UNIVERSITY OF TWENTE.

DINALOG Dutch Institute for Advanced Logistics

DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION

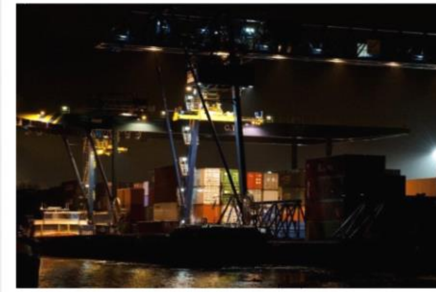
Arturo E. Pérez Rivera & Martijn R.K. Mes

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

ICCL 2015 - Thursday, September 24th
Delft, The Netherlands

CONTENTS

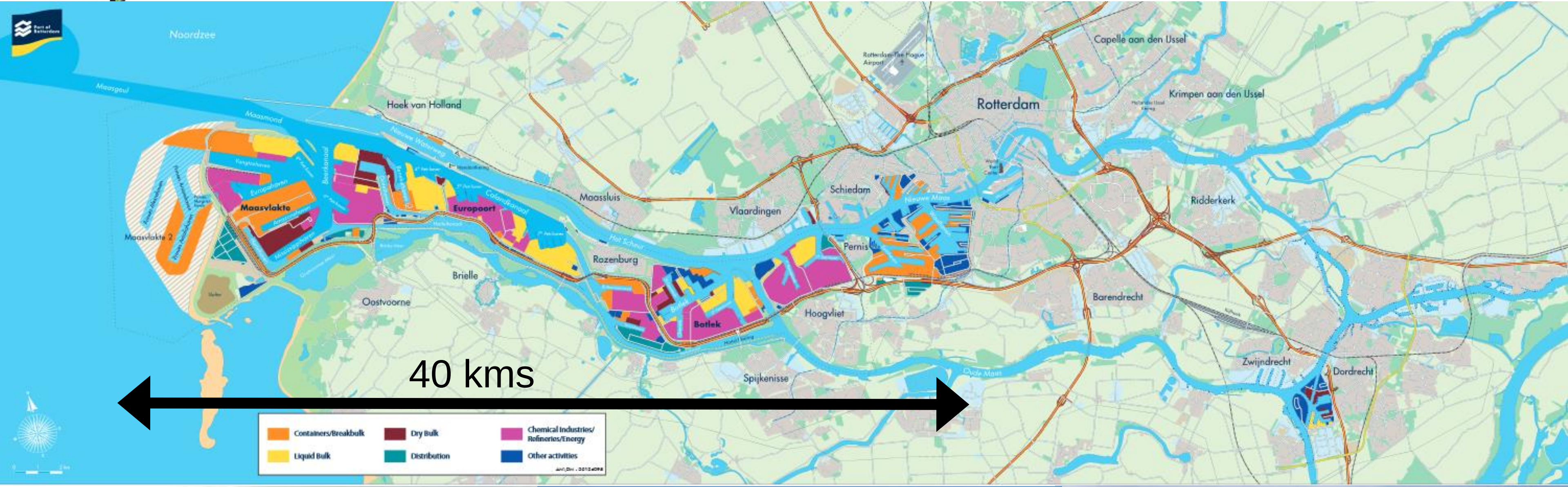
- Motivation
- Problem: dynamic multi-period freight consolidation
- Proposed solution:
  - ➢ *Markov Decision Process model*
  - ➢ *Approximate Dynamic Programming (ADP)*
- Numerical experiments:
  - ➢ *Convergence and Policy-performance*
- What to remember

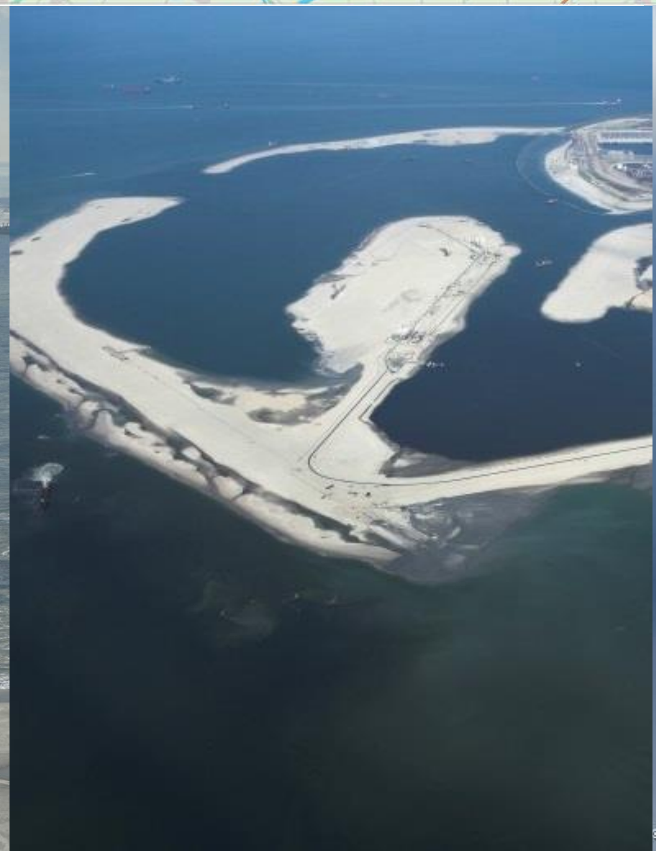




CTT
INTERMODAAL TRANSPORT

TRANSPORTATION OF CONTAINERS FROM THE HINTERLAND TO THE DEEP-SEA PORT

- Long-haul from Hengelo to Rotterdam using ***barges*** through Dutch waterways.
- ***Trucks*** are used/offered as an alternative.
- Approx. 300 containers per day.
- Approx. 14 container terminals in Rotterdam per trip.

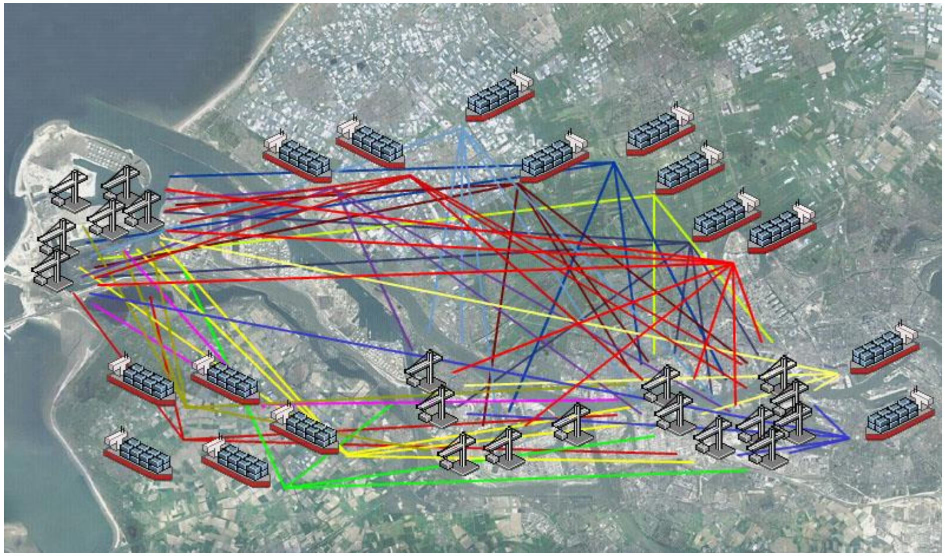

40 kms
Noordzee
Hoek van Holland
Rotterdam
Capelle aan den IJssel
Krimpen aan den IJssel
Maassluis
Schiedam
Vlaardingen
Pernis
Ridderkerk
Rozenburg
Brielle
Oostvoorne
Hoogvliet
Botlek
Spijkenisse
Barendrecht
Zwijndrecht
Dordrecht
Maasvlakte
Maasvlakte 2
Europoort
Containers/Breakbulk
Dry Bulk
Chemical Industries/ Refineries/Energy
Liquid Bulk
Distribution
Other activities




