UNIVERSITY OF TWENTE.

DINALOG
Dutch Institute
for Advanced Logistics

SCHEDULING SYNCHROMODAL FREIGHT TRANSPORT USING APPROXIMATE DYNAMIC PROGRAMMING

Arturo E. Pérez Rivera & Martijn R.K. Mes

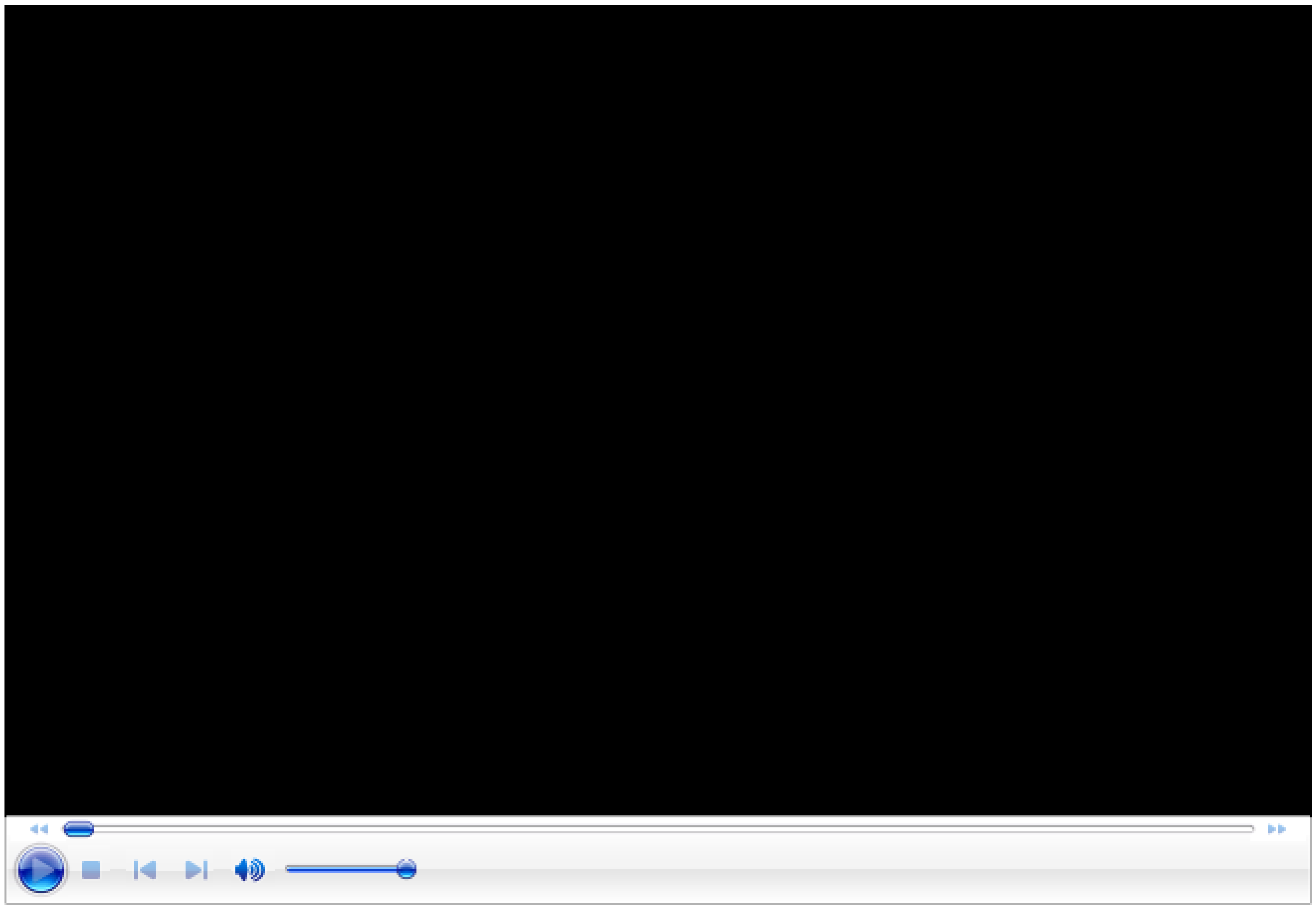
Department of Industrial Engineering and Business Information Systems
University of Twente, The Netherlands

VeRoLog 2017 - Wednesday, July 12th
Amsterdam, The Netherlands

CONTENTS

- Synchromodal freight transport
- Multi-period scheduling problem:
  - *Markov Decision Process model*
- Heuristic solution:
  - *Approximate Dynamic Programming algorithm*
- Numerical results
- What to remember

SYNCHROMODAL FREIGHT TRANSPORT
WHAT IS SYNCHROMODALITY?

