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ANTICIPATORY SCHEDULING OF FREIGHT IN A SYNCHROMODAL TRANSPORT NETWORK

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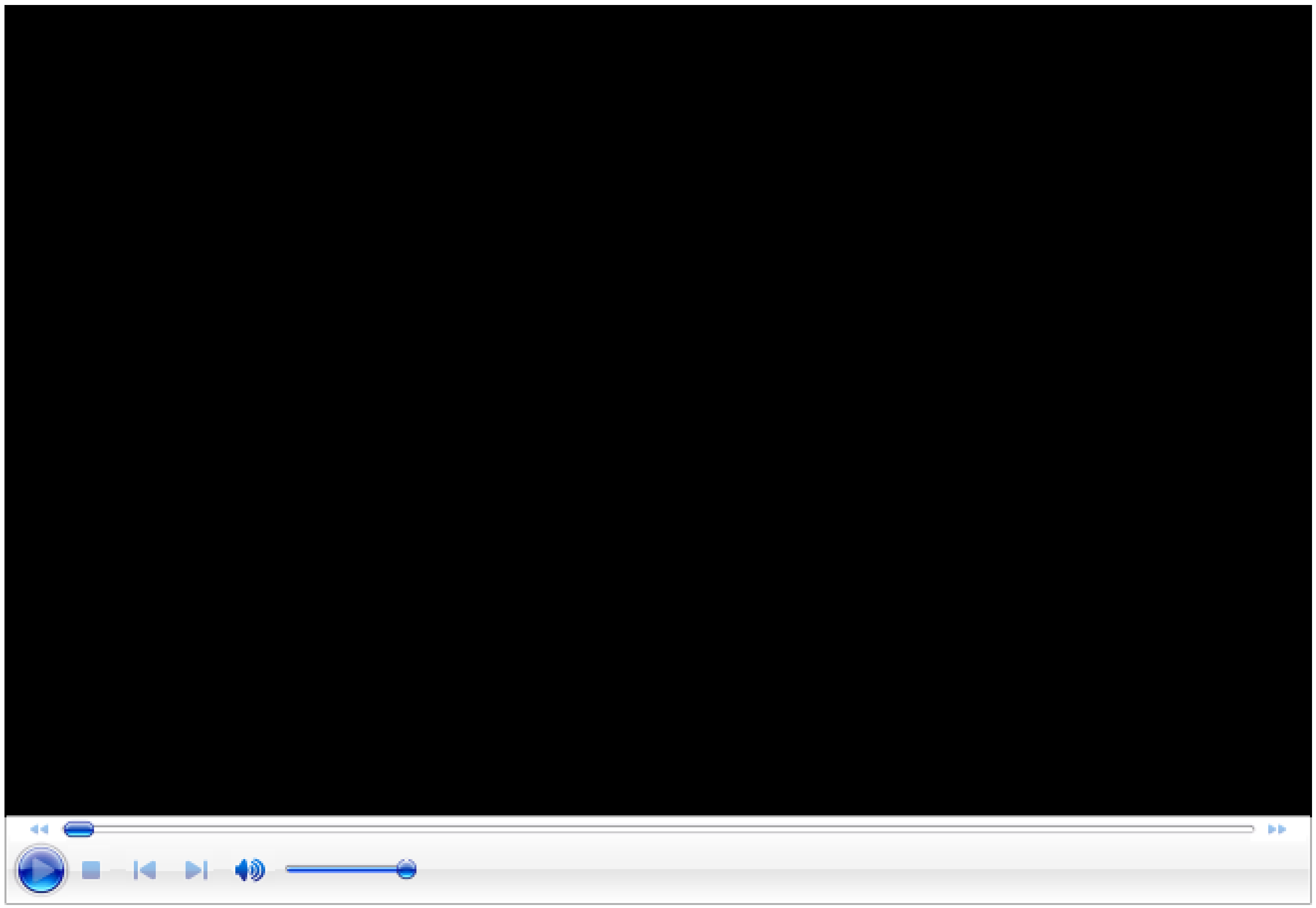
CONTENTS

- Synchromodal transport
- Anticipatory scheduling problem:
  - *Markov Decision Process model*
- Heuristic policy:
  - *Approximate Dynamic Programming algorithm*
- Numerical experiments:
  - *Tuning and benchmark experiments*
- What to remember

SYNCHROMODAL TRANSPORT

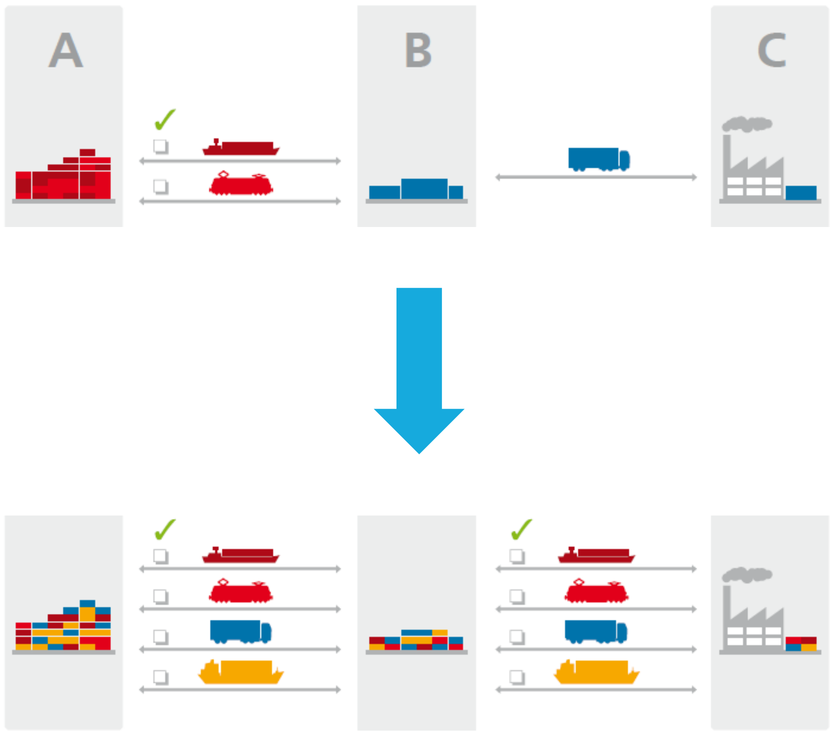
WHAT IS SYNCHROMODALITY?



**Source of video: Dutch Institute for Advanced Logistics (DINALOG) www.dinalog.nl*

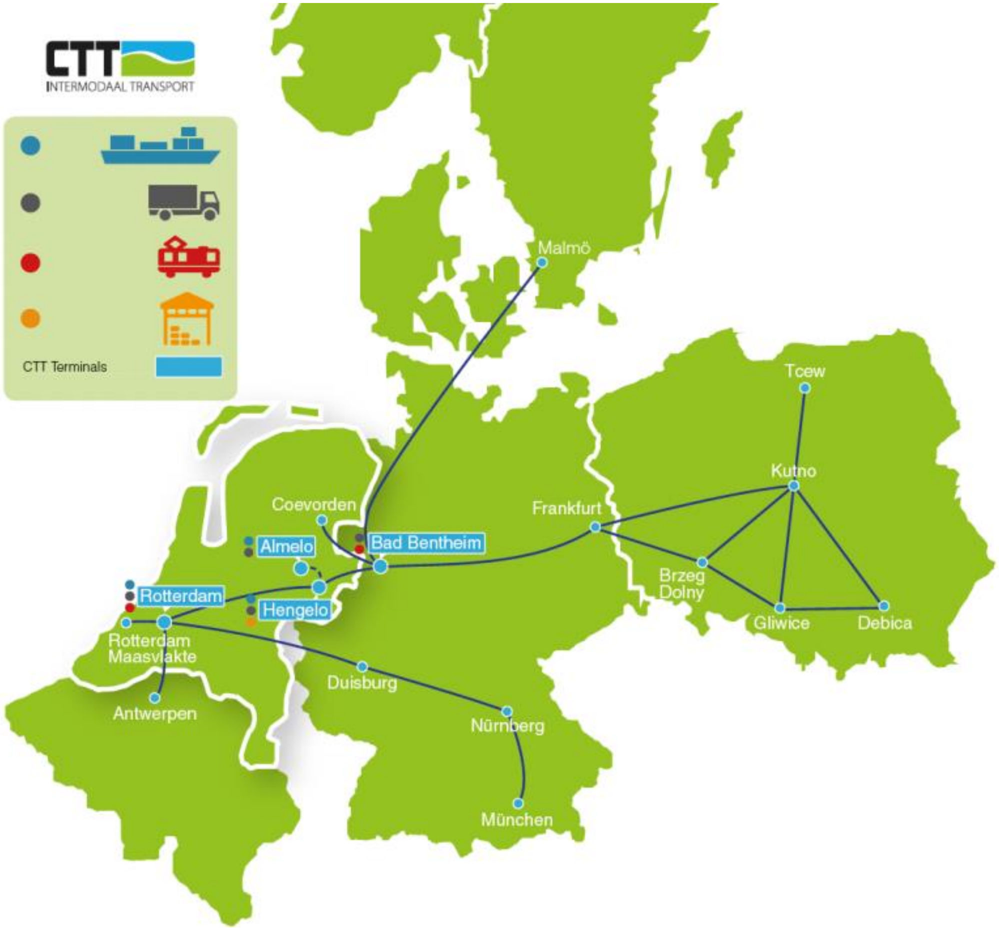
SYNCHROMODAL TRANSPORT
MAIN CHARACTERISTICS

- ***Mode-free booking*** for all freights.
- ***Network-wise scheduling*** at any point in time.
- ***Real-time information*** about the state of the network.
- ***Overall performance*** in both network and time.



