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ANTICIPATORY FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS USING APPROXIMATE DYNAMIC PROGRAMMING

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Rotterdam, The Netherlands

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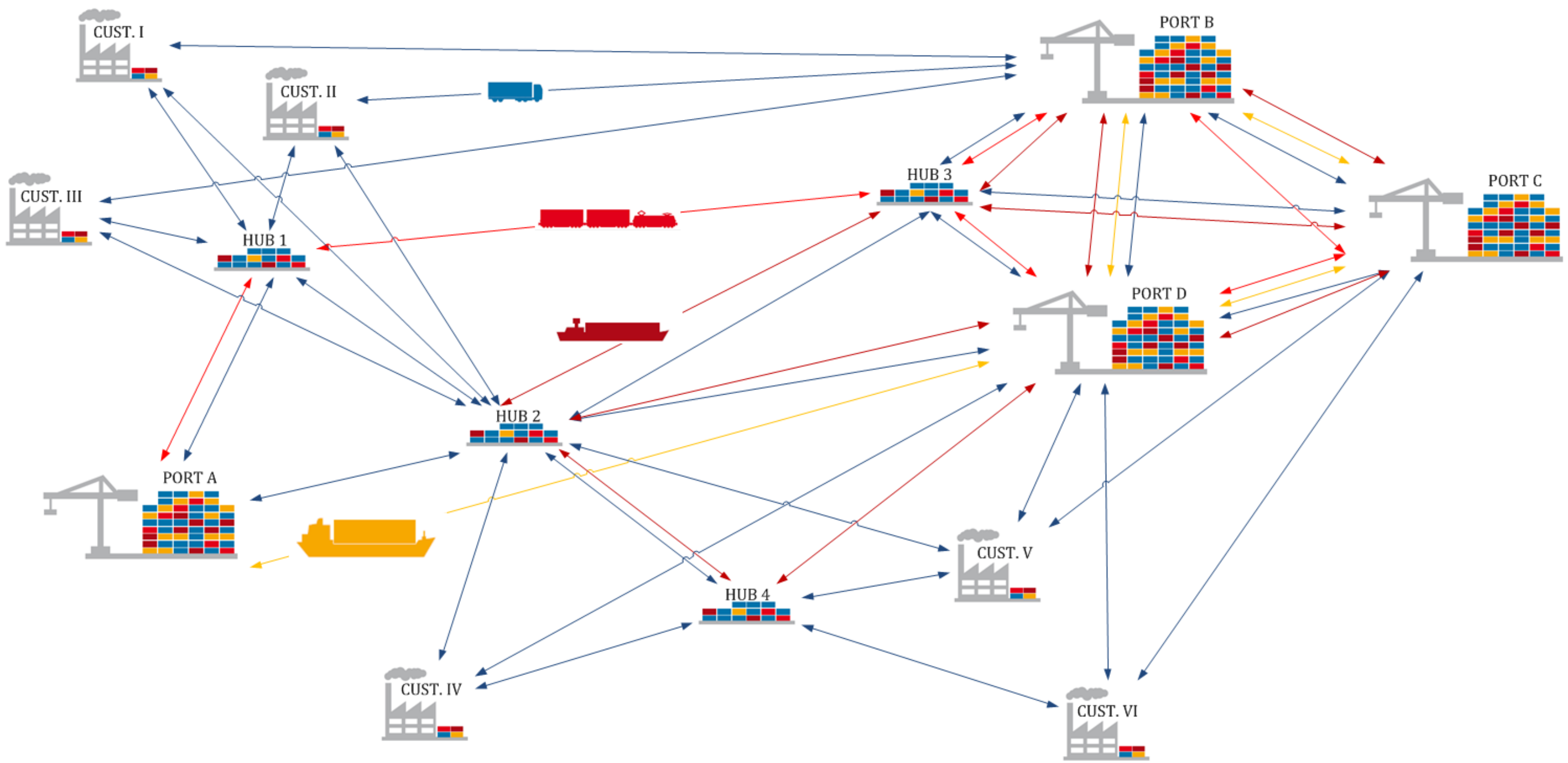
CTT
INTERMODAAL TRANSPORT