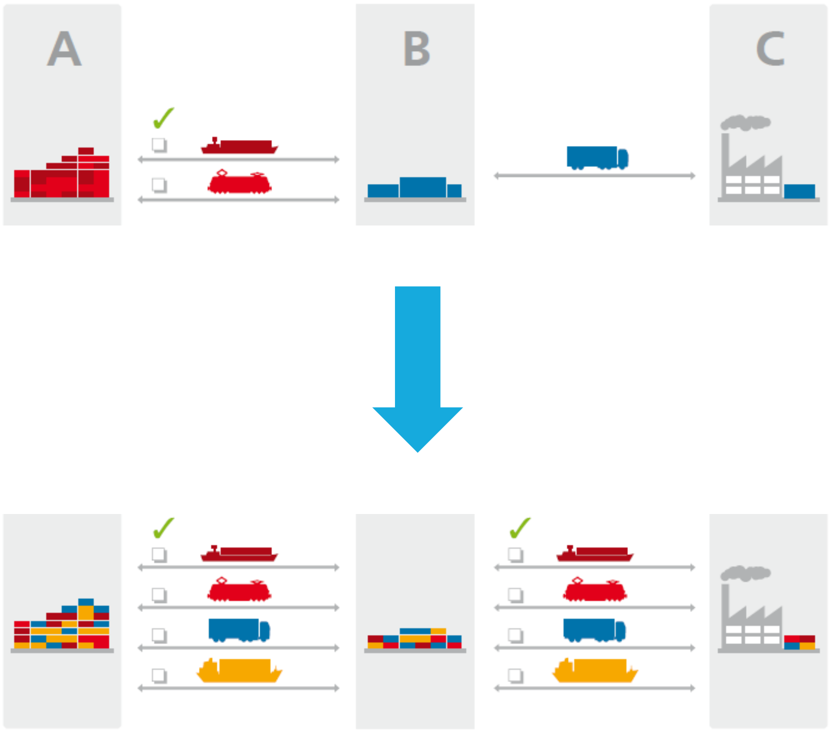


**Source of video: Dutch Institute for Advanced Logistics (DINALOG) www.dinalog.nl*

SYNCHROMODAL FREIGHT TRANSPORT

WHAT ARE ITS CHARACTERISTICS?