**Source of artwork: European Container Terminals (ECT) – The future of freight transport (2011).*

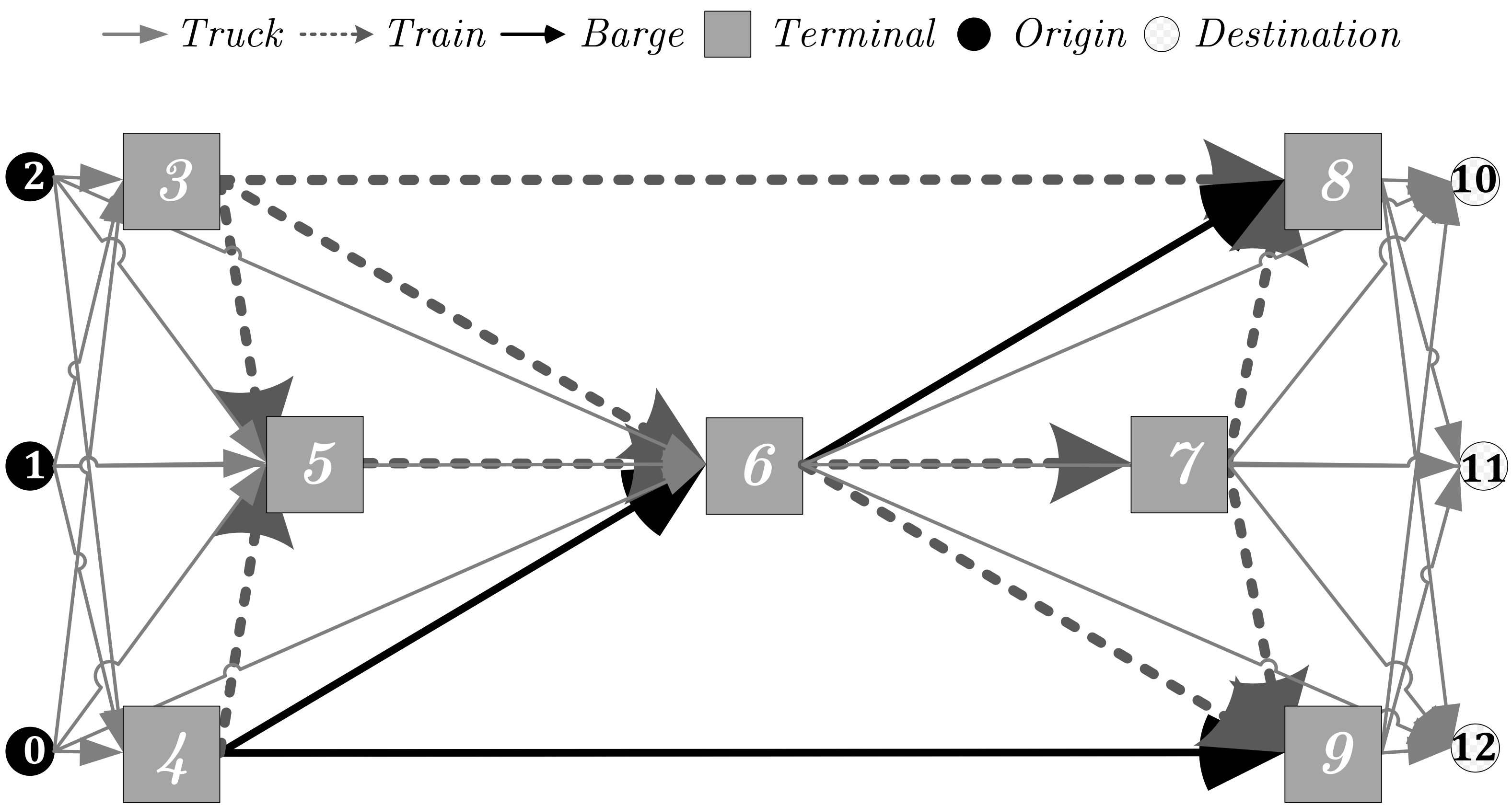
SYNCHROMODAL TRANSPORT
CASE: MOVING CONTAINERS TO/FROM THE HINTERLAND



*Source of artwork: Combi Terminal Twente (CTT) www.ctt-twente.nl

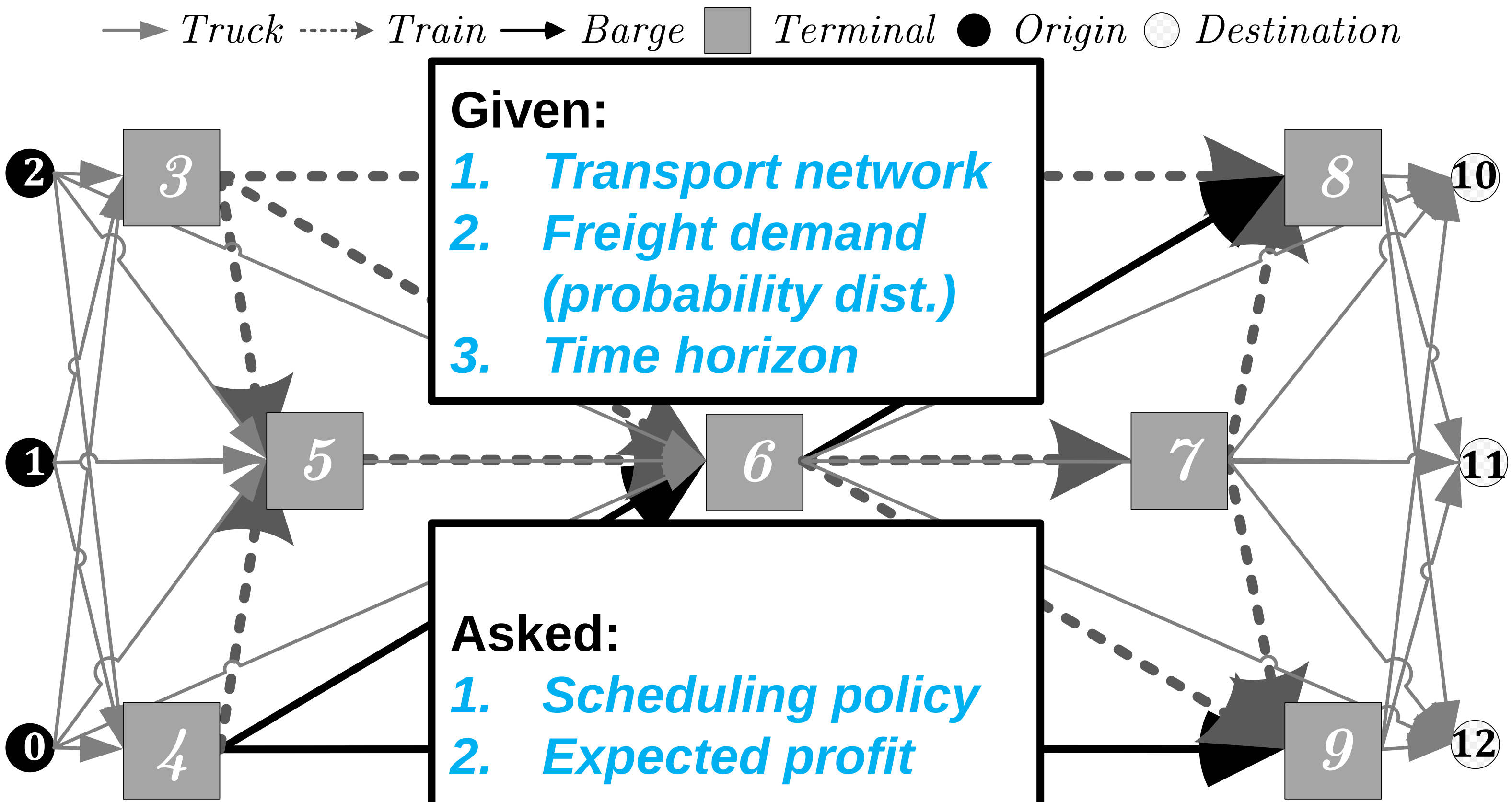
ANTICIPATORY SCHEDULING IN SYNCHROMODALITY