© All Rights Reserved

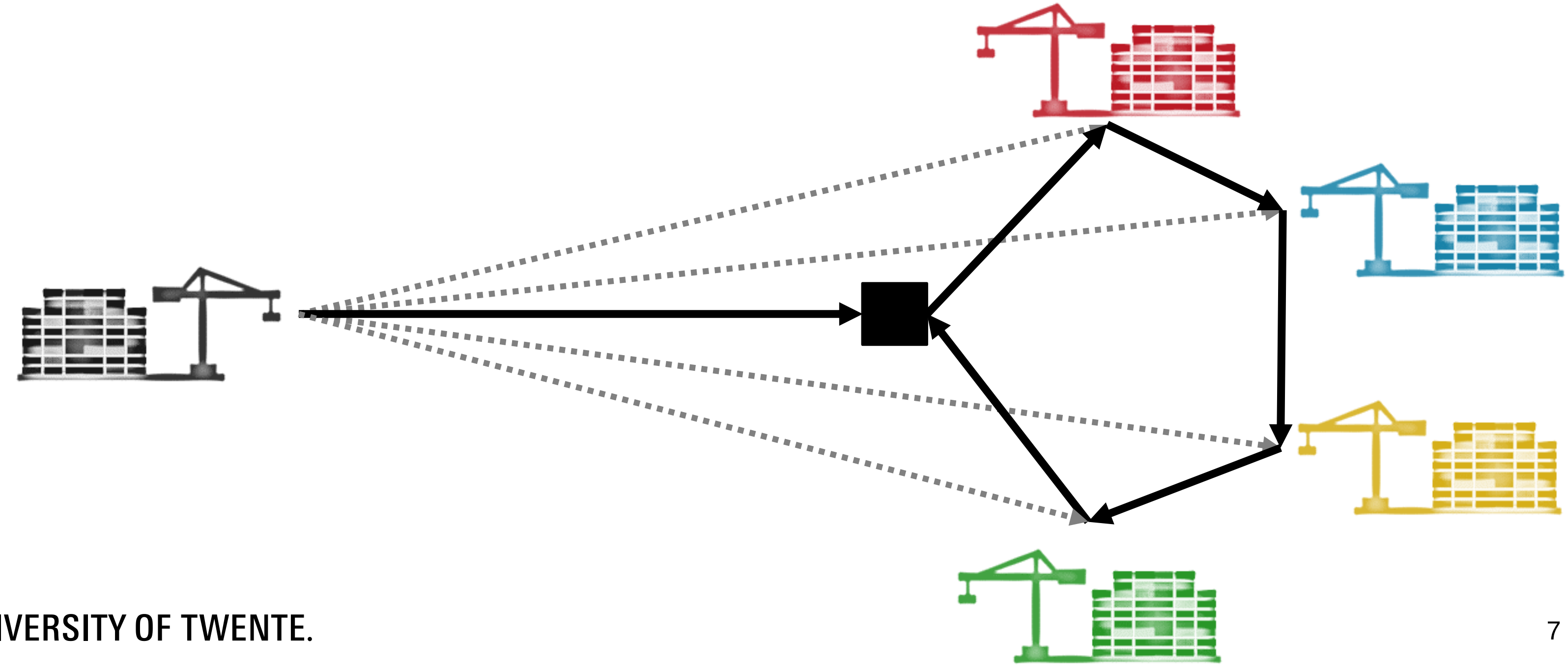
THE BIGGEST COMPLAINT

- Combination of terminals have ***different waiting times*** (e.g., unavailable berths, deep sea vessel arrival, etc.) and managers want barges to be sailing and not waiting!

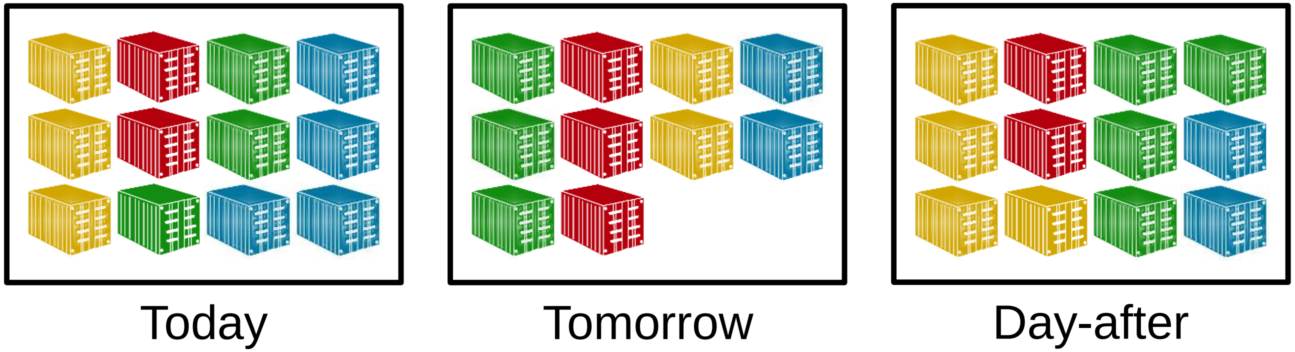


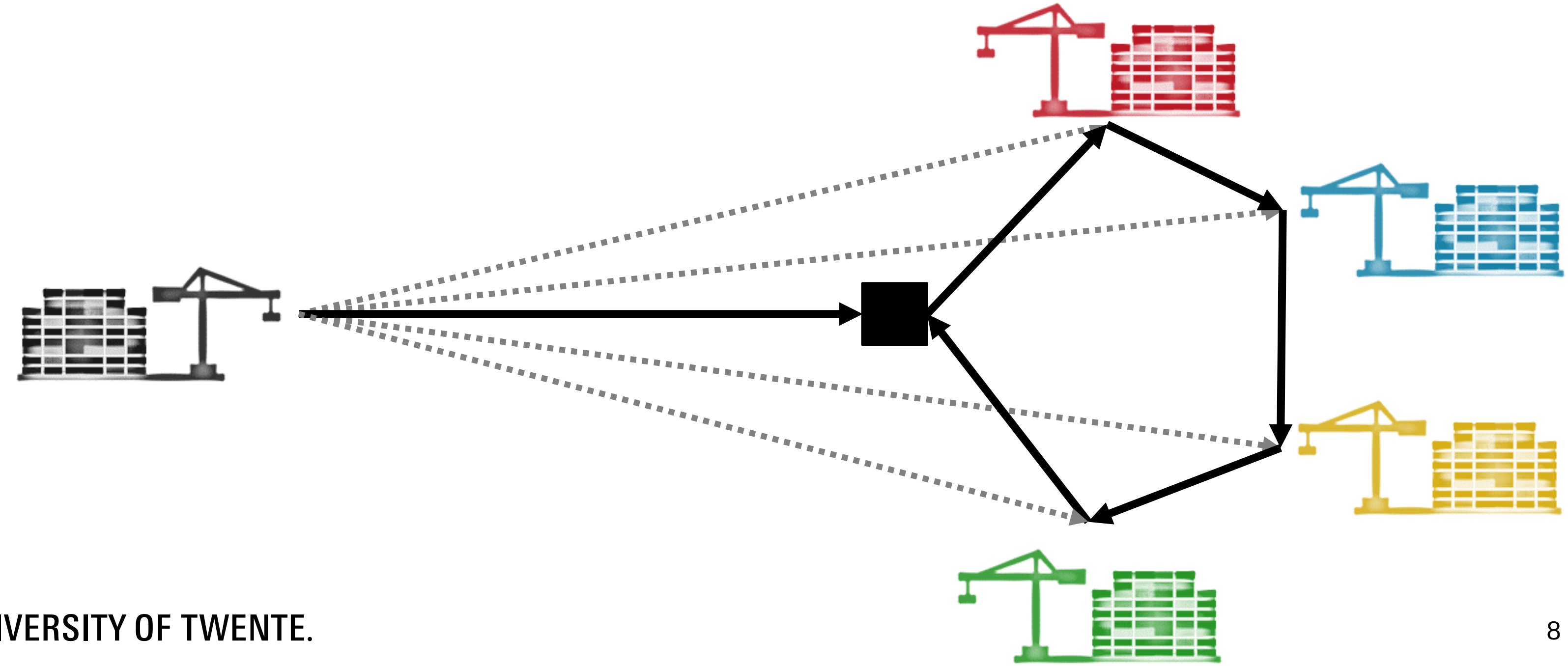
DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION

Today

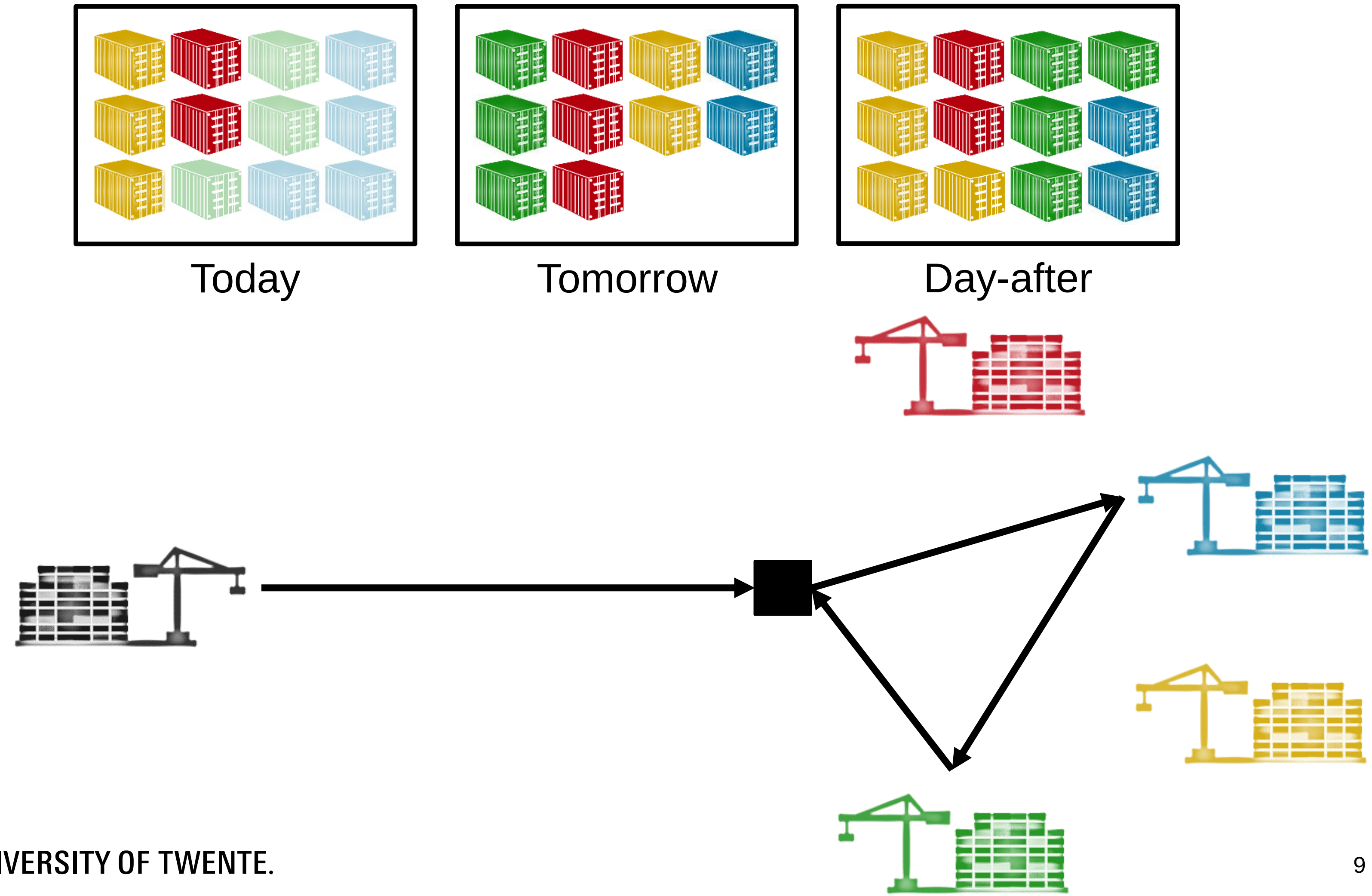


DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION

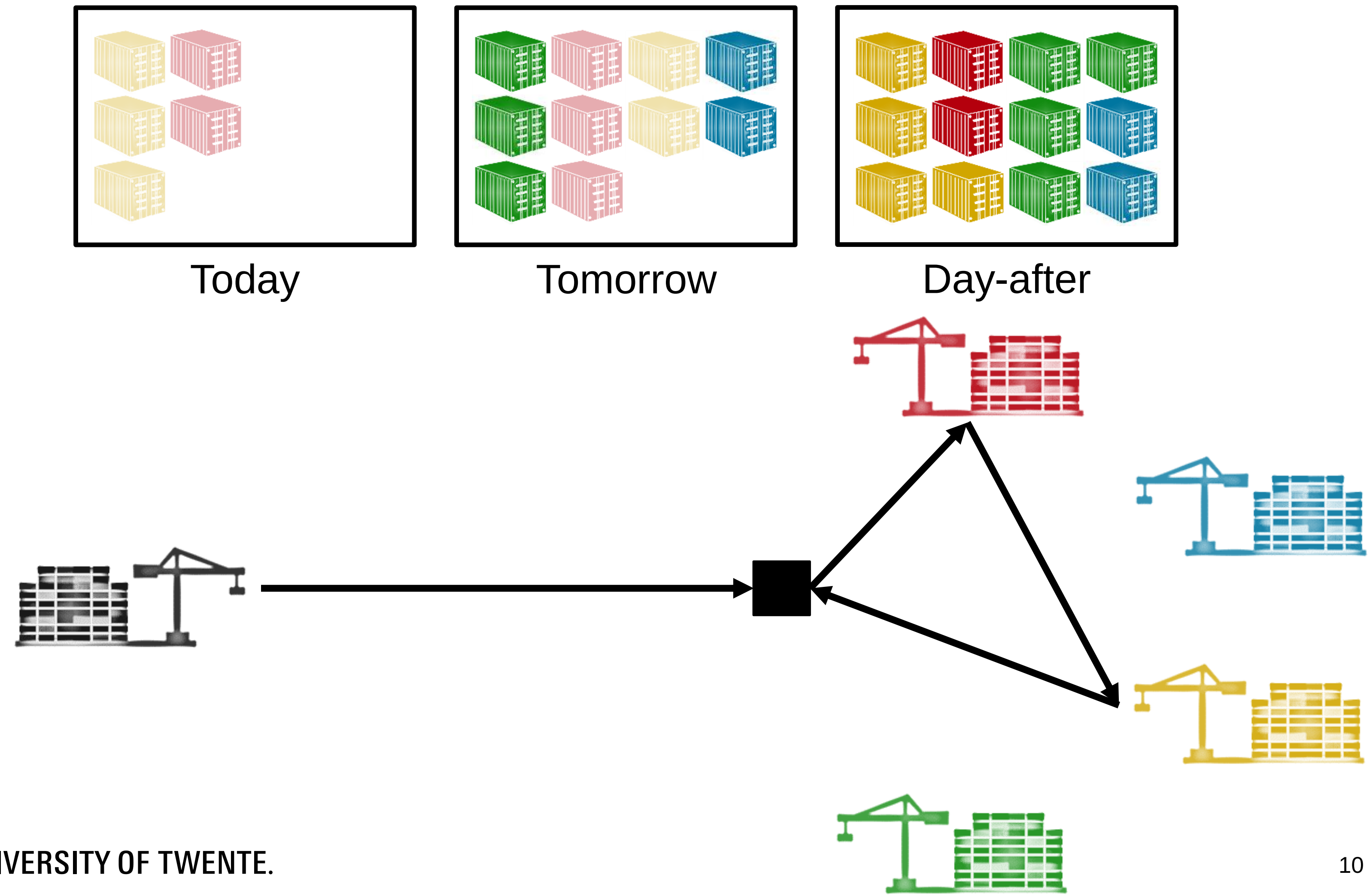




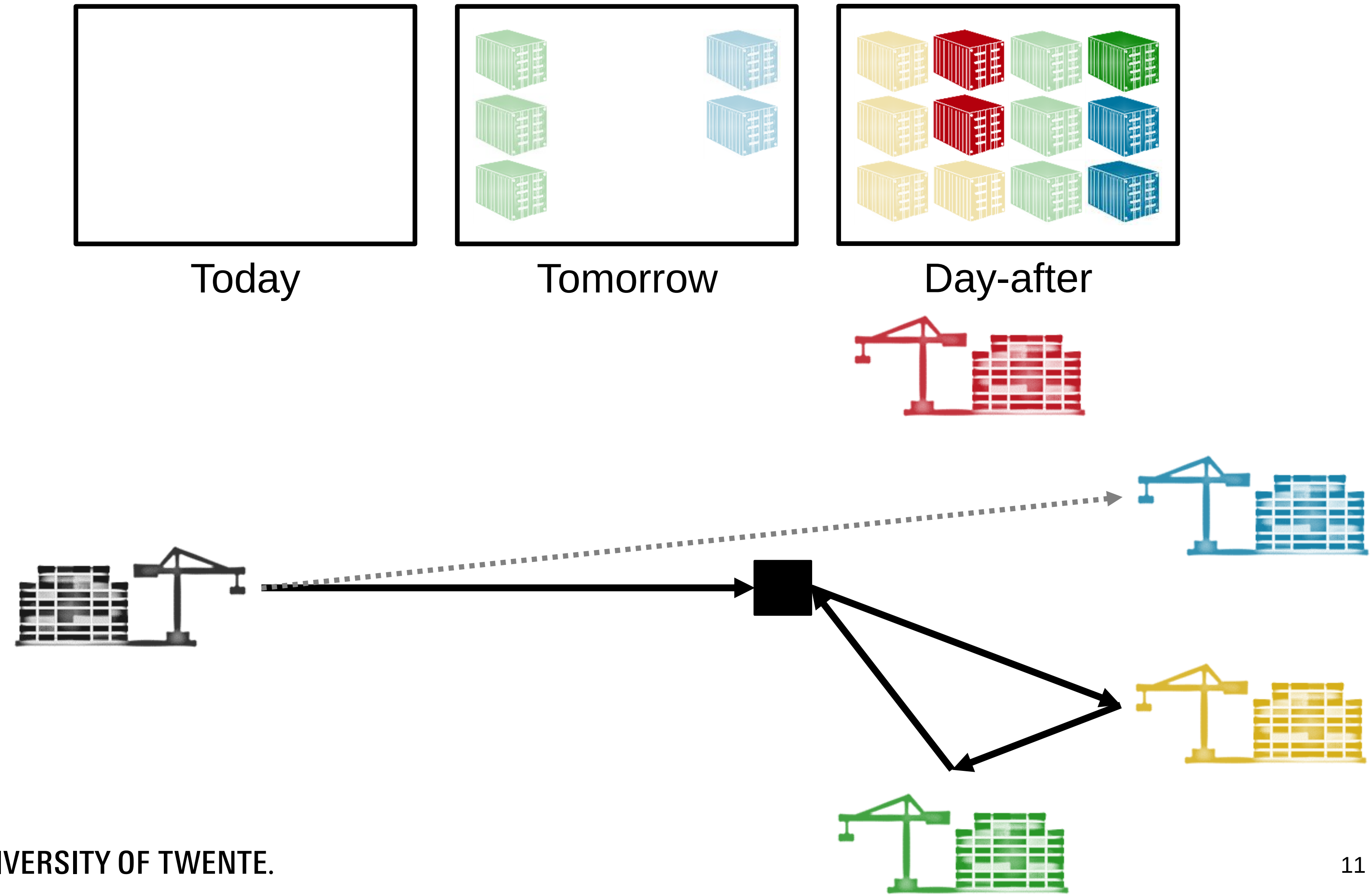
DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION



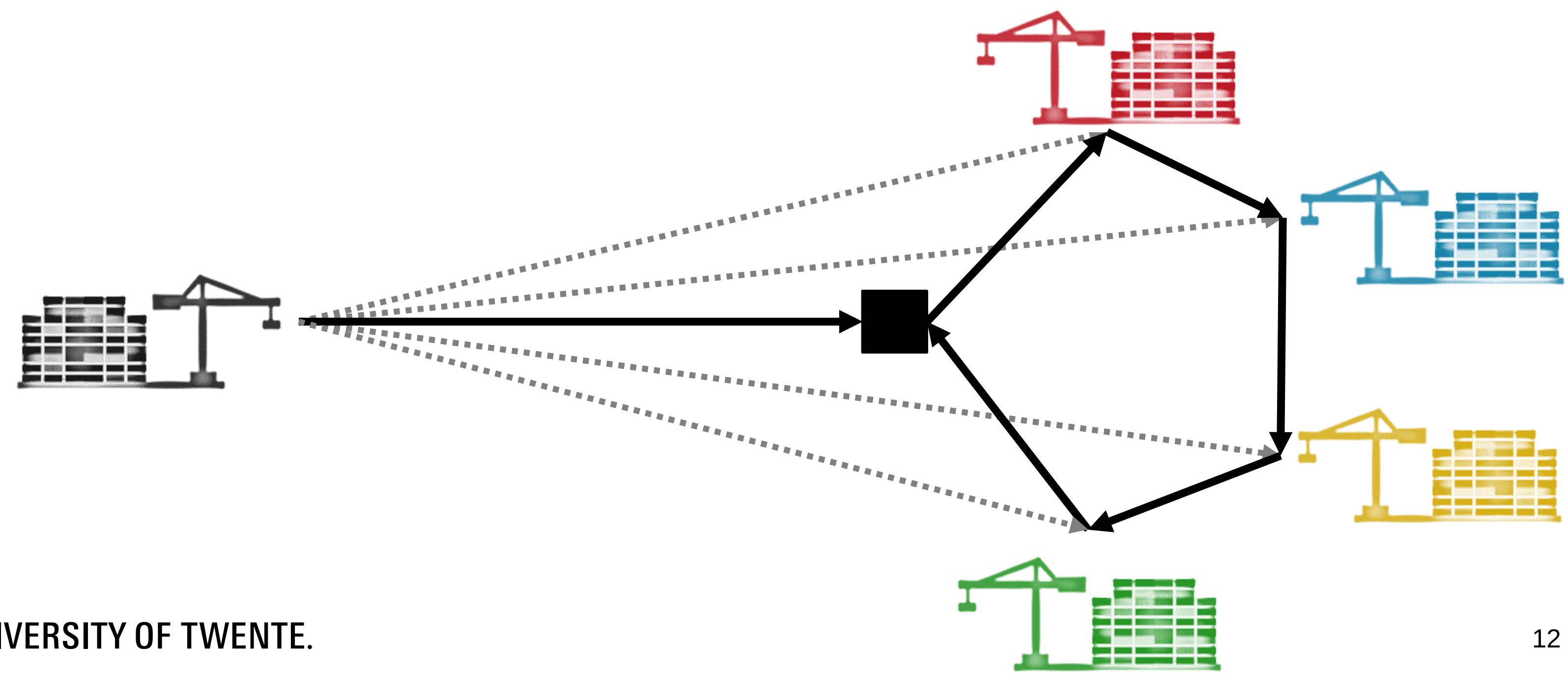
DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION



DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION



DYNAMIC MULTI-PERIOD FREIGHT CONSOLIDATION



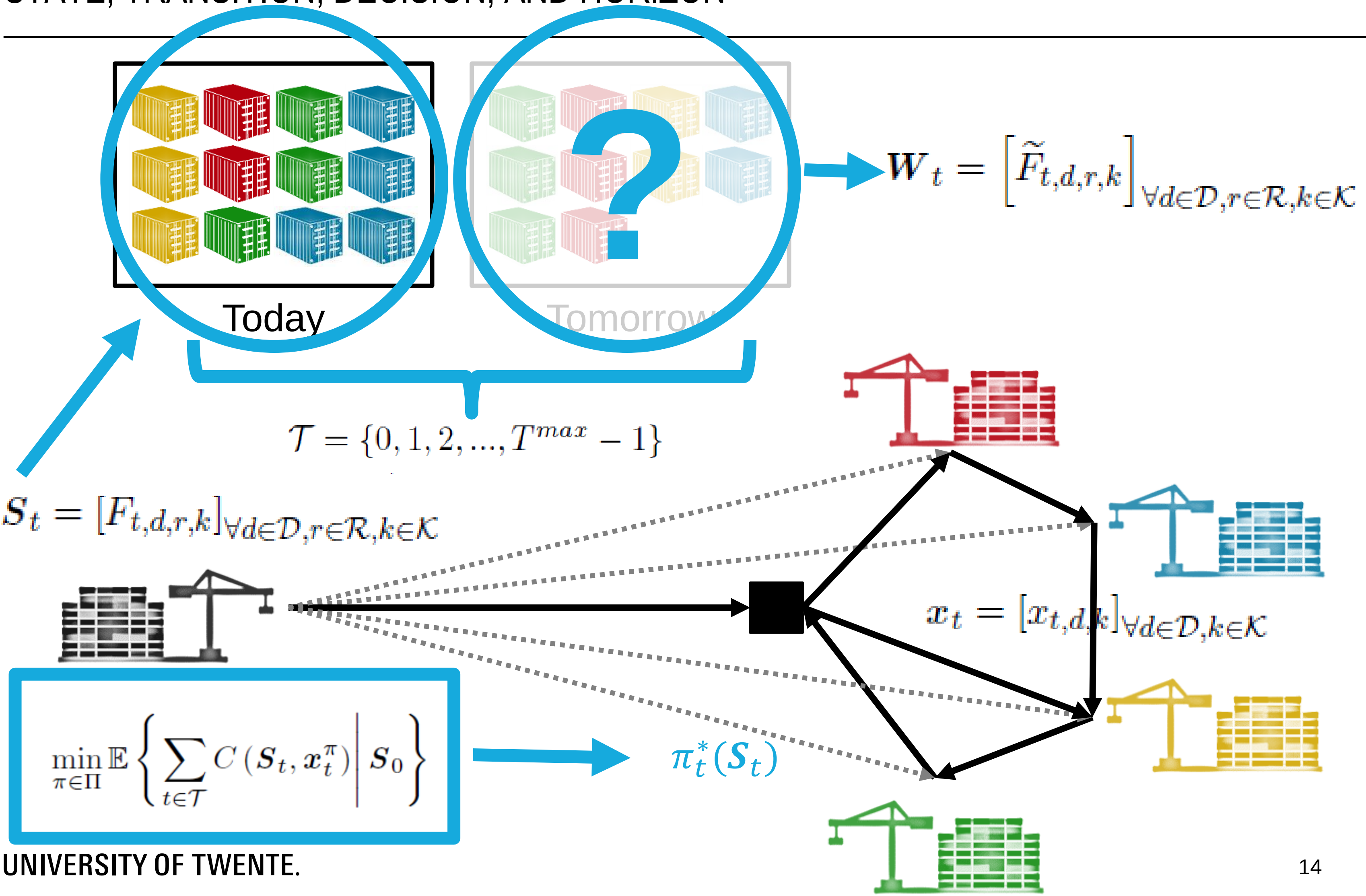
MARKOV DECISION PROCESS MODEL

STOCHASTIC PROCESS UNDER CONTROL

- ***Stochasticity*** in arrival of containers:
  - Number of containers $\mathcal{F} \subseteq \mathbb{Z}^{+}$ p_f^F
  - Terminals $\mathcal{D}$ p_d^{FD}
  - Release-period $\mathcal{R} = \{0, 1, 2, ..., R^{max}\}$ p_r^{FR}
  - Time-window length $\mathcal{K} = \{0, 1, 2, ..., K^{max}\}$ p_k^{FK}
- ***Control*** in which containers to consolidate, and conversely which ones to postpone, every period.
- ***Objective*** to minimize the costs resulting from the combination of terminals visited, over a finite number of periods.

MARKOV DECISION PROCESS MODEL

STATE, TRANSITION, DECISION, AND HORIZON



MARKOV DECISION PROCESS MODEL

HOW TO FIND THE OPTIMAL POLICY?

Using Bellman's principle of optimality and backward induction:

$$V_t\left(\boldsymbol{S}_t\right) = \min_{\boldsymbol{x}_t}\left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) + \mathbb{E}\left\{V_t\left(S^M\left(\boldsymbol{S}_t, \boldsymbol{x}_t, \boldsymbol{W}_{t+1}\right)\right)\right\}\right)$$

$$V_t\left(\boldsymbol{S}_t\right) = \min_{\boldsymbol{x}_t}\left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) + \sum_{\omega\in\Omega}\left(P(\boldsymbol{W}_{t+1} = \omega)\cdot V_t\left(S^M\left(\boldsymbol{S}_t, \boldsymbol{x}_t, \omega\right)\right)\right)\right)$$

All possible decisions in a state!

All possible realizations of the random variables!

All possible states!