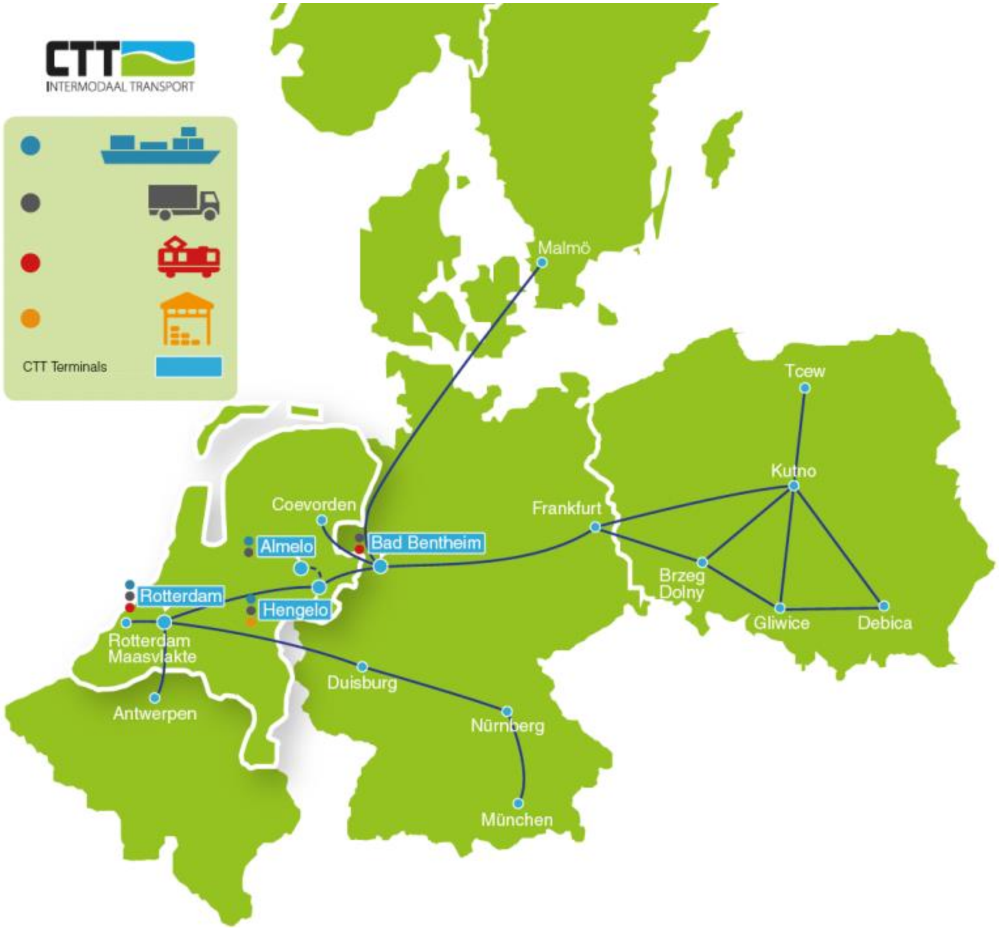
- ***Mode-free booking*** for all freights.
- ***Network-wise scheduling*** at any point in time.
- ***Real-time information*** about the state of the network.
- ***Overall performance*** in both network and time.



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

SYNCHROMODAL FREIGHT TRANSPORT

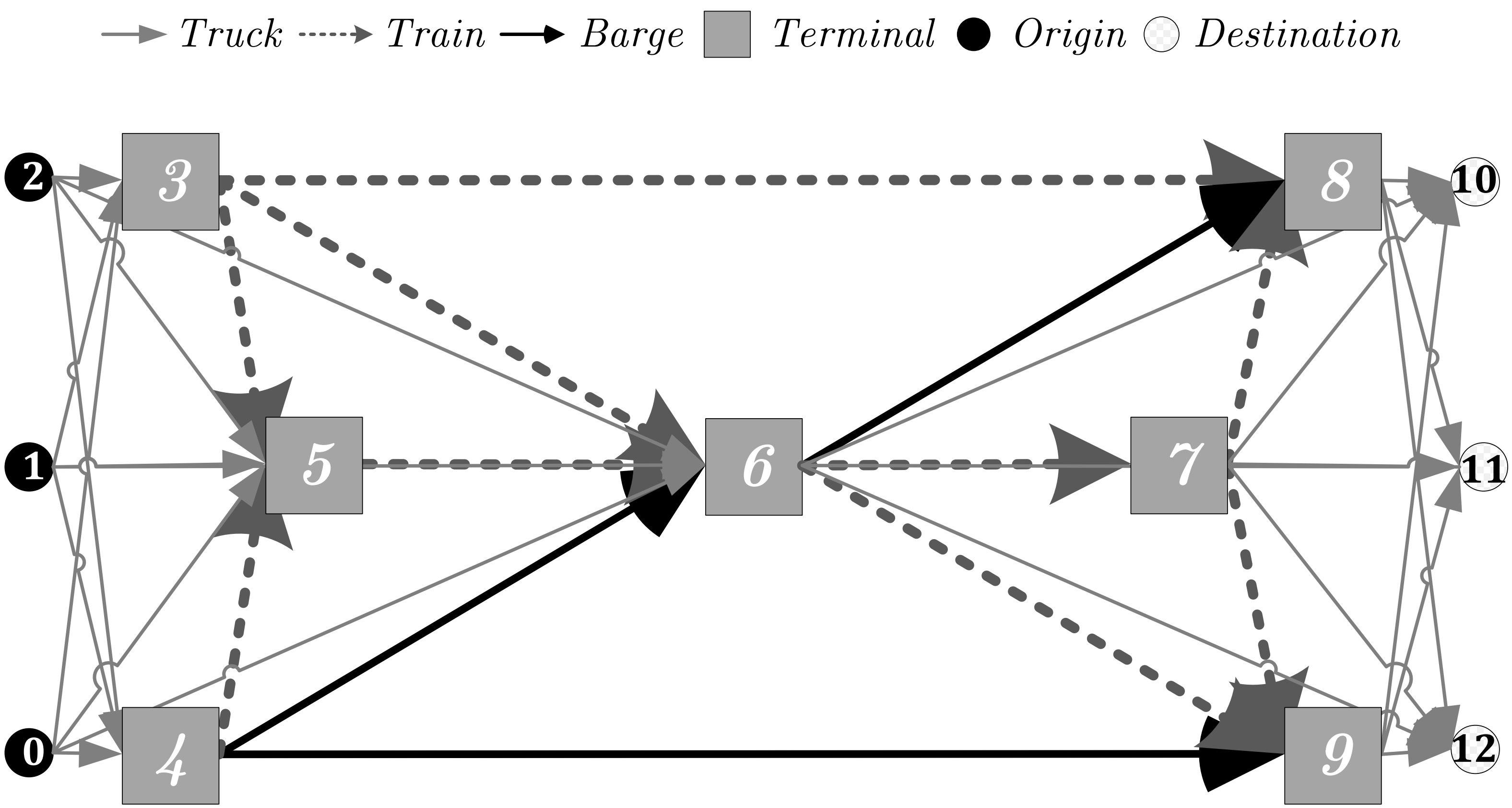
CASE: TRANSPORTATION OF CONTAINERS IN THE HINTERLAND