THE OPTIMIZATION PROBLEM



ANTICIPATORY SCHEDULING IN SYNCHROMODALITY

THE OPTIMIZATION PROBLEM



Given:

1. *Transport network*
2. *Freight demand (probability dist.)*
3. *Time horizon*

Asked:

1. *Scheduling policy*
2. *Expected profit*

MARKOV DECISION PROCESS (MDP) MODEL

OPTIMIZATION OF SEQUENTIAL DECISIONS UNDER UNCERTAINTY

State →

$$S_t = [F_{i,d,r,k,t}]_{\forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, r \in \mathcal{R}_t', k \in \mathcal{K}_t} \quad (1)$$

Decision

$$x_t = [x_{i,j,d,k,t}]_{\forall (i,j) \in \mathcal{A}_t, d \in \mathcal{N}_t^{\mathrm{D}}, k \in}$$

s.t.

$$\sum_{j \in \mathcal{N}_t^{\mathrm{I}} \cup \{d\}} x_{i,j,d,k,t} \le F_{i,d,0,k,t}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}$$

$$x_{i,d,d,L_{i,d,t}^{A},t} \ge F_{i,d,0,L_{i,d,t}^{A},t}, \quad \forall (i,d) \in$$

$$x_{i,j,d,k,t} = 0, \quad \forall (i,j) \in \mathcal{A}_t, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t | k$$

$$\sum_{d \in \mathcal{N}_t^{\mathrm{D}}} \sum_{k \in \mathcal{K}_t} x_{i,j,d,k,t} \le Q_{i,j,t}, \quad \forall (i,j$$

$$x_{i,j,d,k,t} \in \mathbb{N} \cup \{0\}, \quad \forall (i,j) \in \mathcal{A}_t, d \in$$

Exogenous Information

State Transition

$$S_t = S^M (S_{t-1}, x_{t-1}, W_t) \quad (4a)$$

s.t.

$$F_{i,d,0,k,t} = F_{i,d,0,k+1,t-1} - \sum_{j \in \mathcal{A}_t} x_{i,j,d,k+1,t-1} + F_{i,d,1,k,t-1} + \widetilde{F}_{i,d,0,k,t}, \quad (4b)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}, k+1 \in \mathcal{K}_t$$

$$F_{i,d,0,K_t^{\max},t} = F_{i,d,1,K_t^{\max},t-1} + \widetilde{F}_{i,d,0,K_t^{\max},t}, \quad (4c)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}$$

$$F_{i,d,0,k,t} = F_{i,d,0,k+1,t-1} - \sum_{j \in \mathcal{A}_t} x_{i,j,d,k+1,t-1} + F_{i,d,1,k,t-1}$$

$$+ \sum_{\mathcal{A}_t | M_{j,i,t}=1} x_{j,i,d,k+M_{j,i,t},t-1}, \quad (4d)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k+1 \in \mathcal{K}_t$$

$$_{d,r,k,t} = F_{i,d,r+1,k,t-1} + \widetilde{F}_{i,d,r,k,t}, \quad (4e)$$

$$_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}, r+1 \in \mathcal{R}_t | r \ge 1, k \in \mathcal{K}_t$$

$$F_{i,d,R_t^{\max},k,t} = \widetilde{F}_{i,d,R_t^{\max},k,t}, \quad (4f)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t$$

$$_{,r+1,k,t-1} + \sum_{j \in \mathcal{A}_t | M_{j,i,t}=r+1} x_{j,i,d,k+M_{j,i,t},t-1}, \quad (4g)$$

$$_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, r+1 \in \mathcal{R}_t' | r \ge 1, k \in \mathcal{K}_t$$

$$_{,t} = \sum_{j \in \mathcal{A}_t | M_{j,i,t}=|\mathcal{R}_t'|+1} x_{j,i,d,k+M_{j,i,t},t-1}, \quad (4h)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t$$

Reward Function

$$R_t(x_t) = \sum_{(i,j) \in \mathcal{A}_t} \sum_{d \in \mathcal{N}_t^{\mathrm{D}}} \left((A_{i,j,d,t} - C_{i,j,d,t}) \sum_{k \in \mathcal{K}_t} x_{i,j,d,k,t} \right) - \sum_{(i,j) \in \mathcal{A}_t} (B_{i,j,t} \cdot y_{i,j,t}) \quad (5a)$$

where

$$y_{i,j,t} = \begin{cases} 1, & \text{if } \sum_{d \in \mathcal{N}_t^{\mathrm{D}}} \sum_{k \in \mathcal{K}_t} (x_{i,j,d,k,t}) > 0 \\ 0, & \text{otherwise} \end{cases}, \quad \forall (i,j) \in \mathcal{A}_t \quad (5b)$$

Objective →

$$\max_{\pi \in \Pi} \mathbb{E} \left[\sum_{t \in \mathcal{T}} \gamma_t R_t(x_{t,\pi}) \middle| S_0 \right] \quad (6)$$

Bellman's Recursion

$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} (R_t(x_t) + \gamma_t \mathbb{E}[V_{t+1}(S_{t+1})]), \quad \forall S_t \in \mathcal{S} \quad (7)$$

$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} (R_t(x_t) + \gamma_t \mathbb{E}[V_{t+1}(S^M(S_t, x_t, W_{t+1}))]), \quad \forall S_t \in \mathcal{S} \quad (8)$$

$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} \left(R_t(x_t) + \gamma_t \sum_{\omega \in \Omega_{t+1}} p_\omega^{\Omega_{t+1}} (V_{t+1}(S^M(S_t, x_t, \omega))) \right), \quad \forall S_t \in \mathcal{S} \quad (9)$$

MDP MODEL – NETWORK EVOLUTION

A VIRTUAL TIME-WINDOW FOR FREIGHT TYPES

- Freight ***release-day r*** is relative to the current day *t*.
- Freight ***time-window length k*** is relative to the release-day *r*.
- Consider $F_{i,d,r,k,t}$ freights with $k=4$ sent from terminal *i* to terminal *j* using a service that lasts 2 days:

	t=7	t=8	t=9	t=10	t=11
	Monday	Tuesday	Wednesday	Thursday	Friday
i	$F_{i,d,0,4,7}$				
j		$F_{j,d,1,2,8}$	$F_{j,d,0,2,9}$		
d					$F_{d,d,0,0,11}$

MARKOV DECISION PROCESS (MDP) MODEL

OPTIMIZATION OF SEQUENTIAL DECISIONS UNDER UNCERTAINTY

State →

$$S_t = [F_{i,d,r,k,t}]_{\forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, r \in \mathcal{R}_t', k \in \mathcal{K}_t} \quad (1)$$

Decision

$$x_t = [x_{i,j,d,k,t}]_{\forall (i,j) \in \mathcal{A}_t, d \in \mathcal{N}_t^{\mathrm{D}}, k \in}$$

s.t.

$$\sum_{j \in \mathcal{N}_t^{\mathrm{I}} \cup \{d\}} x_{i,j,d,k,t} \le F_{i,d,0,k,t}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}$$

$$x_{i,d,d,L^A_{i,d,t},t} \ge F_{i,d,0,L^A_{i,d,t},t}, \quad \forall (i,d) \in$$

$$\begin{cases} 0, & \text{otherwise} \end{cases}$$

Exogenous Information

$$S_t = S^M(S_{t-1}, x_{t-1}, W_t) \quad (4a)$$

s.t.

$$F_{i,d,0,k,t} = F_{i,d,0,k+1,t-1} - \sum_{j \in \mathcal{A}_t} x_{i,j,d,k+1,t-1} + F_{i,d,1,k,t-1} + \widetilde{F}_{i,d,0,k,t}, \quad (4b)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}, k+1 \in \mathcal{K}_t$$

$$K_t^{\max}, t, \quad (4c)$$

$$+ F_{i,d,1,k,t-1}$$

(4d)

(4e)

(4f)

$$\sum_{j \in \mathcal{A}_t | M_{j,i,t} = r+1} x_{j,i,d,k+M_{j,i,t},t-1}, \quad (4g)$$

$$\mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, r+1 \in \mathcal{R}_t' | r \ge 1, k \in \mathcal{K}_t$$

$$= \sum_{j \in \mathcal{A}_t | M_{j,i,t} = |\mathcal{R}_t'|+1} x_{j,i,d,k+M_{j,i,t},t-1}, \quad (4h)$$

$$\forall i \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t$$

The three curses of dimensionality in our MDP:

1. ***All states***
2. ***All feasible decisions***
3. ***All realizations of uncertain demand***

Objective →

$$\max_{\pi \in \Pi} \mathbb{E} \left[\sum_{t \in \mathcal{T}} \gamma_t R_t(x_{t,\pi}) \middle| S_0 \right] \quad (6)$$

Bellman's Recursion

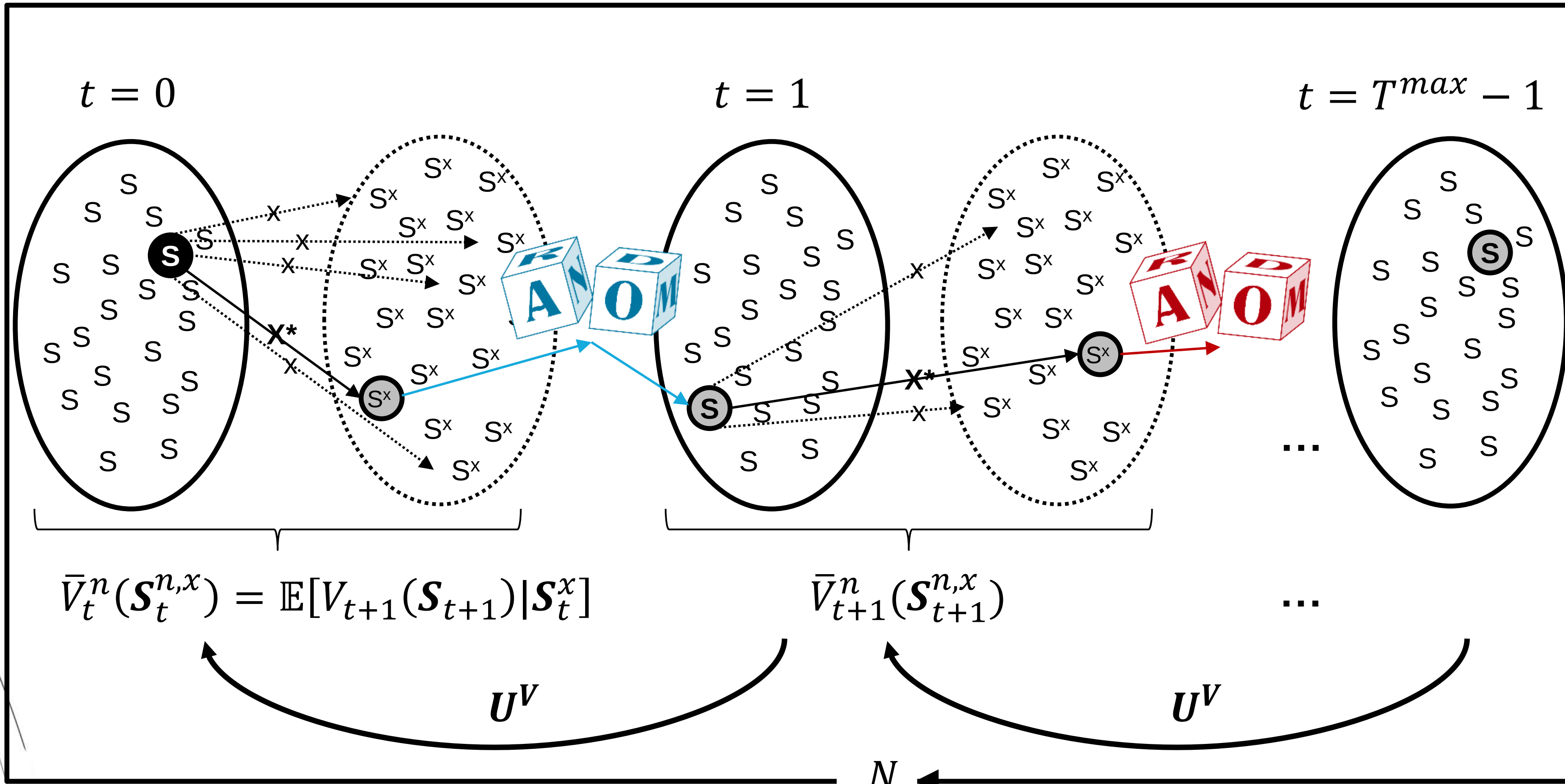
$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} \left(R_t(x_t) + \gamma_t \mathbb{E}\left[V_{t+1}(S_{t+1})\right] \right), \quad \forall S_t \in \mathcal{S} \quad (7)$$

$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} \left(R_t(x_t) + \gamma_t \mathbb{E}\left[V_{t+1}\left(S^M(S_t, x_t, W_{t+1})\right)\right] \right), \quad \forall S_t \in \mathcal{S} \quad (8)$$

$$V_t(S_t) = \max_{x_t \in \mathcal{X}_t} \left(R_t(x_t) + \gamma_t \sum_{\omega \in \Omega_{t+1}} p_\omega^{\Omega_{t+1}} \left(V_{t+1}\left(S^M(S_t, x_t, \omega)\right)\right) \right), \quad \forall S_t \in \mathcal{S} \quad (9)$$

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

HEURISTIC FRAMEWORK FOR SOLVING LARGE MARKOV MODELS.[1]



1. *For a comprehensive explanation see Powell (2010) Approximate Dynamic Programming.*

ADP – THE REDUCED DECISION SPACE $\mathcal{X}_t^{\mathrm{R}}$

RESTRICTED POLICIES (RP) 1 AND 2

RP 1:
Aggregated time-windows at each terminal.
Aggregated time-windows, destinations, and origins, at each origin.

$$x_t \in \mathcal{X}_t \tag{8a}$$

$$x_{i,d,d,k,t} = 0, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t | k > L_{i,d,t}^{A} \tag{8b}$$

$$x_{i,j,d,k,t} \geq \left(F_{i,d,0,k,t}\right)\left(x_{i,j,d,t}^{\mathrm{RG}} - M_{i,j,d,k,t}^{\mathrm{R}}\right), \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, j \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t \tag{8c}$$

$$\sum_{d \in \mathcal{N}_t^{\mathrm{D}}} \sum_{i \in \mathcal{N}_t^{\mathrm{O}}} x_{i,j,d,k,t} = \left|\mathcal{N}_t^{\mathrm{D}}\right| \left|\mathcal{N}_t^{\mathrm{O}}\right| x_{j,t}^{\mathrm{RO}}, \quad \forall j \in \mathcal{N}_t^{\mathrm{I}} | \exists_{\forall i \in \mathcal{N}_t^{\mathrm{O}}} (i,j) \in \mathcal{A}_t^{\mathrm{I}} \tag{8d}$$

RP 2:
Aggregated time-windows at terminals.
Aggregated time-windows and origins, at each origin.

$$x_t \in \mathcal{X}_t \tag{8a}$$

$$x_{i,d,d,k,t} = 0, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t | k > L_{i,d,t}^{A} \tag{8b}$$

$$x_{i,j,d,k,t} \geq \left(F_{i,d,0,k,t}\right)\left(x_{i,j,d,t}^{\mathrm{RG}} - M_{i,j,d,k,t}^{\mathrm{R}}\right), \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, j \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t \tag{8c}$$

$$\sum_{i \in \mathcal{N}_t^{\mathrm{O}}} x_{i,j,d,k,t} = \left|\mathcal{N}_t^{\mathrm{O}}\right| x_{j,d,t}^{\mathrm{RO}}, \quad \forall j \in \mathcal{N}_t^{\mathrm{I}} | \exists_{\forall i \in \mathcal{N}_t^{\mathrm{O}}} (i,j) \in \mathcal{A}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}} \tag{24}$$

ADP – THE REDUCED DECISION SPACE $\mathcal{X}_t^{\mathrm{R}}$

RESTRICTED POLICIES (RP) 1 AND 2

RP 1:

$$x_t \in \mathcal{X}_t \quad (8a)$$

Restricted Policy 1:

1. ***All released freights at a terminal, to a given destination, are scheduled together***
2. ***All released freights at all origins are scheduled together***

RP 2:

$$x_t \in \mathcal{X}_t \quad (8a)$$

Restricted Policy 2:

1. ***All released freights at a terminal, to a given destination, are scheduled together***
2. ***All released freights at all origins, to a given destination, are scheduled together***

ADP – THE VALUE FUNCTION APPROXIMATION (VFA)

PARAMETRIC APPROXIMATION OF DOWNSTREAM REWARDS

VFA →

$$\overline{V}_t^n\left(S_t^{x,n}\right) = \sum_{b \in \mathcal{B}} \theta_{b,t}^n \phi_{b,t}\left(S_t^{x,n}\right) = \phi_t\left(S_t^{x,n}\right)^T \theta_t^n \tag{11}$$

