$ ), becoming class 3 jobs, and then exit the system.

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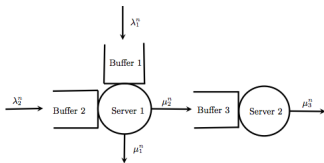
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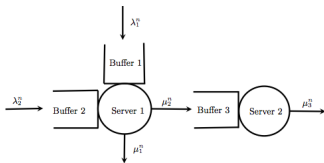
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- Exact solutions not available ...so one considers approximate approaches.

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- A sequence of networks indexed by  $n$ . As  $n \rightarrow \infty$ , the system approaches criticality.
- **Interarrival times:** For  $k = 1, 2$ ,  $\{u_k(i) : i \in \mathbb{N}\}$  are i.i.d. with mean 1 and standard deviation  $\sigma_k$ .

In the  $n$ th network, for  $k = 1, 2$   $\{u_k^n(i) : i \in \mathbb{N}\}$  are the interarrival times for Class  $k$  customers, where  $u_k^n(i) = \frac{1}{\lambda_k^n} u_k(i)$ .

- **Service times:** For  $j = 1, 2, 3$ , let  $\{v_j(i) : i \in \mathbb{N}\}$  a sequence of i.i.d. random variables with mean 1 and standard deviation  $\varsigma_j$ .

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- the sequences of inter-arrival times and service times are mutually independent for each  $n \in \mathbb{N}$ .

## Heavy Traffic Condition.

- For  $k = 1, 2$  and  $j = 1, 2, 3$ , there exist  $\lambda_k, \mu_j \in (0, \infty)$  such that

$$\lim_{n \rightarrow \infty} \lambda_k^n = \lambda_k, \quad \lim_{n \rightarrow \infty} \mu_j^n = \mu_j.$$

- $\frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2} = 1, \quad \frac{\lambda_2}{\mu_3} = 1.$

- There exist  $b_i \in \mathbb{R}, i = 1, 2, 3$ , such that

$$\lim_{n \rightarrow \infty} \sqrt{n} \left( \frac{\lambda_i^n}{\mu_i^n} - \frac{\lambda_i}{\mu_i} \right) = b_i, \quad i = 1, 2, \quad \lim_{n \rightarrow \infty} \sqrt{n} \left( \frac{\lambda_2^n}{\mu_3^n} - 1 \right) = b_3.$$



# Control Problem.

- **Control Policy:**  $T^n(t) = (T_1^n(t), T_2^n(t), T_3^n(t))$ . Here  $T_j^n(t)$  is the amount of time spent on processing class  $j$  jobs over  $[0, t]$ .

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- Let for  $k = 1, 2, j = 1, 2, 3$ ,

$$A_k^n(t) = \max\{m \geq 1 : \sum_{i=1}^m u_k^n(i) \leq t\}, \quad S_j^n(t) = \max\{m \geq 1 : \sum_{i=1}^m v_j^n(i) \leq t\}.$$

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- **State Process:**

$$Q_i^n(t) = A_i^n(t) - S_i^n(T_i^n(t)), \quad i = 1, 2,$$

$$Q_3^n(t) = S_2^n(T_2^n(t)) - S_3^n(T_3^n(t)).$$

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- **Admissibility:**  $T^n$  is an admissible control policy if
  - $T_j^n$  is continuous, non-decreasing and  $T^n(0) = 0$ .
  - $I_1^n(t) = t - T_1^n(t) - T_2^n(t)$ ,  $I_2^n(t) = t - T_3^n(t)$  are non-decreasing processes.
  - $Q^n(t) \geq 0$ .
  - $T^n$  is 'non-anticipative'.

# Control Problem.

- **Cost.** Let  $\hat{Q}^n(t) = \frac{Q^n(nt)}{\sqrt{n}}$ . Let  $c = (c_1, c_2, c_3)' > 0$ . Cost associated with control  $\{T^n\}$ :

$$\hat{J}^n(T^n) \doteq \mathbb{E} \int_0^\infty e^{-\gamma t} c \cdot \hat{Q}^n(t) dt.$$

- **Goal:** Find a sequence  $\{T^n\}$  of control policies which is asymptotically optimal, namely it satisfies

$$\lim_{n \rightarrow \infty} \hat{J}^n(T^n) = \inf \liminf_{n \rightarrow \infty} \hat{J}^n(\tilde{T}^n),$$

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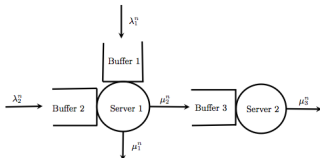
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- **Parameter Regime:** If  $c_1\mu_1 \leq c_2\mu_2 - c_3\mu_2$ , then priority to Buffer 2 is optimal. Here consider  $c_1\mu_1 > c_2\mu_2 - c_3\mu_2$ .