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

*Source of artwork: Combi Terminal Twente B.V. www.ctt-twente.nl

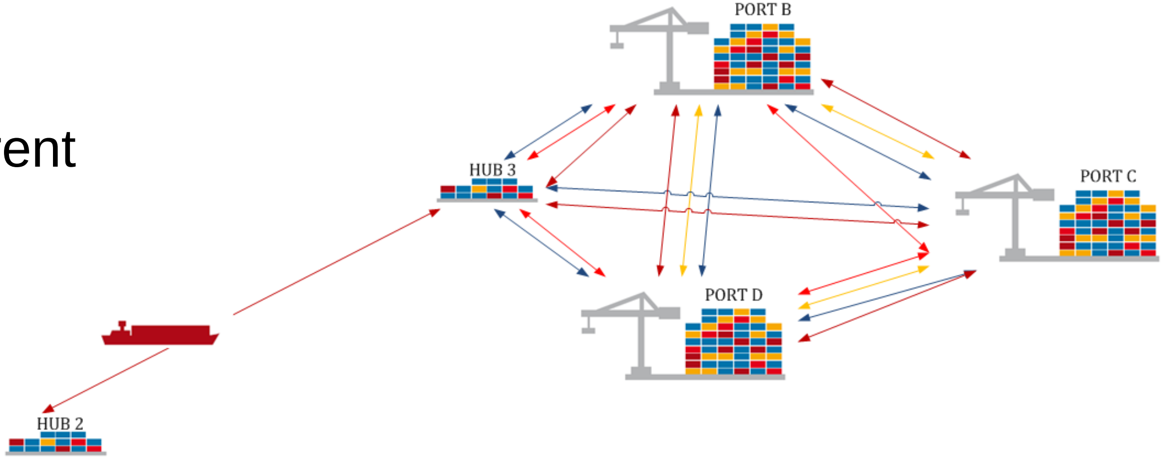
FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS



Source of artwork: Europe Container Terminals "The future of freight transport". www.ect.nl

FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

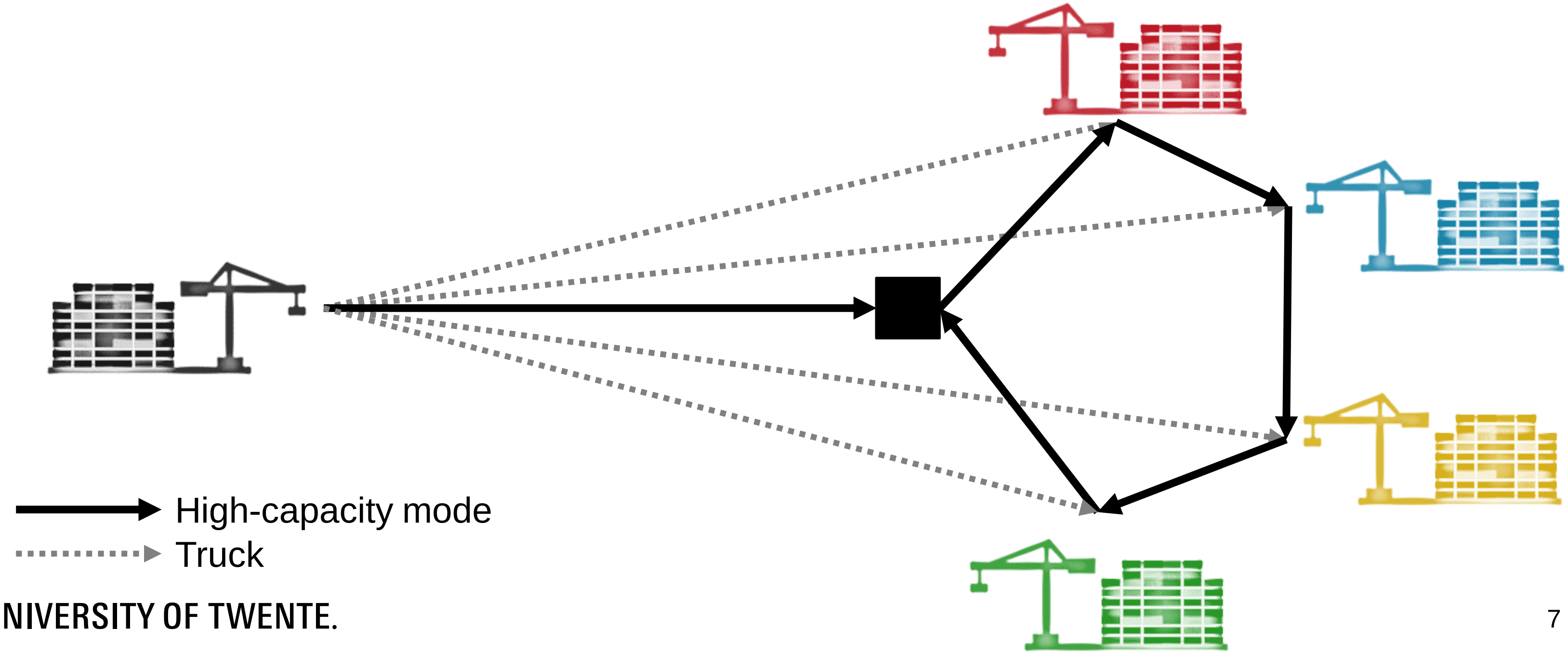
- Freights have different
  - Destination
  - Release day
  - Time-window



- ***Challenge:*** To balance daily and future costs when freights become known gradually over time.