Basis functions

$$\phi_{b(i,d)}\left(S_t^{x,n}\right) = \sum_{k \in \mathcal{K}_t | k < \Psi} \sum_{r \in \mathcal{R}'_t} F_{i,d,r,k,t'}^{x,n}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}} \tag{12a}$$

$$\phi_{b'(i,d)}\left(S_t^{x,n}\right) = \sum_{k \in \mathcal{K}_t | k \geq \Psi} \sum_{r \in \mathcal{R}'_t} F_{i,d,r,k,t'}^{x,n}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}} \tag{12b}$$

$$\phi_{b''(d)}\left(S_t^{x,n}\right) = \sum_{i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}} \sum_{k \in \mathcal{K}_t | k \geq \Psi} \sum_{r \in \mathcal{R}'_t} F_{i,d,r,k,t'}^{x,n}, \quad \forall d \in \mathcal{N}_t^{\mathrm{D}} \tag{12c}$$

$$\phi_{|\mathcal{B}|}\left(S_t^{x,n}\right) = 1 \tag{12d}$$

Recursive least square method for updating the VFA

$$\overline{V}_t^n(S_t^{n,x*}) := U_t^n(\overline{V}_t^{n-1}(S_t^{n,x*}), S_t^{n,x*}, [\hat{v}_t^n]_{\forall t \in \mathcal{T}}) \tag{13a}$$

$$\text{s.t.}$$

$$\theta_t^n = \theta_t^{n-1} - \left(H_t^n\right)^{-1} \phi_t\left(S_t^{x,n}\right) \left(\overline{V}_{t-1}^{n-1}\left(S_{t-1}^{x,n}\right) - \sum_t^{T^{\max}-1} \hat{v}_t^n\right) \tag{13b}$$

$$H_t^n = \lambda^n H_t^{n-1} + \phi_t\left(S_t^{x,n}\right) \phi_t\left(S_t^{x,n}\right)^T \tag{13c}$$

$$\lambda^n = 1 - \frac{\lambda}{n} \tag{13d}$$

ADP – THE VALUE FUNCTION APPROXIMATION (VFA)

PARAMETRIC APPROXIMATION OF DOWNSTREAM REWARDS

VFA →

$$\overline{V}_t^n\left(S_t^{x,n}\right) = \sum_{b\in\mathcal{B}} \theta_{b,t}^n \phi_{b,t}\left(S_t^{x,n}\right) = \phi_t\left(S_t^{x,n}\right)^T \theta_t^n \tag{11}$$

$$\phi_{b(i,d)}\left(S_t^{x,n}\right) = \sum_{k\in\mathcal{K}_t|k<\Psi} \sum_{r\in\mathcal{R}'_t} F_{i,d,r,k,t'}^{x,n}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}} \tag{12a}$$

The features of a post-decision state:

1. ***Intermodal-path freights*** per location, per destination.
2. ***Trucking freights*** per location, per destination.
3. ***Total freights*** per destination.
4. ***Constant***.

Recursive least square method for updating the VFA

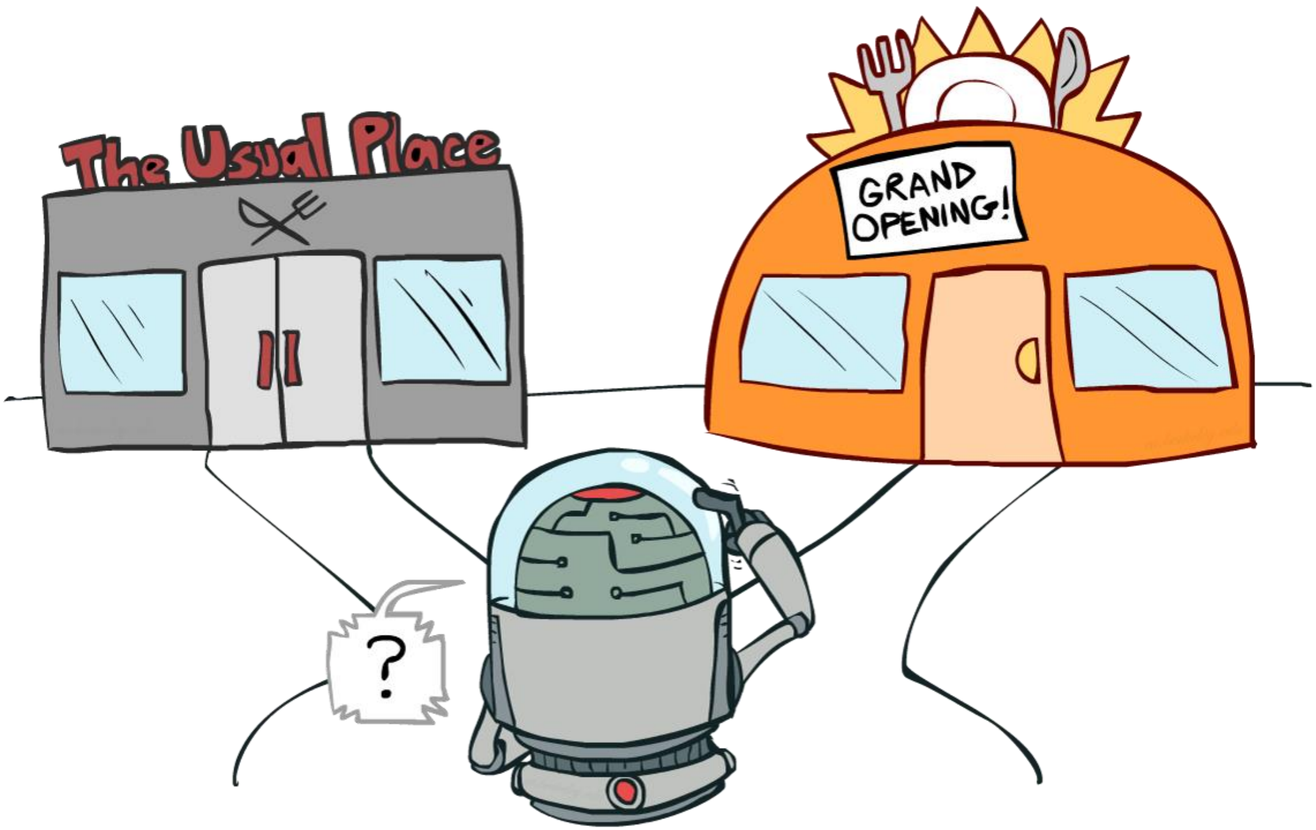
s.t.

$$\theta_t^n = \theta_t^{n-1} - \left(H_t^n\right)^{-1} \phi_t\left(S_t^{x,n}\right)\left(\overline{V}_{t-1}^{n-1}\left(S_{t-1}^{x,n}\right) - \sum_{t}^{T^{\max}-1} \widehat{v}_t^n\right) \tag{13b}$$

$$H_t^n = \lambda^n H_t^{n-1} + \phi_t\left(S_t^{x,n}\right)\phi_t\left(S_t^{x,n}\right)^T \tag{13c}$$