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  - The **Brownian control problem** is to find an  $\mathbb{R}^3$ -valued  $\{\mathcal{F}_t\}$ -adapted RCLL stochastic process  $\tilde{Y} = (\tilde{Y}_1, \tilde{Y}_2, \tilde{Y}_3)'$ , which minimizes

$$\mathbb{E} \left( \int_0^\infty e^{-\gamma t} c \cdot \tilde{Q}(t) dt \right),$$

subject to the following conditions. For all  $t \geq 0$ ,

$$\begin{aligned} 0 &\leq \tilde{Q}_i(t) \doteq q_i + Z_i(t) + \mu_i \tilde{Y}_i(t), \quad i = 1, 2, \\ 0 &\leq \tilde{Q}_3(t) \doteq q_3 + Z_3(t) + \mu_3 \tilde{Y}_3(t) - \mu_2 \tilde{Y}_2(t), \end{aligned}$$

and

$$\tilde{l}_1 \doteq \tilde{Y}_1 + \tilde{Y}_2, \quad \tilde{l}_2 \doteq \tilde{Y}_3 \quad \text{are non-decreasing and nonnegative.}$$



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$$\tilde{l}_1 \doteq \tilde{Y}_1 + \tilde{Y}_2, \quad \tilde{l}_2 \doteq \tilde{Y}_3 \quad \text{are non-decreasing and nonnegative.}$$

- Roughly,

$$\tilde{Q} \approx \hat{Q}^n, \quad \tilde{Y}(t) \approx \sqrt{n} (x^* t - \bar{T}^n(t)), \quad \tilde{l} \approx \hat{l}^n,$$

where  $x^* = (\lambda_1/\mu_1, \lambda_2/\mu_2, 1)$  is the 'nominal allocation' and  $\bar{T}^n(t) = T(nt)/n$ .

# Equivalent Workload Formulation

- Workload Process

$$\tilde{W}_1(t) = \frac{\tilde{Q}_1(t)}{\mu_1} + \frac{\tilde{Q}_2(t)}{\mu_2}, \quad \tilde{W}_2(t) = \frac{\tilde{Q}_2(t)}{\mu_3} + \frac{\tilde{Q}_3(t)}{\mu_3}.$$

# Equivalent Workload Formulation

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## ■ Effective Cost Fix $w_1, w_2 \in [0, \infty)$ . Consider the LP:

$$\text{minimize}_{q_j} \quad c_1 q_1 + c_2 q_2 + c_3 q_3, \quad \text{subject to} \quad \frac{q_1}{\mu_1} + \frac{q_2}{\mu_2} = w_1, \quad \frac{q_2}{\mu_3} + \frac{q_3}{\mu_3} = w_2, \quad q_j \geq 0.$$

## ■ Value of LP:

$$h(w_1, w_2) = \begin{cases} (c_1 \mu_1) w_1 + \frac{\mu_3}{\mu_2} (c_2 \mu_2 - c_1 \mu_1) w_2, & \text{when } \mu_3 w_2 \leq \mu_2 w_1, \\ (c_2 \mu_2 - c_3 \mu_2) w_1 + (c_3 \mu_3) w_2, & \text{when } \mu_3 w_2 \geq \mu_2 w_1, \end{cases}$$

## ■ Solution of LP:

$$q_1^* = \frac{\mu_1}{\mu_2} (\mu_2 w_1 - \mu_3 w_2), \quad q_2^* = \mu_3 w_2, \quad q_3^* = 0, \quad \text{if } \mu_3 w_2 \leq \mu_2 w_1, \\ q_1^* = 0, \quad q_2^* = \mu_2 w_1, \quad q_3^* = \mu_3 w_2 - \mu_2 w_1, \quad \text{if } \mu_3 w_2 \geq \mu_2 w_1.$$