APPROXIMATE DYNAMIC PROGRAMMING

ALGORITHMIC APPROACH FOR SOLVING LARGE MARKOV MODELS.[1]

Algorithm 1 Approximate Dynamic Programming Solution Algorithm

Require: $\mathcal{T}, \mathcal{F}, \mathcal{G}, \mathcal{D}, \mathcal{R}, \mathcal{K}, [C_{\mathcal{D}'}]_{\forall \mathcal{D}' \subseteq \mathcal{D}}, B_d, Q, \boldsymbol{S}_0, N$

Initialize $\bar{V}_t^0, \ \forall t \in \mathcal{T}$

$n \leftarrow 1$

while $n \leq N$ **do**

  $\boldsymbol{S}_0^n \leftarrow \boldsymbol{S}_0$

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

    $\hat{v}_t^n \leftarrow \min_{\boldsymbol{x}_t^n} \left(C\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^n\right) + \bar{V}_t^{n-1}\left(S^{M,x}\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^n\right)\right)\right)$

    if $t > 0$ **then**

      $\bar{V}_{t-1}^n(\boldsymbol{S}_{t-1}^{n,x*}) \leftarrow U^V(\bar{V}_{t-1}^{n-1}(\boldsymbol{S}_{t-1}^{n,x*}), \boldsymbol{S}_{t-1}^{n,x*}, \hat{v}_t^n)$

    end if

    $\boldsymbol{x}_t^{n*} \leftarrow \arg\min_{\boldsymbol{x}_t^n} \left(C\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^n\right) + \bar{V}_t^{n-1}\left(S^{M,x}\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^n\right)\right)\right)$

    $\boldsymbol{S}_t^{n,x*} \leftarrow S^{M,x}\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^{n*}\right)$

    $\boldsymbol{W}_t^n \leftarrow \mathrm{RandomFrom}\left(\Omega\right)$

    $\boldsymbol{S}_{t+1}^n \leftarrow S^M\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^{n*}, \boldsymbol{W}_t^n\right)$

  end for

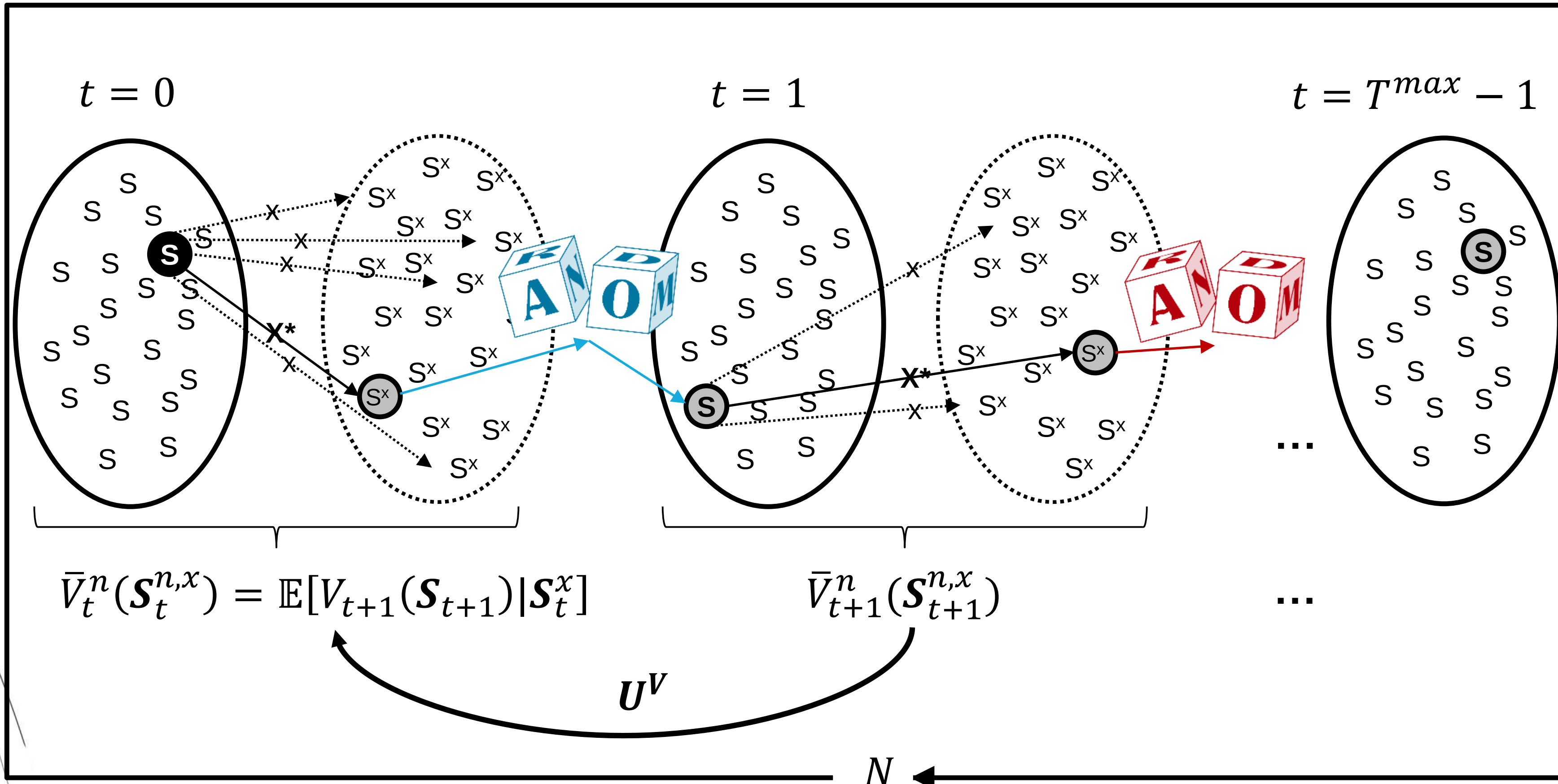
end while

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

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

APPROXIMATE DYNAMIC PROGRAMMING

ALGORITHMIC APPROACH FOR SOLVING LARGE MARKOV MODELS.



APPROXIMATE DYNAMIC PROGRAMMING
THE APPROXIMATING FUNCTION

We use a weighted combination of ***post-decision characteristics***:

$$\bar{V}_t^n(\boldsymbol{S}_t^{n,x}) = \sum_{a \in \mathcal{A}} \left(\phi_a(\boldsymbol{S}_t^{n,x}) \cdot \theta_a\right)$$

where θ_a is a weight for each characteristic $a \in \mathcal{A}$, and $\phi_a(\boldsymbol{S}_t^{n,x})$ is the "value" of the particular characteristic given the post-decision state $\boldsymbol{S}_t^{n,x}$.

Post-decision characteristics we use:

1. ***Number of must-go freights***
2. ***Number of may-go freights***
3. ***Number of future freights***
4. ***Number of must-go destinations***
5. ***Number of may-go destinations***
6. ***Number of future destinations***

APPROXIMATE DYNAMIC PROGRAMMING
UPDATING THE APPROXIMATING FUNCTION

After every iteration n, we have observed the actual costs we estimated, and thus we can improve our approximation:

$$\bar{V}^n_{t-1}(S^{n,x}_{t-1}) \leftarrow U^V\left(\bar{V}^{n-1}_{t-1}(S^{n,x}_{t-1}), S^{n,x}_{t-1}, \hat{v}^n_t\right), \ \forall t \in \mathcal{T}$$

In our case, $U^V(\cdot)$ updates the weights θ^n_a using a ***recursive least squares (LSQ) method for non-stationary data***[1]:

$$\theta^n_a = \theta^{n-1}_a - (G^n)^{-1}\phi_a(S^{n,x}_t)\left(\bar{V}^{n-1}_{t-1}(S^{n,x}_{t-1}) - \hat{v}^n_t\right)$$

LSQ Optimization Matrix

Observed Characteristic

Prediction Error

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

NUMERICAL EXPERIMENTS

We carry out two types of experiments:

1. ***Convergence of the approximation method***

   Convergence to the optimal value obtained via the Markov model

2. ***Policy-performance***

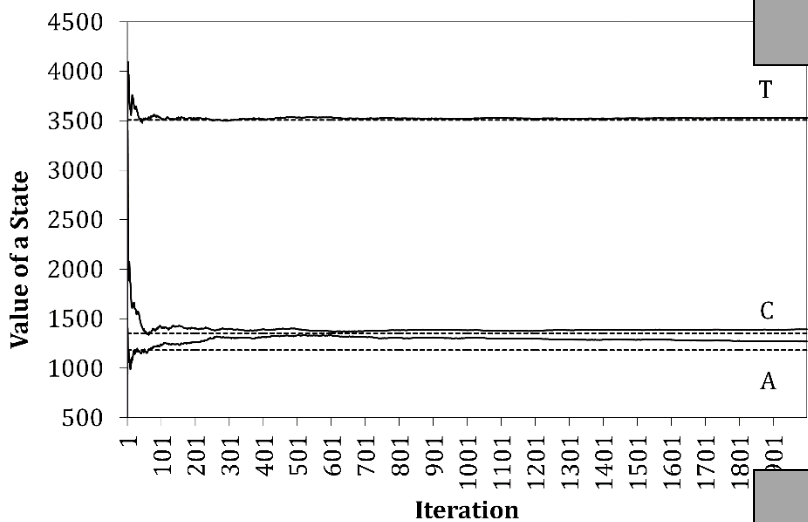
   Decisions using common practice heuristics and the ADP-policy.