$$\lambda^n = 1 - \frac{\lambda}{n} \tag{13d}$$

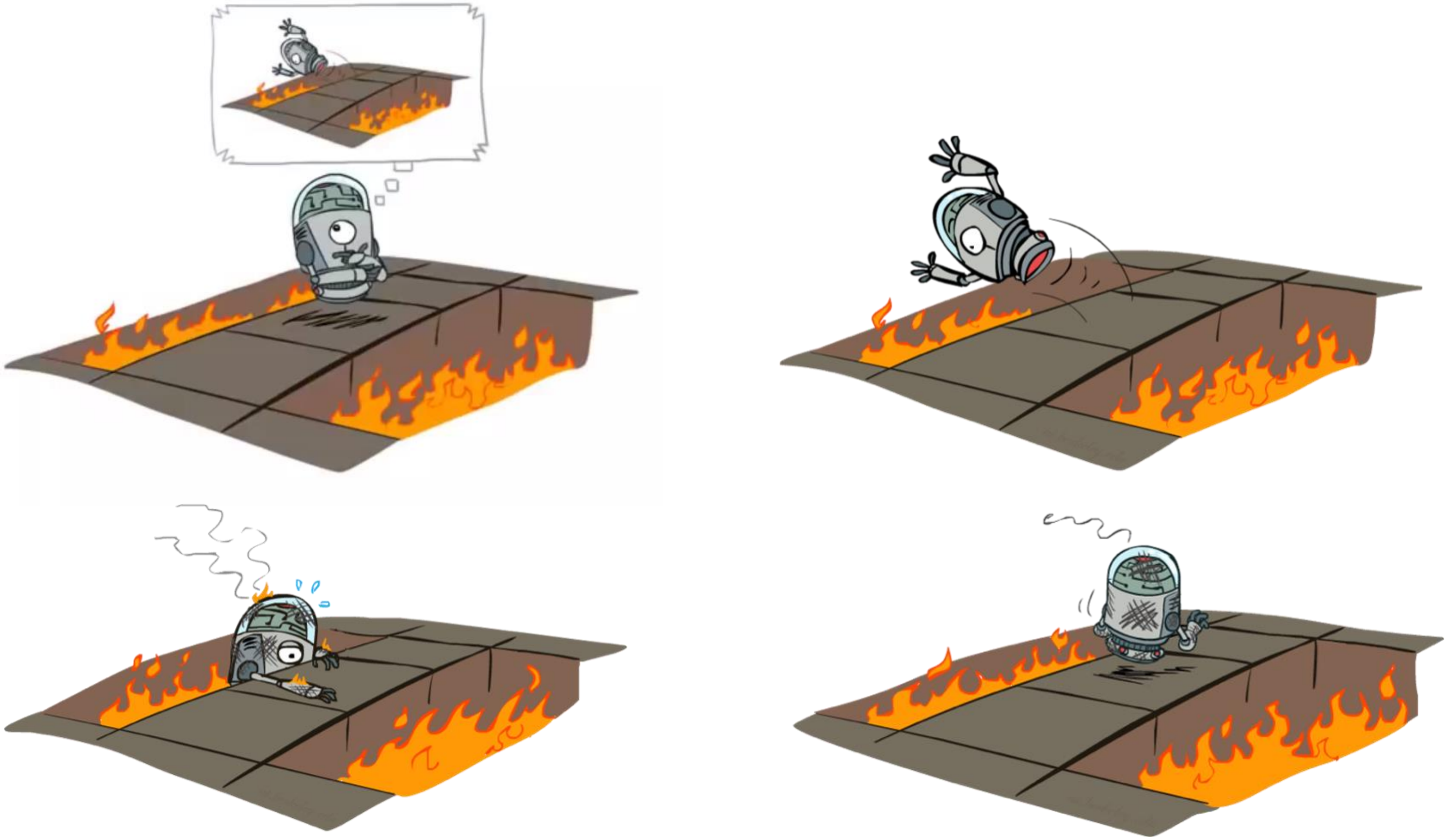
ADP – EXPLORATION VS. EXPLOITATION
ESCAPING LOCAL OPTIMA …



**Source of artwork: Dan Klein and Pieter Abbeel – Reinforcement Learning (2013), University of California at Berkeley*

ADP – EXPLORATION VS. EXPLOITATION

… OR AVOIDING LOCAL NADIR!



**Source of artwork: Dan Klein and Pieter Abbeel – Reinforcement Learning (2013), University of California at Berkeley*

ADP – EPSILON GREEDY EXPLORATION

ESCAPING LOCAL OPTIMA

Algorithm 1 ADP Algorithm

Initialize $\left[\overline{V}_t^0\right]_{\forall t \in \mathcal{T}}$

for $n = 1$ **to** N **do**

  $S_0^n := S_0$

  for $t = 0$ **to** $T^{max} - 1$ **do**

    $x_t^{n*} := \arg\max_{x_t^n \in \mathcal{X}_t^{\mathrm{R}}} \left(R_t\left(x_t^n\right) + \gamma_t \overline{V}_t^{n-1}\left(S^{M,x}\left(S_t^n, x_t^n\right)\right)\right)$

    $S_t^{n,x*} := S^{M,x}\left(S_t^n, x_t^{n*}\right)$

    $\widehat{v}_t^n := \left(R_t\left(x_t^{n*}\right) + \gamma_t \bar{V}_t^{n-1}\left(S_t^{n,x*}\right)\right)$

    $W_{t+1}^n := \mathrm{Random}\left(\Omega\right)$

    $S_{t+1}^n := S^M\left(S_t^n, x_t^{n*}, W_{t+1}^n\right)$

  end for

  for $t = T^{max} - 1$ **to** 0 **do**

    $\overline{V}_t^n(S_t^{n,x*}) := U_t^n(\overline{V}_t^{n-1}(S_t^{n,x*}), S_t^{n,x*}, [\widehat{v}_t^n]_{\forall t \in \mathcal{T}})$

  end for

end for

return $\left[\overline{V}_t^N\right]_{\forall t \in \mathcal{T}}$

ADP – EPSILON GREEDY EXPLORATION

ESCAPING LOCAL OPTIMA

Algorithm 1 ADP Algorithm

Initialize $\left[\overline{V}_t^0\right]_{\forall t \in \mathcal{T}}$
for $n = 1$ **to** N **do**
  $S_0^n := S_0$
  for $t = 0$ **to** $T^{max} - 1$ **d**
    $x_t^{n*} := \underset{x_t^n \in \mathcal{X}_t^{\mathrm{R}}}{\arg\max} \left(\ldots (x \right.$
    $S_t^{n,x*} := S^{M,x}\left(S_t^n, x_t^{n}\right.$
    $\widehat{v}_t^n := \left(R_t\left(x_t^{n*}\right) + \gamma_t \bar{V}_t\right.$
    $W_{t+1}^n := \mathrm{Random}\left(\Omega\right)$
    $S_{t+1}^n := S^M\left(S_t^n, x_t^{n*}, W_{t+1}^n\right)$
  end for
  for $t = T^{max} - 1$ **to** 0 **do**
    $\overline{V}_t^n(S_t^{n,x*}) := U_t^n(\overline{V}_t^{n-1}(S_t^{n,x*}), S_t^{n,x*}, [\widehat{v}_t^n]_{\forall t \in \mathcal{T}})$
  end for
end for
return $\left[\overline{V}_t^N\right]_{\forall t \in \mathcal{T}}$

Algorithm 2 ϵ-greedy strategy for exploration

if Random $[0,1) < \epsilon$ **then**
  $x_t^{n*} := \mathrm{Random}\left(\mathcal{X}_t^{\mathrm{R}}\right)$
else
  $x_t^{n*} := \underset{x_t^n \in \mathcal{X}_t^{\mathrm{R}}}{\arg\max} \left(R_t\left(x_t^n\right) + \gamma_t \bar{V}_t^{n-1}\left(S^{M,x}\left(S_t^n, x_t^n\right)\right)\right)$
end if

ADP – VALUE OF PERFECT INFORMATION (VPI)

EXPLORATION BASED ON A BAYESIAN BELIEF

Exploration decision

$$x_t^{n*} = \underset{x_t^n \in \mathcal{X}_t^{\mathrm{R}}}{\arg\max} \left(v_t^{E,n}(K_t^n, S_t^n x_t^n) \right) \tag{14}$$

Bayesian belief

$$K_t^n = (\overline{V}_t^n, C_t^n) = (\phi_t, \theta_t^n, C_t^n) \tag{15}$$

Value of exploration

$$v_t^{E,n}(K_t^n, S_t^n, x_t^n) = \sqrt{\sigma_t^{2,n}(K_t^n, S_t^{x,n})} f \left(- \frac{\delta(S_t^{x,n})}{\sqrt{\sigma_t^{2,n}(K_t^n, S_t^{x,n})}} \right) \tag{16a}$$

s.t.

$$\delta(S_t^{x,n}) = \left| \overline{V}_t^{x,n} \left(S_t^{x,n}\right) - \max_{y_t^n \in \mathcal{X}_t^{\mathrm{R}} | y \neq x_t^n} \overline{V}_t^{x,n} \left(S_t^{y,n}\right) \right| \tag{16b}$$

$$\sigma_t^{2,n}(K_t^n, S_t^{x,n}) = \phi\left(S_t^{x,n}\right)^T C_t^n \phi\left(S_t^{x,n}\right) \tag{16c}$$

Update VFA and belief

$$\theta_t^n = \theta_t^{n-1} - \frac{\left(\theta_t^{n-1}\right)^T \phi\left(S_t^{x,n}\right) - \sum_t^{T^{\max}-1} \widehat{v}_t^n}{\sigma^{2,\mathrm{E}} + \sigma_t^{2,n-1}\left(S_t^{x,n}\right)} C_t^n \phi\left(S_t^{x,n}\right) \tag{17}$$

$$C_t^n = C_t^{n-1} - \frac{C_t^{n-1} \phi\left(S_t^{x,n}\right) \phi\left(S_t^{x,n}\right)^T C_t^{n-1}}{\sigma^{2,\mathrm{E}} + \sigma_t^{2,n}\left(S_t^{x,n-1}\right)} \tag{18}$$

ADP – VALUE OF PERFECT INFORMATION (VPI)

EXPLORATION BASED ON A BAYESIAN BELIEF

Exploration decision

$x_t^{n*} = \arg$ (14)

(15)

(16a)

(16b)

(16c)