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

MULTI-PERIOD SCHEDULING IN SYNCHROMODALITY

PROBLEM EXAMPLE



MULTI-PERIOD SCHEDULING IN SYNCHROMODALITY

PROBLEM DESCRIPTION

Input:

- ***Transport network***: services, terminals, schedules, durations, capacity, costs, revenues.
- ***Freight demand***: origin (or location), destination, release-day, due-day, size.
- ***Probability distributions***: (1) number of freights, (2) their origin, (3) their destination, (4) release-day, and (5) time-window length.

Output:

- ***Schedule***: which service to use for each freight, if any.
- ***Performance***: revenue and costs of the schedule.

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.

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

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

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

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

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

Exogenous Information

State Transition

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

s.t.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

VIRTUAL TIME-WINDOWS FOR FREIGHT

- The ***release-day r*** is relative to the current day *t*.
- The ***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					$F_{d,d,0,0,11}$

MDP MODEL – SOLUTION CHALLENGES

- ***Three-curses of dimensionality*** restrain the size of networks whose MDP model can be solved to optimality.

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

- ***Multi-period revenues and costs*** can make heuristics flounder and get stuck in local-optima.

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

where

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

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

HEURISTIC FRAMEWORK FOR SOLVING LARGE MARKOV MODELS.[1]