## Equivalent Workload Formulation

- **EFWF** Let  $B_1(t) = \frac{Z_1(t)}{\mu_1} + \frac{Z_2(t)}{\mu_2}$ ,  $B_2(t) = \frac{Z_2(t)}{\mu_3} + \frac{Z_3(t)}{\mu_3}$ . The EFWF of the BCP is to find an  $\mathbb{R}_+^2$ -valued  $\{\mathcal{F}_t\}$ -adapted stochastic process  $\tilde{I} = (\tilde{I}_1, \tilde{I}_2)'$ , which minimizes

$$J(w, \tilde{I}) \doteq \mathbb{E} \left( \int_0^\infty e^{-\gamma t} h(\tilde{W}(t)) dt \right),$$

subject to, for all  $t \geq 0$ ,

$$0 \leq \tilde{W}_1(t) \doteq w_1 + B_1(t) + \tilde{I}_1(t),$$

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$$\tilde{Y}_1^*(t) \doteq -\frac{Z_3(t)}{\mu_2} + \tilde{I}_1^*(t) - \frac{\mu_3}{\mu_2} \tilde{I}_2^*(t), \quad \tilde{Y}_2^*(t) \doteq \frac{Z_3(t)}{\mu_2} + \frac{\mu_3}{\mu_2} \tilde{I}_2^*(t), \quad \tilde{Y}_3^*(t) \doteq \tilde{I}_2^*(t),$$

and when  $\mu_3 \tilde{W}_2^*(t) \geq \mu_2 \tilde{W}_1^*(t)$ ,

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The corresponding optimal queue length:

if  $\mu_3 \tilde{W}_2^*(t) < \mu_2 \tilde{W}_1^*(t)$ ,

$$\tilde{Q}_1^*(t) = \frac{\mu_1}{\mu_2} (\mu_2 \tilde{W}_1^*(t) - \mu_3 \tilde{W}_2^*(t)), \quad \tilde{Q}_2^*(t) = \mu_3 \tilde{W}_2^*(t), \quad \tilde{Q}_3^*(t) = 0,$$

if  $\mu_3 \tilde{W}_2^*(t) \geq \mu_2 \tilde{W}_1^*(t)$ ,

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- Similar BCP/EWF can be written for a broad family of SPN.
- Harrison proposes the following approach.
  - Solve the BCP.
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# Solving the EWF

- Recall the EWF: Minimize

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- Since  $w_2 \mapsto h(w_1, w_2)$  is nondecreasing, optimal  $(I_2^*, W_2^*)$  is characterized as

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Then the value function  $V$  of the EWF is the unique **constrained viscosity solution** on  $\mathbb{R}_+^2$  of the PDE

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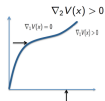
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- (B.-Ross(2008))  $V$  is  $C^1$  and  $\nabla_2 V(x) > 0$  for all  $x_2 > 0$ . Also  $\nabla_i V \geq 0$ .



## Case IIB (B.–Ross(2008))

- Free boundary:

$$\Psi(z_2) \doteq \sup\{z_1 \geq 0 : \nabla_1 V(z_1, z_2) = 0\}, \quad z_2 \in [0, \infty).$$

- $\Psi$  is nondecreasing,  $\Psi(0) = 0$  and  $\Psi(u) \rightarrow \infty$  as  $u \rightarrow \infty$ .
- $\Psi(z_2) - \Psi(z_1) \leq \frac{\mu_3}{\mu_2}(z_2 - z_1)$ ,  $0 \leq z_1 \leq z_2 < \infty$ .

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- Candidate optimal control:

$$I_1^*(t) \doteq \sup_{0 \leq s \leq t} [w_1 + B_1(s) - \Psi(W_2^*(s))]^-.$$

- Corresponding state process:

$$W_1^*(t) = w_1 + B_1(t) + \sup_{0 \leq s \leq t} [w_1 + B_1(s) - \Psi(W_2^*(s))]^-$$

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■ Let  $G = \{w \in \mathbb{R}_+^2 : w_1 \geq \Psi(w_2)\}$ ,

$$\partial_1 G = \{w \in G : w_1 = \Psi(w_2)\}, \quad \partial_2 G = \{w \in G : w_2 = 0\}.$$

■  $\nabla_i V(w) = 0$  for  $w \in \partial_i G$  and  $\nabla_i V(w) > 0$  for  $w \in G^\circ$ .

■  $\gamma V(w) + AV(w) - h(w) = 0$  for  $w \in G^\circ$ . Thus  $V$  is  $C^2$  in  $G^\circ$ .

■  $G^\varepsilon \doteq \{w \in \mathbb{R}^2 : d(w, G) < \varepsilon\}$ .

$$e = \left( (2 + 3\frac{\mu_3}{\mu_2}), 2 \right)', \quad w(\varepsilon) = w + \varepsilon e \in G^\circ \text{ if } w \in G^\varepsilon.$$

■ Let  $V^\varepsilon(w) = V(w(\varepsilon))$ .  $V^\varepsilon$  is  $C^2$  on  $G^\varepsilon$  and

$$|\gamma V^\varepsilon(w) + AV^\varepsilon(w) - h(w)| \leq c\varepsilon, \quad w \in G^\varepsilon.$$