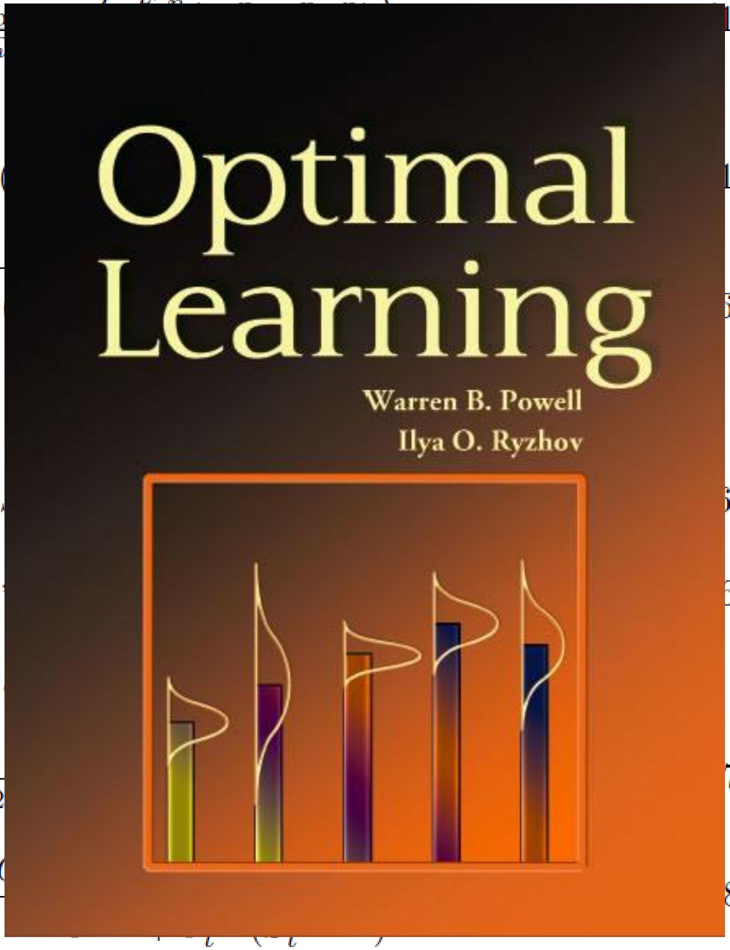
(17)

and belief

$C_t^n = C_t^{n-1} -$ (18)

Dearden et al. (1999) Model based Bayesian exploration:

The value of perfect information is the ***expected improvement in future decision quality*** arising from the information acquired by exploration.



ADP – VPI MODIFICATIONS

BE MORE CONSERVATIVE IN EXPLORATION AND UPDATING

1. Exploration decisions that focus on more than just the value of exploration:

$$x_t^{\mathrm{E2}} = \arg\max \left(\overline{V}_t^{x,n}\left(S_t^{x,n}\right) + v_t^{E,n}(S_t^n, K_t^n, x_t) \right)$$

$$x_t^{\mathrm{E3}} = \arg\max \left(R_t\left(S_t^n, x_t\right) + \overline{V}_t^{x,n}\left(S_t^{x,n}\right) + v_t^{E,n}(S_t^{x,n}, K_t^n, x_t) \right)$$

$$x_t^{\mathrm{E4}} = \arg\max \left((1-\alpha^n) \left(R_t\left(S_t^n, x_t\right) + \overline{V}_t^{x,n}\left(S_t^{x,n}\right) \right) + \alpha^n v_t^{E,n}(S_t^{x,n}, K_t^n, x_t) \right)$$

2. Update VFA and belief with stage or post-decision state dependent noise:

$$\sigma_t^{2,\mathrm{E2}} = \frac{T^{\max} - t}{T^{\max}} \eta^{\mathrm{E}}$$

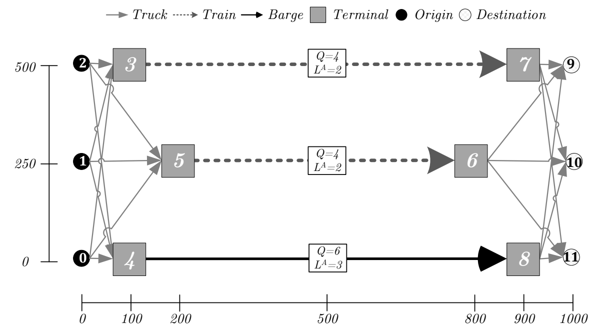
$$\sigma_t^{2,\mathrm{E3}} = \sigma_t^{2,n}(S_t^{x,n})$$

$$\sigma_{t,n}^{2,\mathrm{E4}} = \frac{T^{\max} - t}{T^{\max}} \eta^{\mathrm{E}} + \sigma_t^{2,n}(S_t^{x,n})$$

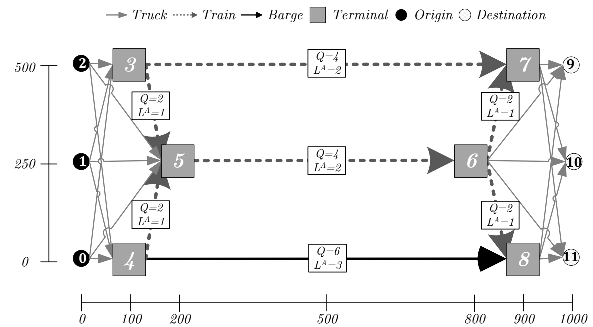
NUMERICAL EXPERIMENTS
EXPERIMENTAL SETUP

i. Tuning experiments:
- Relatively certain freight demand.
- Test all ADP designs, and tune their parameters.
- ***Goal: define the best ADP design.***

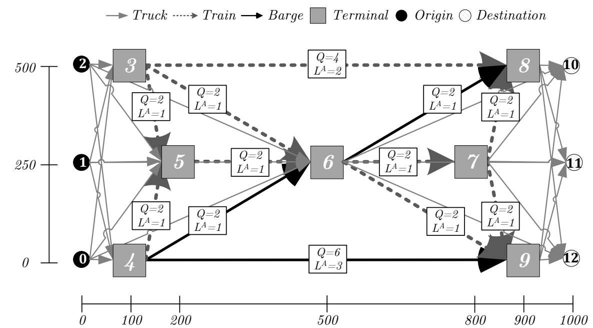
ii. Benchmark experiments:
- Various uncertain demand profiles.
- Compare against two smart benchmark heuristics.
- ***Goal: study the gains (or losses) of using our ADP design.***



Network 1



Network 2



Network 3

NUMERICAL EXPERIMENTS

TUNING EXP. [1/3]: MAXIMUM REALIZED REWARD PER ADP DESIGN

Performance:

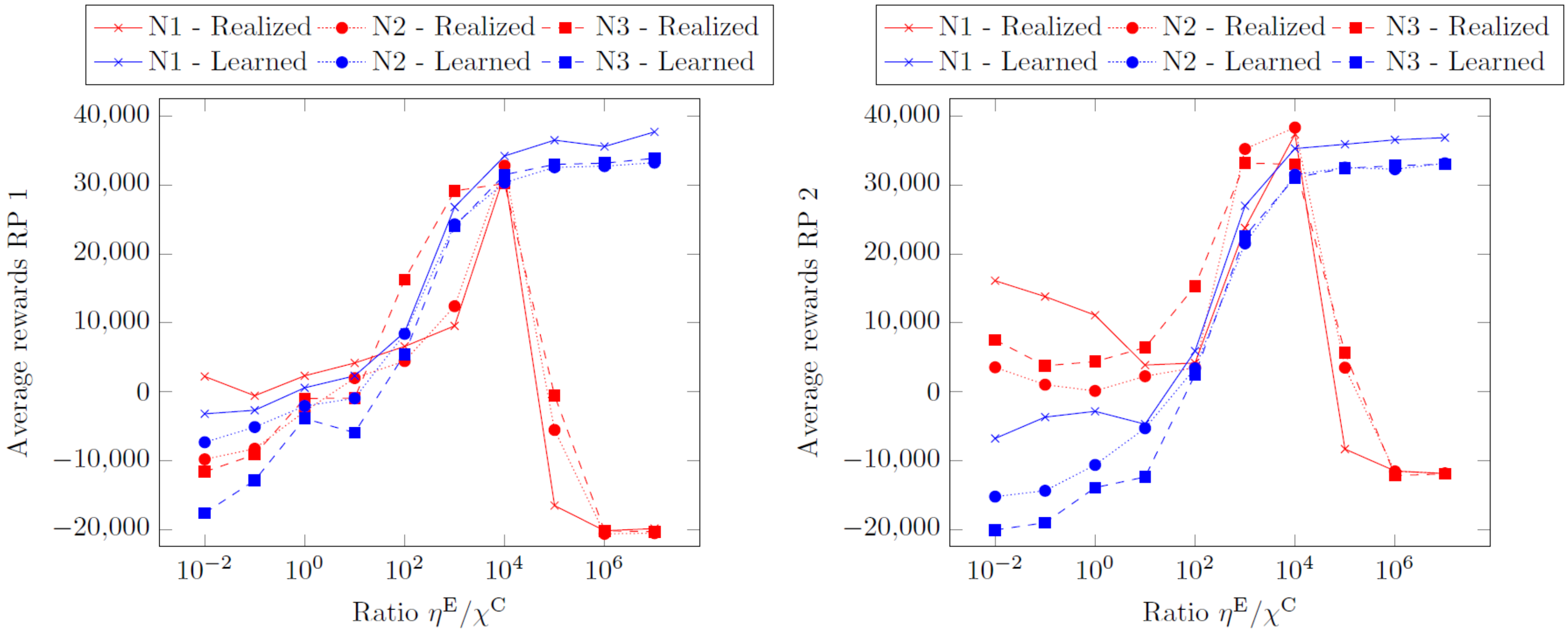
Learned rewards are those ADP thinks the resulting policy will achieve.
Realized rewards are the actual rewards (i.e., profit) achieved in a simulation of the resulting policy.