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**

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

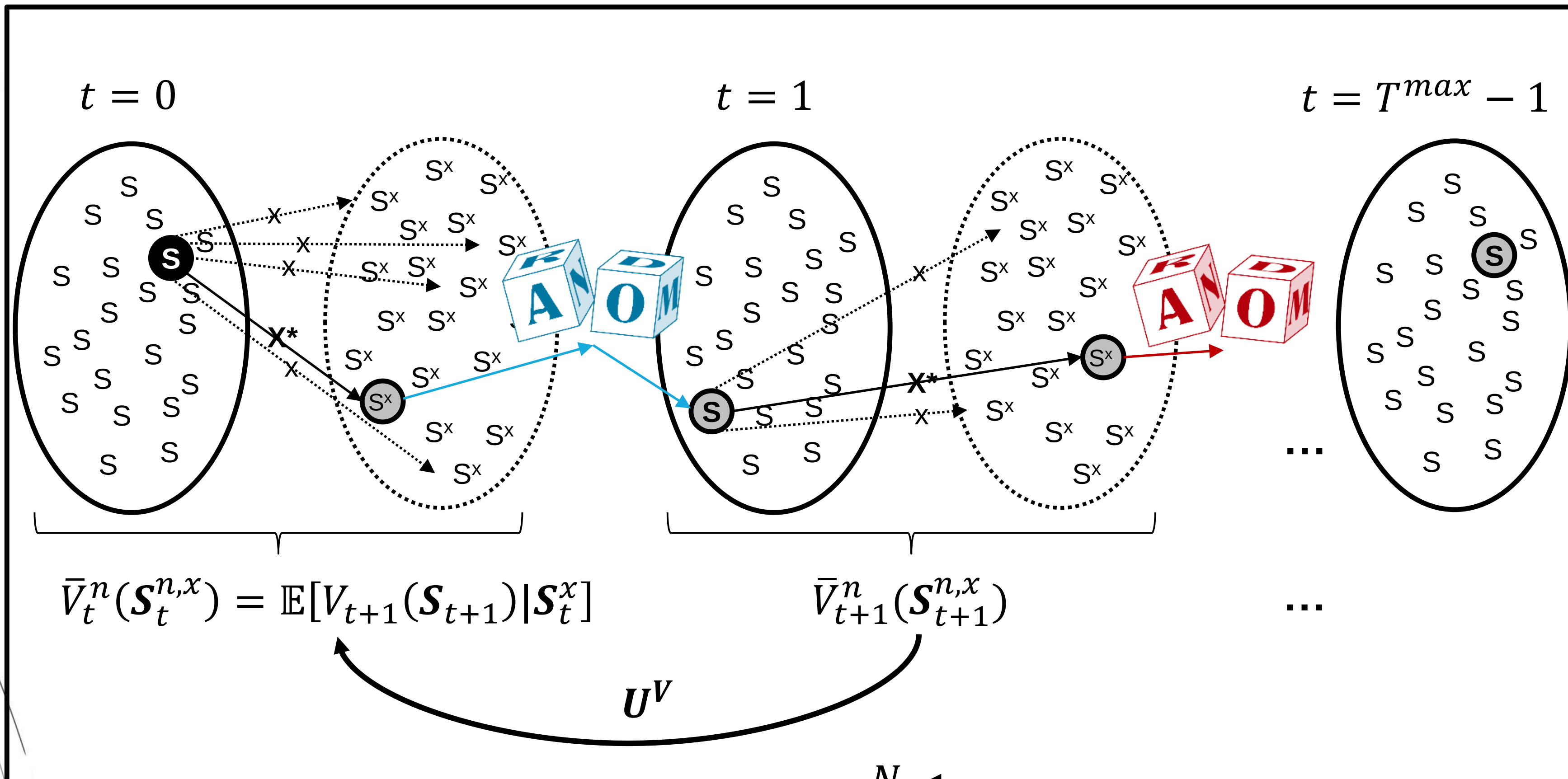
  end for

end for

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

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

ADP – ALGORITHM EXEMPLIFICATION



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

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

s.t.

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

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

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

ADP – 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***.

s.t.

Recursive least square method for updating the VFA

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

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

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

ADP – 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**
        $x_t^{n*} := \underset{x_t^n \in \mathcal{X}_t^{\mathrm{R}}}{\arg\max} \ldots (x$
        $S_t^{n,x*} := S^{M,x}\left(S_t^n, x_t^{n}\right.$
        $\widehat{v}_t^n := \left(R_t\left(x_t^{n*}\right) + \gamma_t \bar{V}_t\right.$
        $W_{t+1}^n := \mathrm{Random}\left(\Omega\right)$
        $S_{t+1}^n := S^M\left(S_t^n, x_t^{n*}, W_{t+1}^n\right)$
    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

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

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

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

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

ADP – VALUE OF PERFECT INFORMATION (VPI)

EXPLORATION BASED ON A BAYESIAN BELIEF

Exploration decision

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

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

Dearden et al., 1999: the expected improvement in future decision quality arising (through a better VFA) from the information acquired by exploration.

Update VFA and belief

Rhyzov et al., 2017: update is analogous to the recursive least square method with the addition of the current uncertainty knowledge through covariance matrix.

