

Computing the Value of Transshipment Flexibility in Distribution Networks

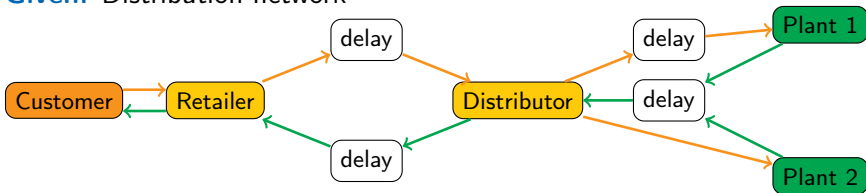
Marco Laumanns, ETH Zurich, Institute for Operations Research
with F. Cassim, J. Chastenet and J. Uffer (EPF Lausanne)
and M. Reimann (Warwick Business School)

Bremen, 11 January 2008



Problem Setting

Given: Distribution network



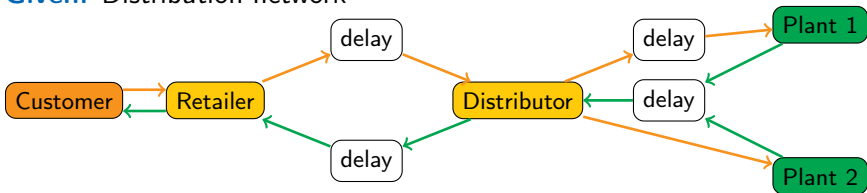
Nodes: Facilities

Links: Flows

- Information flows (orders)
- ← Material flows (shipments)

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Goal: Determine optimal shipment policy

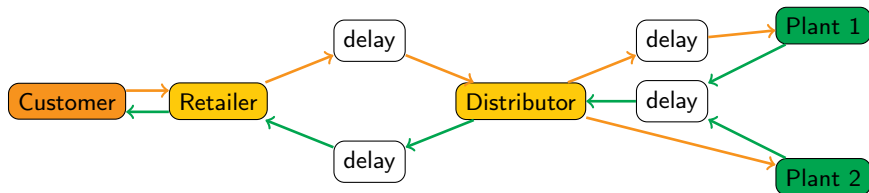
Overview

- 1 Supply Networks as Controlled Dynamical Systems
- 2 Stochastic Robust Optimal Control
- 3 Examples
 - Dual Suppliers
 - Lateral Inventory Transshipments

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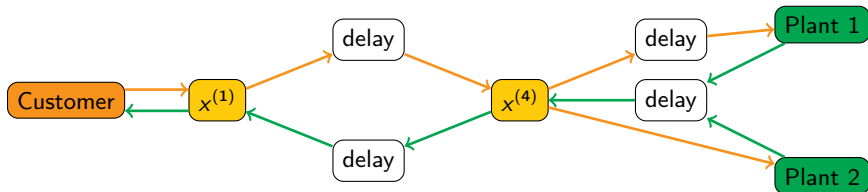
Discrete-time Supply Network Model



Nodes $v \in V$: Places where material is stored

Edges $e \in E$: Information and material flow

Discrete-time Supply Network Model

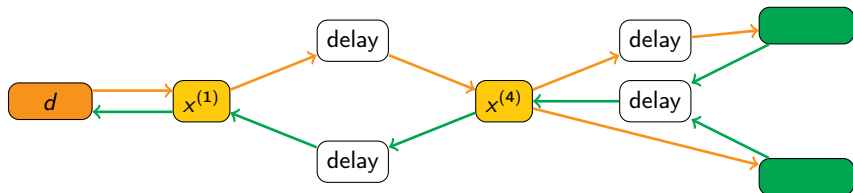


Nodes $v \in V$: Places where material is stored

- State variables $x^{(v)}$ for the **inventories**

Edges $e \in E$: Information and material flow

Discrete-time Supply Network Model

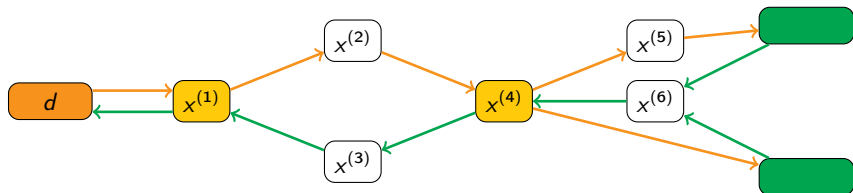


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- State variables $x^{(v)}$ for the **inventories**
- Sink node: generate **demand** d (stochastic)
- Source nodes: infinite **supply**

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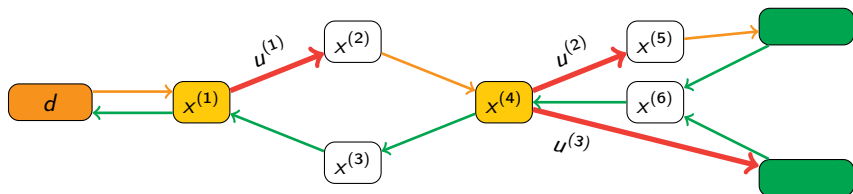
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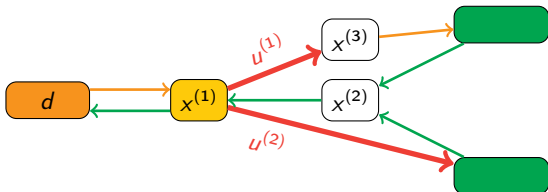
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Control: **Orders** $u^{(e)}$ of facilities