# Proof of Optimality (Ctd.)

- Applying Itô's formula to  $V^\varepsilon$  with  $W^*$ :

$$V^\varepsilon(w) = \mathbb{E}e^{-\gamma t} V^\varepsilon(W^*(t)) + \mathbb{E} \int_0^t e^{-\gamma s} (\gamma V^\varepsilon(W^*(s)) + AV^\varepsilon(Z^*(s))) ds \\ - \sum_{i=1}^2 \mathbb{E} \int_0^t \nabla_i V^\varepsilon(W^*(s)) dJ_i^*(s)$$

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$$V(w) \geq \mathbb{E}e^{-\gamma t} V(W^*(t)) + \mathbb{E} \int_0^t e^{-\gamma s} h(W^*(s)) ds \\ - \sum_{i=1}^2 \mathbb{E} \int_0^t \nabla_i V(W^*(s)) dl_i^*(s) \\ = \mathbb{E}e^{-\gamma t} V(W^*(t)) + \mathbb{E} \int_0^t e^{-\gamma s} h(W^*(s)) ds.$$

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# Constructing an Asymp. Opt. Policy

- Recall: The optimal queue length is:

$$\text{if } \tilde{Q}_3^*(t) < \frac{\mu_2}{\mu_1} \tilde{Q}_1^*(t)$$

$$\tilde{Q}_1^*(t) = \frac{\mu_1}{\mu_2}(\mu_2 \tilde{W}_1^*(t) - \mu_3 \tilde{W}_2^*(t)), \quad \tilde{Q}_2^*(t) = \mu_3 \tilde{W}_2^*(t), \quad \tilde{Q}_3^*(t) = 0,$$

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- A good policy should:

- Keep  $\hat{Q}_3^n(t)$  close to 0 when  $Q_3^n(t) < \frac{\mu_2^n}{\mu_1^n} Q_1^n(t)$ .

- Keep  $\hat{Q}_1^n(t)$  close to 0, when  $Q_3^n(t) \geq \frac{\mu_2^n}{\mu_1^n} Q_1^n(t)$ .

- $\hat{W}^n(t) \in G$  for all  $t$  approximately and no idling when  $\hat{W}^n(t) \in G^\circ$ .

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$$\Lambda_{a,k} \doteq \log \mathbb{E}(e^{zu_k(1)/\lambda_k}) < \infty, \quad \Lambda_{s,j} \doteq \log \mathbb{E}(e^{zv_j(1)/\mu_j}) < \infty.$$



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- Fix  $c, l_0 \in (1, \infty)$ . Define

$$L^n \doteq \lfloor l_0 \log n \rfloor, \quad C^n \doteq \lfloor cl_0 \log n \rfloor - 1, \quad D^n = C^n - L^n + 3.$$

- **Control Policy.** At time  $s \in [0, \infty)$ ,

$$\text{if } Q_3^n(s) - \frac{\mu_2^n}{\mu_1^n} Q_1^n(s) < L^n,$$

serve **Class 1 customers** (provided the queue is non-empty) if either  $Q_3^n(s) \geq C^n$  or  $Q_2^n(s) = 0$ ,

serve **Class 2 customers** if  $Q_3^n(s) < C^n$  and  $Q_2^n(s) > 0$ ;

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- **Theorem** (B., Liu and Saha (2015)) There exist  $c, l_0 \in (1, \infty)$  such that the sequence of scheduling controls  $\{T^n\}$  satisfies

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# Asymptotic Optimality

- **Theorem** (B., Liu and Saha (2015)) There exist  $c, l_0 \in (1, \infty)$  such that the sequence of scheduling controls  $\{T^n\}$  satisfies

$$\lim_{n \rightarrow \infty} \hat{J}^n(T^n) = \inf \liminf_{n \rightarrow \infty} \hat{J}^n(\tilde{T}^n) = V,$$

where the infimum is taken over all admissible control policy sequences  $\{\tilde{T}^n\}$ .

- **Proof** (Sketch)

- For any admissible sequence  $\{\tilde{T}^n\}$ ,  $\liminf_{n \rightarrow \infty} \hat{J}^n(\tilde{T}^n) \geq V$  from B.– Ghosh(2006).
- With  $c, l_0$  as above,  $\lim_{n \rightarrow \infty} \hat{J}^n(T^n) = V$ .
- **Main step**  $(\hat{W}^n, \hat{I}^n) \Rightarrow (W^*, I^*)$ .