ADP – VPI MODIFICATIONS

BE MORE CONSERVATIVE IN EXPLORATION AND UPDATING

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

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

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

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

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

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

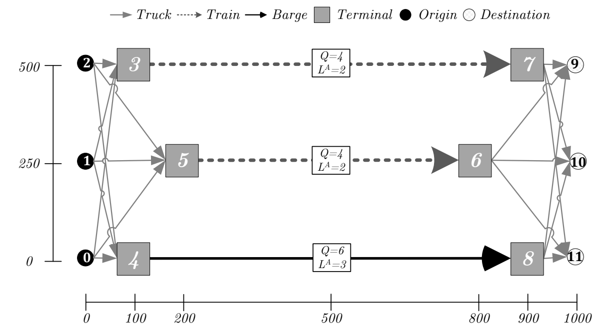
$$\sigma_t^{2,\mathrm{E3}} = \sigma_t^{2,n}(S_t^{x,n})$$

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

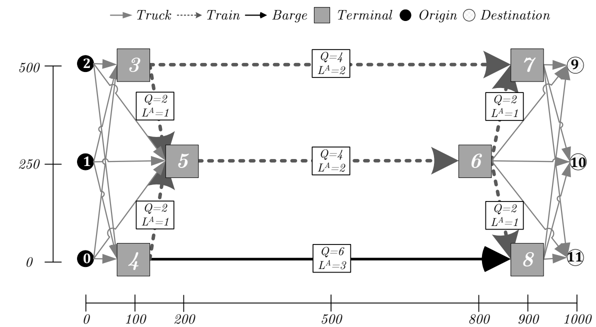
NUMERICAL RESULTS

PROBLEM INSTANCE SETTINGS

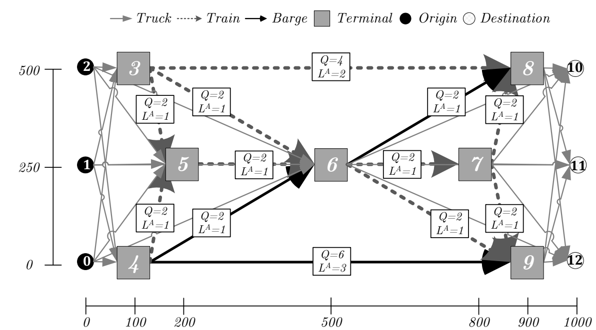
- Cost differs by vehicle, capacity, and distance (Janic, 2007), ***revenue received at pick-up***.
- 50 day horizon, at least 14 freight intermodal capacity, at most ***three days traveling time***.
- Up to 12 freights per day, different destination probability per origin.
- Freights are immediately released and have a 6 day time-window.



Network 1



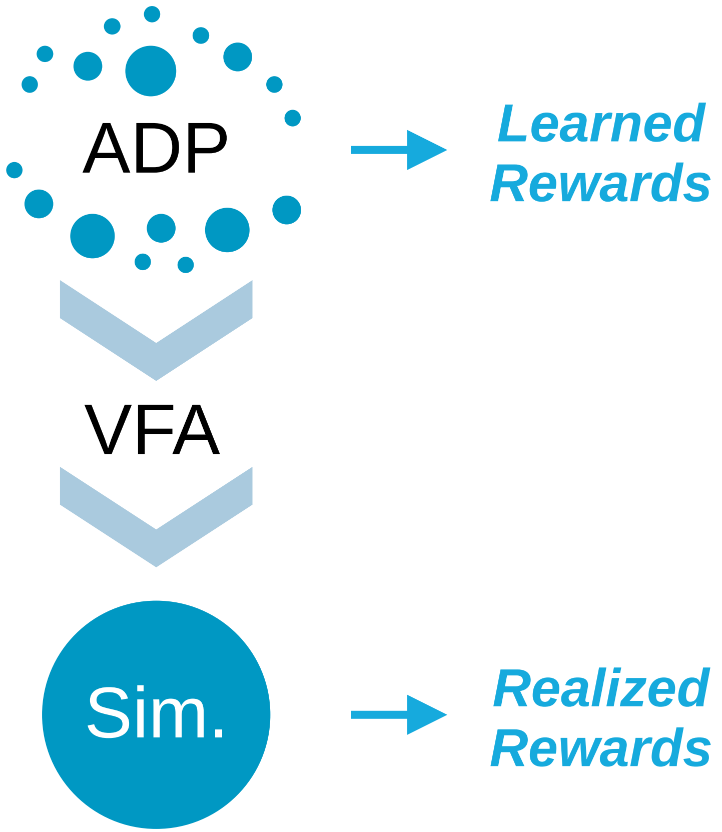
Network 2



Network 3

NUMERICAL RESULTS
EXPERIMENTAL SETTINGS

- Initial state with six freights.
- ***Benchmark heuristic***: Use a service for a freight if the cost difference between the cheapest and second cheapest intermodal path to a freights destination is more than setup cost of the first.
- ***Three ADP Designs***: basis functions only, epsilon-greedy, VPI, for 50 iterations.
  - Weights (VFA) initialized to 0, except the constant, which is initialized with the benchmark.