ADP Design		Network 1		Network 2		Network 3	
		Realized	Learned	Realized	Learned	Realized	Learned
RP 1	*BF*	*-7,994*	*38,219*	*-11,247*	*33,720*	*-16,548*	*-17,928*
	BF + ε-greedy	*-4,628*	*-6,984*	*-11,485*	*33,228*	*-18,172*	*-18,507*
	BF + VPI	*34,044*	*36,571*	*34,284*	*29,493*	*34,898*	*23,285*
RP 2	*BF*	*-4,912*	*-3,803*	*-11,734*	*34,060*	*-11,949*	*34,495*
	BF + ε-greedy	*880*	*37,386*	*-11,450*	*-12,091*	*-11,949*	*33,356*
	BF + VPI	*40,439*	*35,407*	*40,195*	*31,107*	*38,314*	*30,791*

Suppose that there are two freights at each location in Network 3, then :
RP 1 *has 1.9x10^4 decisions, or* ***0.01 % of decision space!***
RP 2 *has 5.8x10^4 decisions, or* ***0.02 % of decision space!***

NUMERICAL EXPERIMENTS

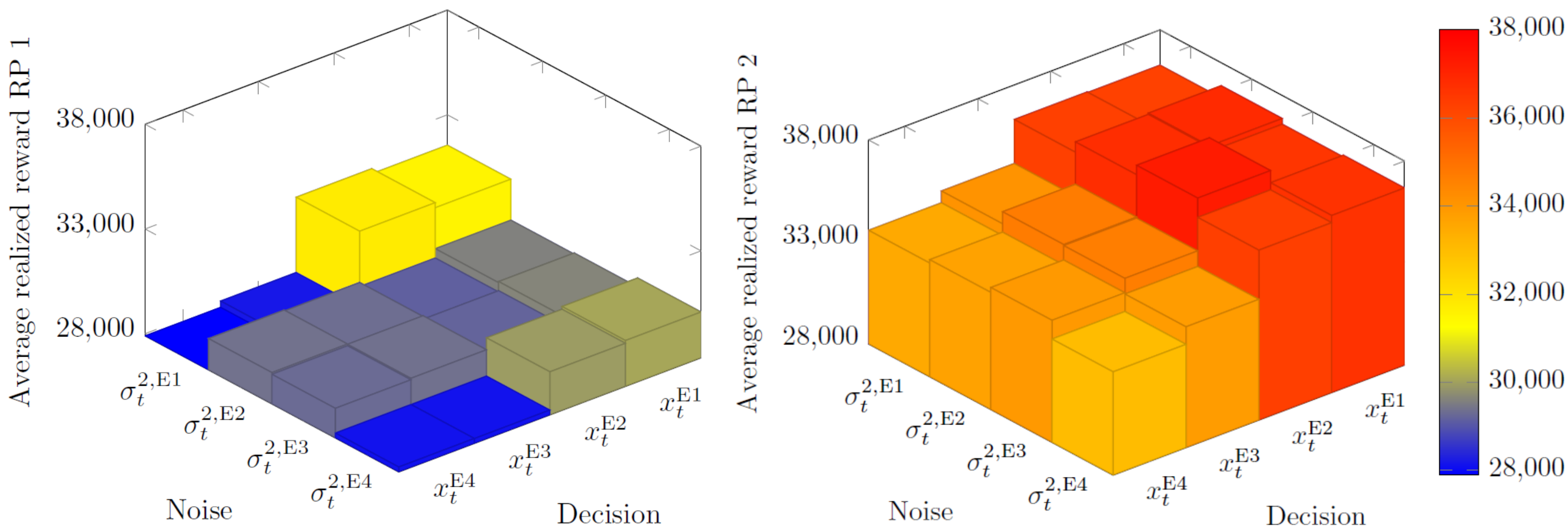
TUNING EXP. [2/3]: NOISE AND COVARIANCE PARAMETERS IN VPI



Similar to other literature of VPI, we observed that there seems to be an ***optimal ratio of the noise parameters*** *in our problem, around 10^4.*

NUMERICAL EXPERIMENTS

TUNING EXP. [3/3]: PROPOSED VPI MODIFICATIONS OVER ALL NETWORKS



*From our proposed modifications, **including the downstream rewards in the exploration decision** and **updating with a noise term equal to the variance of a post-decision state** seems to perform the best.*

NUMERICAL EXPERIMENTS

BENCHMARK EXP. [1/2]: DEMAND PROFILES WITH VARIOUS TIME-WINDOW DIST.

Release-day (RD) : 0, 1, 2 days
Time-window (TW) length: 4, 5, 6 days

Average realized rewards (over ten replications)

RD distribution	TW distribution	Network 1 BH	Network 1 ADP	Network 2 BH	Network 2 ADP	Network 3 BH	Network 3 ADP
Short	Short	*17,862*	*12,131*	*12,339*	*11,289*	*22,191*	*(19)*
	Medium	*25,286*	*22,775*	*18,232*	*23,486*	*26,634*	*15,001*
	Long	*33,007*	*35,111*	*25,805*	*32,524*	*30,680*	*29,745*
Medium	Short	*17,812*	*10,938*	*12,160*	*9,877*	*22,141*	*209*
	Medium	*25,302*	*22,267*	*18,052*	*23,015*	*26,573*	*14,612*
	Long	*32,805*	*34,508*	*25,420*	*31,806*	*30,473*	*29,502*
Long	Short	*17,773*	*10,724*	*12,062*	*9,281*	*22,256*	*(44)*
	Medium	*25,276*	*21,956*	*17,951*	*23,422*	*26,568*	*14,167*
	Long	*32,876*	*34,511*	*25,401*	*32,462*	*30,467*	*29,274*

NUMERICAL EXPERIMENTS

BENCHMARK EXP. [2/2]: DEMAND PROFILES WITH VARIOUS TIME-WINDOW DIST.

Release-day (RD) : 0, 1, 2 days
Time-window (TW) length: 4, 5, 6 days

Average realized rewards (over ten replications)

RD distribution	TW distribution	Network 1 BH+RP	Network 1 ADP	Network 2 BH+RP	Network 2 ADP	Network 3 BH+RP	Network 3 ADP
Short	Short	*9,273*	*12,131*	*9,014*	*11,289*	*9,374*	*(19)*
	Medium	*9,677*	*22,775*	*9,244*	*23,486*	*9,537*	*15,001*
	Long	*10,151*	*35,111*	*9,601*	*32,524*	*9,728*	*29,745*
Medium	Short	*9,322*	*10,938*	*9,003*	*9,877*	*9,494*	*209*
	Medium	*9,814*	*22,267*	*9,338*	*23,015*	*9,728*	*14,612*
	Long	*10,341*	*34,508*	*9,719*	*31,806*	*9,881*	*29,502*
Long	Short	*9,438*	*10,724*	*9,074*	*9,281*	*9,601*	*(44)*
	Medium	*10,037*	*21,956*	*9,485*	*23,422*	*9,890*	*14,167*
	Long	*10,643*	*34,511*	*9,944*	*32,462*	*10,150*	*29,274*

WHAT TO REMEMBER

- In scheduling freight in synchromodal transport using ADP, ***VPI exploration significantly improves the policy, and learned values, of traditional ADP designs.***

- To apply VPI in a finite-horizon ADP with basis functions, ***exploring and updating should be slightly more conservative*** than in conventional infinite-horizon VPI.

- For larger networks, further research in the ***reduction of the decision space*** is necessary for ADP to achieve the largest gains over competing policies in synchromodal transport.

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THANKS FOR YOUR ATTENTION!

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