Example



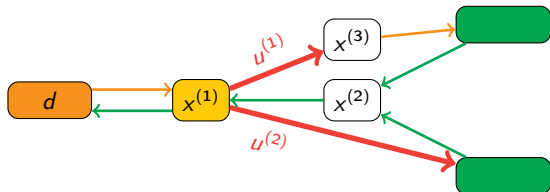
Dynamics of inventories

$$x_{k+1}^{(1)} = x_k^{(1)} + x_k^{(2)} - d_k \quad (1)$$

$$x_{k+1}^{(2)} = x_k^{(3)} + u_k^{(1)} \quad (2)$$

$$x_{k+1}^{(3)} = u_k^{(2)} \quad (3)$$

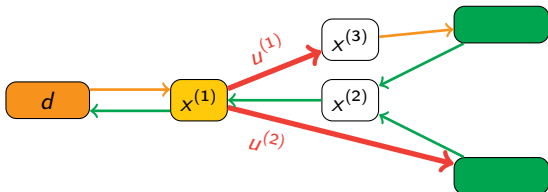
Example



Dynamics of inventories

$$\mathbf{x}_{k+1} = \underbrace{\begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}}_{:=\mathbf{A}} \mathbf{x}_k + \underbrace{\begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}}_{:=\mathbf{B}} \mathbf{u}_k + \mathbf{d}_k$$

Example



Dynamics of inventories

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Finite Horizon Robust Optimal Control

Given

- Dynamics $\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{d}_k$
- Linear constraints on state and controls $\mathbf{F}\mathbf{x} + \mathbf{G}\mathbf{u} \leq \mathbf{g}$
- Linear costs on state ($\mathbf{p}^T \mathbf{x}$) and control ($\mathbf{q}^T \mathbf{u}$)
- Stochastic disturbances $\mathbf{d}_k \in \mathbf{D} := \{\mathbf{d}^1, \mathbf{d}^2, \dots, \mathbf{d}^\ell\}$
- Fixed time horizon N

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$$\bar{J}(\mathbf{x}_0, \pi) := \mathbb{E} \left(\mathbf{p}^T \mathbf{x}_N + \sum_{i=0}^{N-1} \mathbf{p}^T \mathbf{x}_i + \mathbf{q}^T \mathbf{u}_i(\mathbf{x}_i) \right)$$

where $\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k(\mathbf{x}_k) + \mathbf{d}_k$.

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Let $\mathbf{u}_k(\mathbf{x}_k)$ denote the control input when system is in state \mathbf{x} at time k and $\pi = (\mathbf{u}_0, \dots, \mathbf{u}_{N-1})$. The **worst-case** cost is

$$\hat{J}(\mathbf{x}_0, \pi) := \max_{(\mathbf{d}_k)_{k=0}^{N-1}} \mathbf{p}^T \mathbf{x}_N \sum_{i=0}^{N-1} [\mathbf{p}^T \mathbf{x}_i + \mathbf{q}^T \mathbf{u}_i(\mathbf{x}_i)]$$

where $\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k(\mathbf{x}_k) + \mathbf{d}_k$.

Stochastic Dynamic Programming

Let $J_k^* : \mathcal{X}_k \rightarrow \mathbb{R}$ the **optimal value** function at time k .

Terminal condition: $J_N^*(\mathbf{x}) = \mathbf{p}_N^T \mathbf{x}$ and $\mathcal{X}_N = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{H}_N \mathbf{x} \leq \mathbf{h}_N\}$.

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$$\begin{aligned} J_k^*(\mathbf{x}_k) &= \min_{\mathbf{u}_k \in \mathcal{U}_k} \left\{ \mathbf{p}^T \mathbf{x} + \mathbf{q}^T \mathbf{u} + \mathbb{E}\{J_{k+1}^*(\mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{d})\} \right\} \\ &\text{s.t. } \mathbf{F}\mathbf{x}_k + \mathbf{G}\mathbf{u}_k \leq \mathbf{q} \\ &\text{and } \mathcal{U}_k = \{\mathbf{u} \in \mathbb{R}^{n_u} : \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{d} \in \mathcal{X}_{k+1} \forall \mathbf{d} \in \mathcal{D}\} \end{aligned}$$

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Remark: Problem is a **parametric LP** (with state \mathbf{x} as parameter) if

- J_{k+1}^* is piecewise linear and convex
- \mathcal{X}_{k+1} is a polyhedron

Properties

Theorem

- Value function $J_k^*(\mathbf{x}_k)$ is piecewise affine and convex in x .
- Optimal solution $\mathbf{u}_k^*(\mathbf{x}_k)$ is piecewise affine and continuous in \mathbf{x}_k .

$$\begin{cases} J_k^*(\mathbf{x}) = \mathbf{V}_k^{(i)} \mathbf{x} + \mathbf{W}_k^{(i)} \\ \mathbf{u}_k^*(\mathbf{x}) = \mathbf{R}_k^{(i)} \mathbf{x} + \mathbf{S}_k^{(i)} \end{cases} \quad \text{for } \mathbf{x} \in \mathcal{R}_k^{(i)}.$$

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Consequence: Solve N pLPs to recursively obtain $J_0^*(\mathbf{x}_0)$ and $\mathbf{u}_0^*(\mathbf{x}_0)$.