NUMERICAL RESULTS

PERFORMANCE OF DIFFERENT ADP DESIGNS

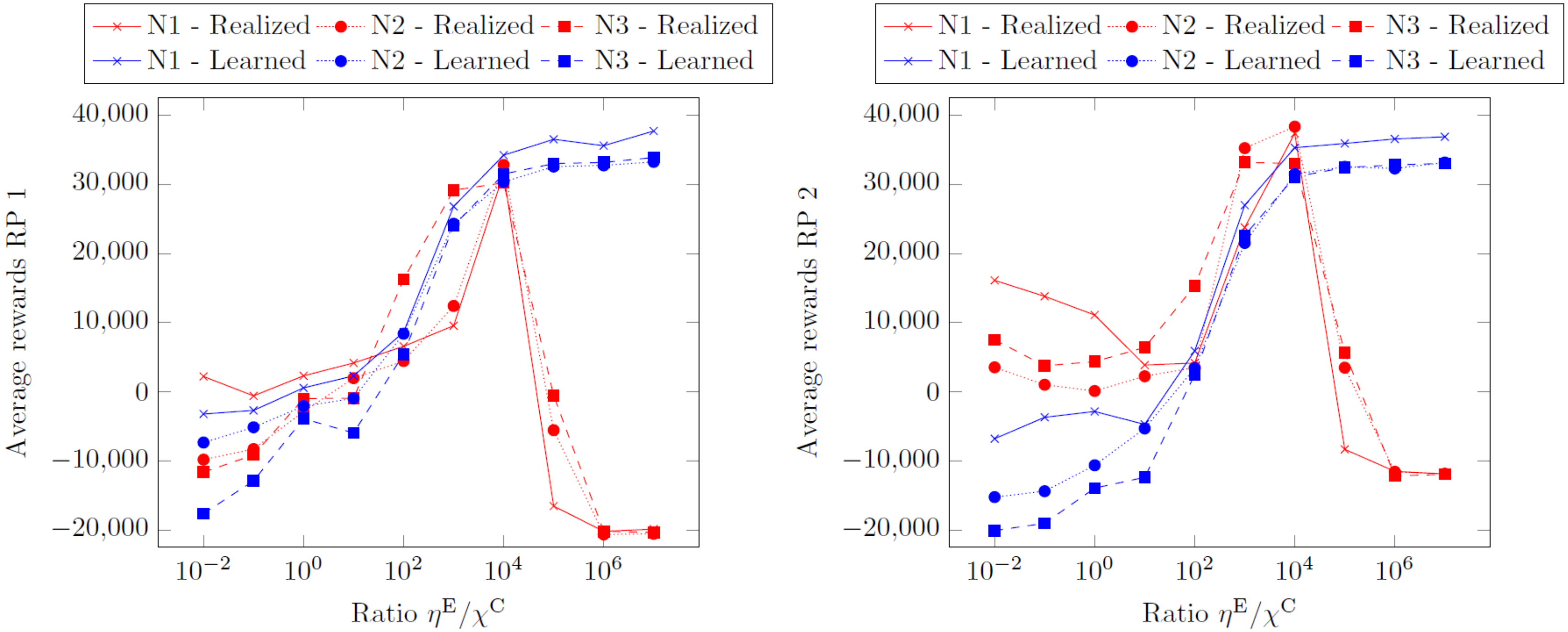
RP 1:
Aggregated time-windows at each terminals.
Aggregated time-windows, destinations, and origins at each origin.