# Convergence of Scaled Processes

- With  $\hat{I}_1^n(t) = \sqrt{n}(t - \bar{T}_1^n(t) - \bar{T}_2^n(t))$ ,  $\hat{I}_2^n(t) = \sqrt{n}(t - \bar{T}_3^n(t))$

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- Proof of  $\int_0^\cdot \mathbf{1}_{\mathbf{A}(n, s)} d\hat{I}_2^n(s) \rightarrow 0$  uses exponential moments and large deviation estimates.

## Convergence of Scaled Processes

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- Thus

$$\begin{aligned} \hat{W}_1^n &\Rightarrow \Gamma \left( w_1 + B_1^* - \Psi(\hat{W}_2^*(\cdot)) \right) (\cdot) + \Psi(\hat{W}_2^*(\cdot)) \\ &= w_1 + B_1^* + \sup_{0 \leq s \leq \cdot} [w_1 + B_1^*(s) - \Psi(\hat{W}_2^*(s))] = W_1^*. \end{aligned}$$

# Problem: Case IID

- Case IID:  $c_2\mu_2 - c_3\mu_2 < 0$ ,  $c_2\mu_2 - c_1\mu_1 < 0$ .

- Recall the running cost in the EWF:

$$h(w_1, w_2) = \begin{cases} (c_1\mu_1)w_1 + \frac{\mu_3}{\mu_2}(c_2\mu_2 - c_1\mu_1)w_2, & \text{when } \mu_3w_2 \leq \mu_2w_1, \\ (c_2\mu_2 - c_3\mu_2)w_1 + (c_3\mu_3)w_2, & \text{when } \mu_3w_2 \geq \mu_2w_1, \end{cases}$$

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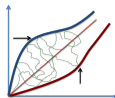
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- **Conjecture.** There are functions  $\Psi_i : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ ,  $i = 1, 2$  such that  $\Psi_i$  are Lipschitz,  $\Psi_i(0) = 0$ ,  $\Psi_i(u) \rightarrow \infty$  as  $u \rightarrow \infty$ , and an optimal state process  $Z^*$  is the unique solution of

$$Z_1^*(t) = B_1(t) + \sup_{0 \leq s \leq t} [B_1(s) - \Psi_1(Z_2^*(s))]^-$$

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# Problem: Free Boundary Characterizations for general SCSC

- Characterize optimal controls for general singular control problems with state constraints.
- 2D with no state constraints (i.e. state space is  $\mathbb{R}^2$ ) studied by Shreve and Soner (1989, 1991).
  - Under suitable smoothness and growth conditions, value function is shown to be  $C^2$ .
  - Using this the free boundary is shown to be  $C^{2,\alpha}$ .
  - An optimal process is then constructed using Lions and Sznitman(1984).
- State Constraints?

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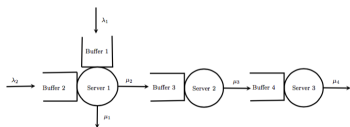
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- Multiclass networks require more care (see eg. Dai-Lin(2007)).
- Consider the network below for which Stations 1 and 3 are critical and Station 2 is subcritical. I.e.

$$\frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2} = 1, \quad \frac{\lambda_1}{\mu_3} < 1, \quad \frac{\lambda_1}{\mu_4} = 1.$$



Let  $J(q^n, T^n) = \mathbb{E} \int_0^\infty e^{-\gamma t} c \cdot \hat{Q}^n(t) dt$ , where  $\hat{Q}^n$  is the diffusion scaled queue-length process and  $q^n = \hat{Q}^n(0) \rightarrow q$ .

# Problem: Control of Bottleneck Subnetworks



- Consider the three dimensional BCP obtained by removing the subcritical node:

$$\text{minimize } \mathbb{E} \left( \int_0^{\infty} e^{-\gamma t} c \cdot \tilde{Q}(t) dt \right),$$

subject to

$$0 \leq \tilde{Q}_i(t) \doteq q_i + Z_i(t) + \mu_i \tilde{Y}_i(t), \quad i = 1, 2,$$

$$0 \leq \tilde{Q}_4(t) \doteq q_3 + Z_4(t) + \mu_4 \tilde{Y}_3(t) - \mu_2 \tilde{Y}_2(t),$$

and

$$\tilde{l}_1 \doteq \tilde{Y}_1 + \tilde{Y}_2, \quad \tilde{l}_3 \doteq \tilde{Y}_3 \quad \text{are non-decreasing, and } \tilde{l}_i(0) = 0, \quad i = 1, 3.$$

- Let  $V(q)$  be the value of the BCP.
- **Problem.**  $\lim_{n \rightarrow \infty} \inf_{\{T^n\}} J(q^n, T^n) = V(q)$ ?
- **An intermediate step:**  $\hat{Q}_3^n \rightarrow 0$  for all 'reasonable' policies.