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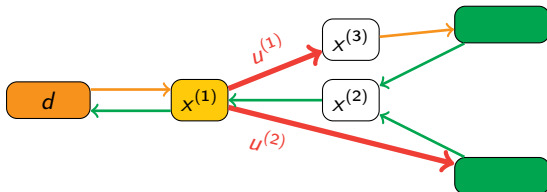
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Goal: We would like to approximate $\mathbf{u}^* = \lim_{N \rightarrow \infty} \mathbf{u}_0^*$.

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Example: One Retailer With Two Suppliers



$$\mathbf{x}_{k+1} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{x}_k + \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{u}_k + \mathbf{d}_k$$

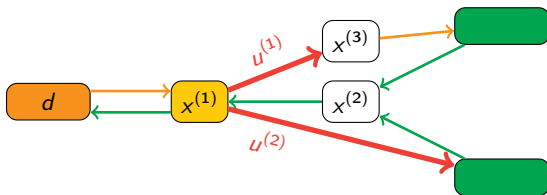
$u^{(1)}$: orders at supplier 1 with lead time 1 and unit cost 4

$u^{(2)}$: orders at supplier 2 with lead time 2 and unit cost 1

$u^{(1)}, u^{(2)} \leq 8$

$\mathbf{d}_k = (-\delta, 0, 0)^T$ where $\delta \in [0, 8]$

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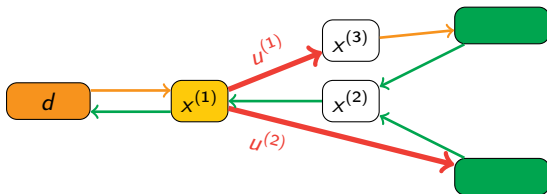
Resulting optimal control law:

(w.r.t. worst-case cost)

$$u^{(1)*} = \min\{\max\{20 - x_1 - x_2 - x_3, 0\}, 4\}$$

$$u^{(2)*} = \max\{16 - x_1 - x_2 - x_3, 0\}$$

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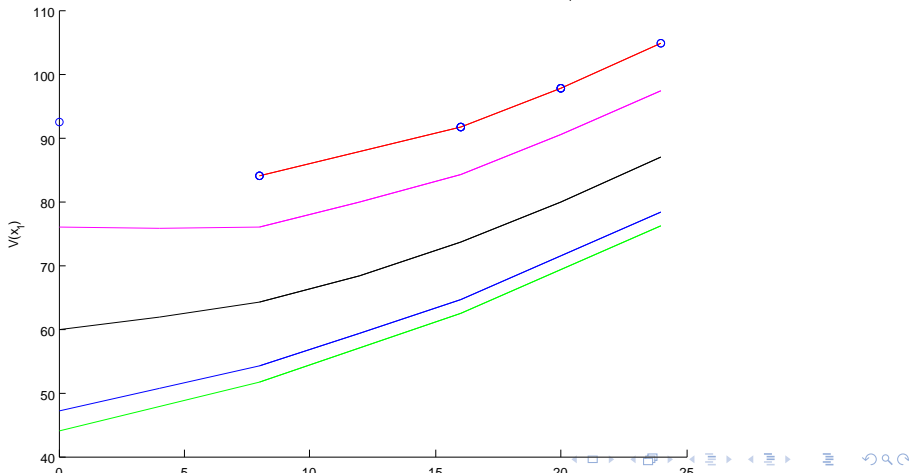
(w.r.t. average cost if $\delta \sim \mathcal{U}_{\{0,1,\dots,8\}}$)

$$u^{(1)*} = \min\{\max\{22 - x_1 - x_2 - x_3 - x_4, 0\}, 4\}$$

$$u^{(2)*} = \max\{16 - x_1 - x_2 - x_3 - x_4, 0\}$$

Results for Transshipment Problem

Discounted expected cost-to-go as a function of inventory x_1



Conclusions

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- Able to compute **explicit** state-feedback control policies for general networks if
 - the dynamics of the nodes is linear
 - cost and constraints are piecewise linear and convex
- Use of the model here:
 - Determine the **value function** (expected discounted infinite-time cost when starting at a given state) for different scenarios (flexibility options)
 - Valuate flexibility options by **cost decrease** versus base case
 - (i) using typical/nominal states (here)
 - (ii) via Markov chain: cost of stationary distribution (in progress)