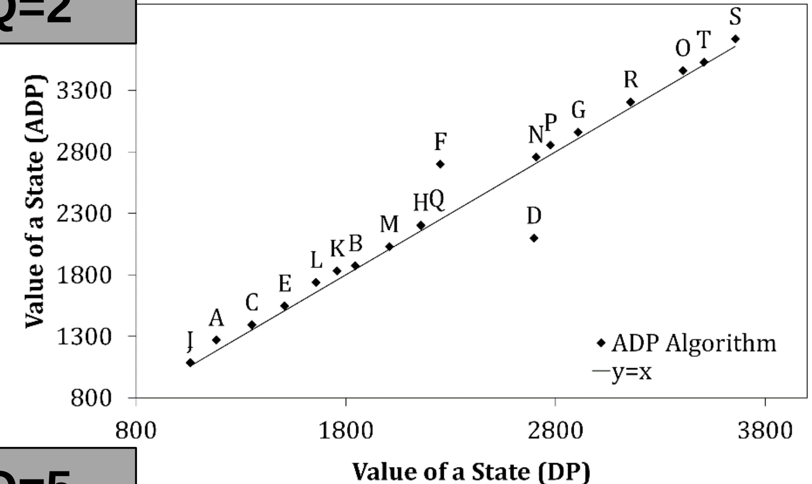
Input Parameter	Small Instances	Large Instances
1. Freights arriving per day (F)	$\{1, 2\}$	$\{1, 2, 3, 4\}$
$\rightarrow$Probability (p_f^F)	$\{0.8, 0.2\}$	$\{0.25, 0.25, 0.25, 0.25\}$
2. Destinations (D)	$\{1, 2, 3\}$	$\{1, 2, 3, 4, 5, 6, 7\}$
$\rightarrow$Probability (p_d^D)	$\{0.1, 0.8, 0.1\}$	$\{0.1, 0.2, 0.1, 0.1, 0.3, 0.1, 0.1\}$
3. Release-days (R)	$\{0\}$	$\{0, 1, 2\}$
$\rightarrow$Probability (p_r^R)	$\{1\}$	$\{0.3, 0.3, 0.4\}$
4. Time-window lengths (K)	$\{0, 1, 2\}$	$\{0, 1, 2\}$
$\rightarrow$Probability (p_k^K)	$\{0.2, 0.3, 0.5\}$	$\{0.2, 0.3, 0.5\}$
5. Long-haul vehicle Cost ($C_{\mathcal{D}'}$)	$[250, 1000]$	$[250, 2050]$
6. Alternative mode Cost (B_d)	$[500, 1000]$	$[300, 800]$

NUMERICAL EXPERIMENTS

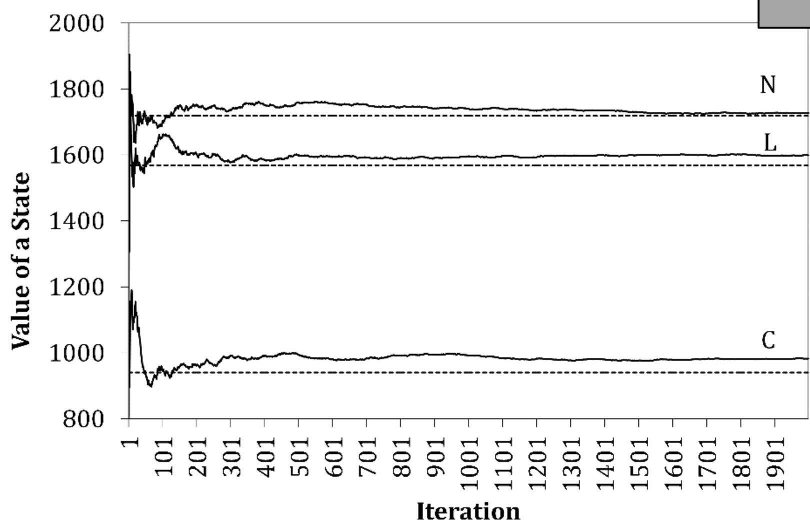
CONVERGENCE OF THE APPROXIMATION METHOD

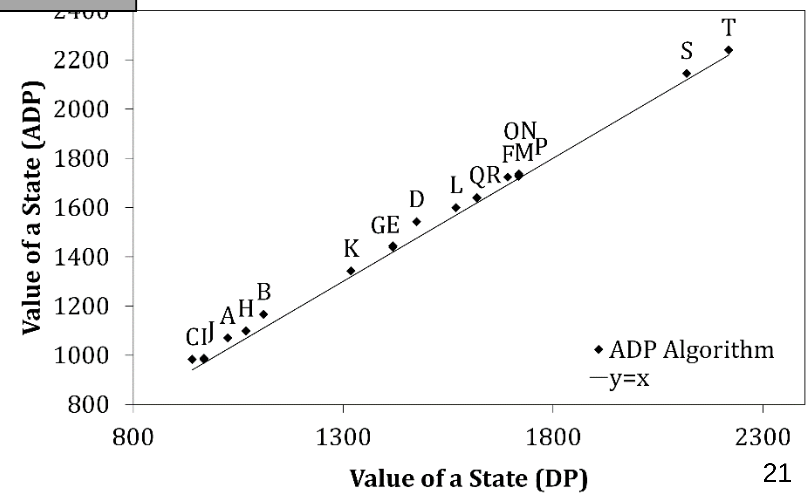
Q=2





Q=5





NUMERICAL EXPERIMENTS

POLICY PERFORMANCE – SMALL INSTANCES

			Q=2					Q=5		
State	**Optimal**	**Heuristic**	**Diff.**	**ADP**	**Diff.**	**Optimal**	**Heuristic**	**Diff.**	**ADP**	**Diff.**
Small A	1182.3	1343.4	13.6%	1330.0	12.5%	1025.2	1052.5	2.7%	1143.2	11.5%
Small B	1845.0	2887.8	56.5%	1920.1	4.1%	1110.5	1127.7	1.5%	1224.1	10.2%
Small C	1351.9	2414.7	78.6%	1465.6	8.4%	940.3	960.9	2.2%	1019.7	8.4%
Small D	2697.8	2773.6	2.8%	3050.9	13.1%	1475.2	1502.5	1.9%	1593.2	8.0%
Small E	1508.0	1602.0	6.2%	1597.3	5.9%	1418.6	1433.1	1.0%	1523.6	7.4%
Small F	2250.3	2990.0	32.9%	3065.6	36.2%	1692.1	1701.0	0.5%	1791.1	5.9%
Small G	2908.0	3002.0	3.2%	2997.3	3.1%	1418.6	1433.1	1.0%	1523.6	7.4%
Small H	2158.0	2252.0	4.4%	2247.3	4.1%	1068.6	1083.1	1.3%	1173.6	9.8%
Small I	1058.0	1152.0	8.9%	1147.3	8.4%	968.6	983.1	1.5%	1073.6	10.8%
Small J	1058.0	1152.0	8.9%	1147.3	8.4%	968.6	983.1	1.5%	1073.6	10.8%
Small K	1758.0	2202.0	25.3%	1847.3	5.1%	1318.6	1333.1	1.1%	1423.6	8.0%
Small L	1658.0	1802.0	8.7%	1747.3	5.4%	1568.6	1633.1	4.1%	1673.6	6.7%
Small M	2008.0	2502.0	24.6%	2097.3	4.4%	1718.6	1733.1	0.8%	1823.6	6.1%
Small N	2708.0	3202.0	18.2%	2797.3	3.3%	1718.6	1733.1	0.8%	1823.6	6.1%
Small O	3408.0	3902.0	14.5%	3497.3	2.6%	1718.6	1733.1	0.8%	1823.6	6.1%
Small P	2775.7	3122.7	12.5%	2857.7	3.0%	1718.6	1733.1	0.8%	1823.6	6.1%
Small Q	2158.0	3152.0	46.1%	2247.3	4.1%	1618.6	1633.1	0.9%	1723.6	6.5%
Small R	3158.0	4152.0	31.5%	3247.3	2.8%	1618.6	1633.1	0.9%	1723.6	6.5%
Small S	3658.0	4652.0	27.2%	3747.3	2.4%	2118.6	2633.1	24.3%	2223.6	5.0%
Small T	3508.0	3852.0	9.8%	3597.3	2.5%	2218.6	2333.1	5.2%	2323.6	4.7%
		Average	**21.7%**	**Average**	**7.0%**		**Average**	**2.7%**	**Average**	**7.6%**