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

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*
Benchmark		*38,036*	-	*33,445*	-	*33,889*	-

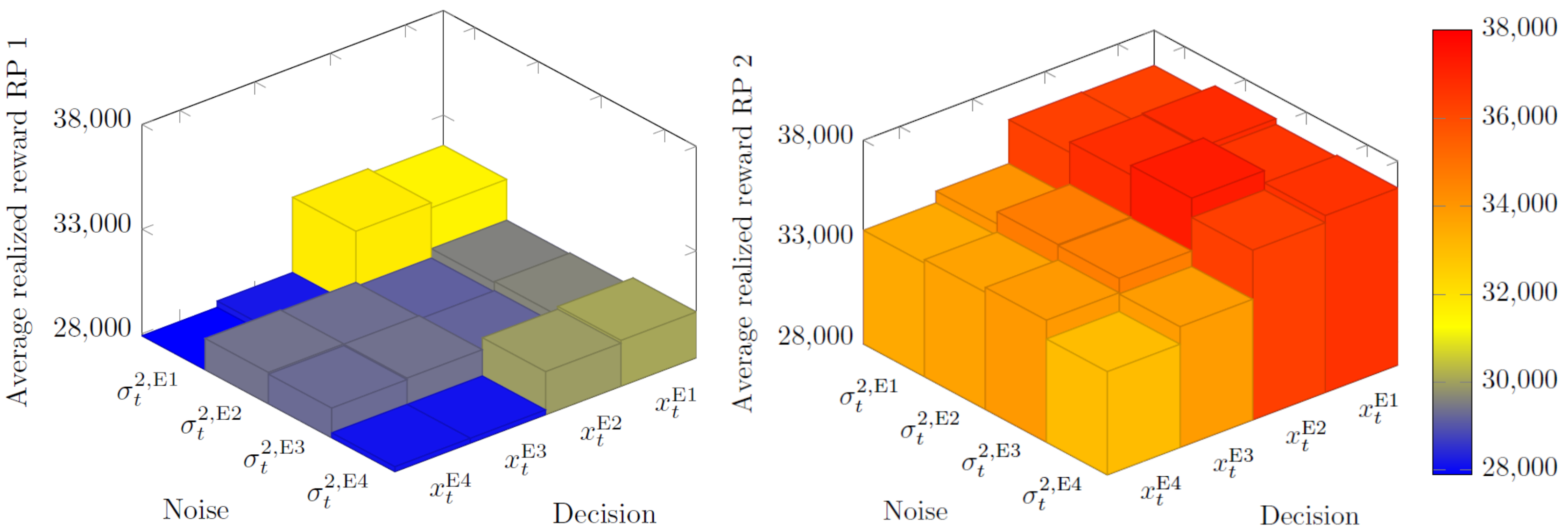
NUMERICAL RESULTS

NOISE AND UNCERTAINTY IN VPI



NUMERICAL RESULTS

THE PROPOSED VPI MODIFICATIONS OVER ALL NETWORKS



NUMERICAL EXPERIMENTS
SENSITIVITY ANALYSIS OF TIME-PARAMETER UNCERTAINTY

New settings:
Release-day : 0, 1, 2 days
Time-window length: 4, 5, 6 days

Average realized rewards for Network 2

Time-window length	Release-day: Short		Release-day: Medium		Release-day: Long	
Short	*12,339* *11,289*	*-9%*	*12,160* *9,877*	*-19%*	*12,062* *9,281*	*-23%*
Medium	*18,232* *23,486*	*29%*	*18,052* *23,015*	*27%*	*17,951* *23,422*	*30%*
Long	*25,805* *32,524*	*26%*	*25,420* *31,806*	*25%*	*25,401* *32,462*	*28%*

Benchmark, ADP with VPI

WHAT TO REMEMBER

- We exemplified how ***VPI exploration improves ADP in scheduling synchromodal freight transport*** considering uncertainty in the demand and performance over time.
- To apply VPI in a finite-horizon ADP with basis functions, ***exploring and updating should be slightly more conservative*** than in traditional VPI.
- For larger networks, further research in the ***reduction of the decision space and its interaction with the VFA*** is necessary for ADP to work properly.

UNIVERSITY OF TWENTE.

DINALOG
Dutch Institute
for Advanced Logistics

THANKS FOR YOUR ATTENTION!

ARTURO E. PÉREZ RIVERA

PhD Candidate

Department of Industrial Engineering and Business Information Systems

University of Twente, The Netherlands

https://www.utwente.nl/bms/iebis/staff/perezrivera/

a.e.perezrivera@utwente.nl

VeRoLog 2017 - Wednesday, July 12th
Amsterdam, The Netherlands