NUMERICAL EXPERIMENTS

POLICY PERFORMANCE – LARGE INSTANCES

	Q=4			Q=10		
State	**Heuristic**	**ADP**	**Difference**	**Heuristic**	**ADP**	**Difference**
Large A	2962.9	2579.4	-12.9%	1723.1	1743.0	1.2%
Large B	9687.9	8729.4	-9.9%	6448.1	5568.0	-13.6%
Large C	5937.9	5579.4	-6.0%	3223.1	2918.0	-9.5%
Large D	1737.9	1754.4	1.0%	1523.1	1543.0	1.3%
Large E	2162.9	1804.4	-16.6%	1523.1	1543.0	1.3%
Large F	1362.9	1254.4	-8.0%	848.1	868.0	2.3%
Large G	1362.9	1254.4	-8.0%	848.1	868.0	2.3%
Large H	2187.9	2079.4	-5.0%	1298.1	1318.0	1.5%
Large I	3585.5	3550.0	-1.0%	1766.3	1782.2	0.9%
Large J	2537.9	2179.4	-14.1%	1523.1	1543.0	1.3%
Large K	3462.9	2979.4	-14.0%	1123.1	1143.0	1.8%
Large L	1778.1	1677.1	-5.7%	1082.4	1101.2	1.7%
		Average	**-8.3%**		**Average**	**-0.6%**

NUMERICAL EXPERIMENTS
POLICY PERFORMANCE – CTT SIZED INSTANCES

	# of Freights			# of Destinations					
State	**MustGo**	**MayGo**	**Future**	**MustGo**	**MayGo**	**Future**	**Myopic (ILP)**	**ADP**	**%Diff.**
1	Low	Low	Low	Low	Low	Low	2978.85	2608.10	-12.4%
2	Low	Low	Medium	Low	Medium	High	5194.60	5146.40	-0.9%
3	Low	Medium	Low	High	High	Medium	5396.90	2148.10	-60.2%
4	Low	Medium	High	High	Low	High	7941.40	6365.10	-19.8%
5	Low	High	Medium	Medium	High	Low	14730.35	7301.40	-50.4%
6	Low	High	High	Medium	Medium	Medium	12069.95	10206.45	-15.4%
7	Medium	Low	Medium	High	High	Medium	5868.20	5740.30	-2.2%
8	Medium	Low	High	High	Medium	Low	13070.95	8839.30	-32.4%
9	Medium	Medium	Low	Medium	Medium	High	6443.05	6348.10	-1.5%
10	Medium	Medium	Medium	Medium	Low	Low	9895.95	8432.55	-14.8%
11	Medium	High	Low	Low	Low	Medium	14567.95	14534.15	-0.2%
12	Medium	High	High	Low	High	High	13764.55	13636.65	-0.9%
13	High	Low	Low	Medium	High	High	10173.15	10045.25	-1.3%
14	High	Low	High	Medium	Low	Medium	10429.00	10286.90	-1.4%
15	High	Medium	Medium	Low	Medium	Medium	10111.50	10033.90	-0.8%
16	High	High	Low	High	Medium	Low	9680.75	9667.55	-0.1%
17	High	High	Medium	High	Low	High	9881.80	9872.05	-0.1%
								Average Diff	**-12.6%**

NUMERICAL EXPERIMENTS

POLICY PERFORMANCE – CTT SIZED INSTANCES

	# of Freights			# of Destinations				Approx. per state		Approx. for all states	
State	**MustGo**	**MayGo**	**Future**	**MustGo**	**MayGo**	**Future**	**Myopic (ILP)**	**ADP**	**%Diff.**	**ADP**	**%DIFF**
1	Low	Low	Low	Low	Low	Low	2978.85	2608.10	-12.4%	2578.55	-13.4%
2	Low	Low	Medium	Low	Medium	High	5194.60	5146.40	-0.9%	5139.15	-1.1%
3	Low	Medium	Low	High	High	Medium	5396.90	2148.10	-60.2%	5297.55	-1.8%
4	Low	Medium	High	High	Low	High	7941.40	6365.10	-19.8%	7941.40	0.0%
5	Low	High	Medium	Medium	High	Low	14730.35	7301.40	-50.4%	8503.65	-42.3%
6	Low	High	High	Medium	Medium	Medium	12069.95	10206.45	-15.4%	10218.75	-15.3%
7	Medium	Low	Medium	High	High	Medium	5868.20	5740.30	-2.2%	5757.90	-1.9%
8	Medium	Low	High	High	Medium	Low	13070.95	8839.30	-32.4%	8626.05	-34.0%
9	Medium	Medium	Low	Medium	Medium	High	6443.05	6348.10	-1.5%	5927.90	-8.0%
10	Medium	Medium	Medium	Medium	Low	Low	9895.95	8432.55	-14.8%	9127.35	-7.8%
11	Medium	High	Low	Low	Low	Medium	14567.95	14534.15	-0.2%	14540.20	-0.2%
12	Medium	High	High	Low	High	High	13764.55	13636.65	-0.9%	13654.25	-0.8%
13	High	Low	Low	Medium	High	High	10173.15	10045.25	-1.3%	10062.85	-1.1%
14	High	Low	High	Medium	Low	Medium	10429.00	10286.90	-1.4%	10318.70	-1.1%
15	High	Medium	Medium	Low	Medium	Medium	10111.50	10033.90	-0.8%	10036.45	-0.7%
16	High	High	Low	High	Medium	Low	9680.75	9667.55	-0.1%	9671.55	-0.1%
17	High	High	Medium	High	Low	High	9881.80	9872.05	-0.1%	9880.35	0.0%
								Average Diff.	**-12.6%**	**Average Diff.**	**-7.6%**

WHAT TO REMEMBER

- We proposed the use of an ***ADP algorithm to dynamically consolidate and postpone freights*** in a long-haul and last-mile intermodal transportation optimization problem.

- There are some ***problem settings where it pays off to have a look-ahead policy***, and some others where a myopic policy seems to be the optimal decision-rule.

- Our ADP algorithm requires a ***tailored application in practice*** when real-time decision making is required.

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

http://www.utwente.nl/mb/iebis/staff/perezrivera/

a.e.perezrivera@utwente.nl

ICCL 2015 - Thursday, September 24th
Delft, The Netherlands