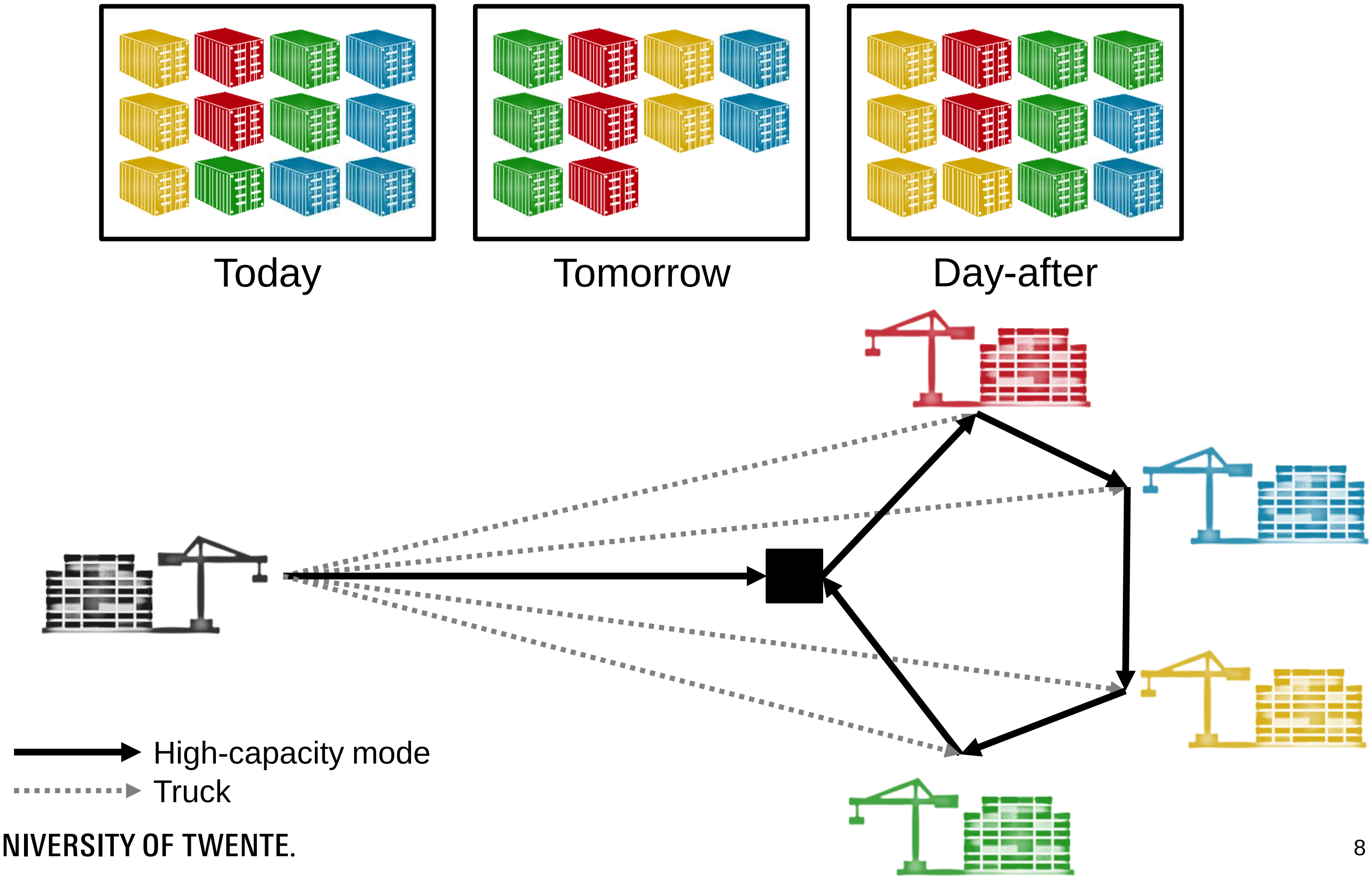
FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

Today



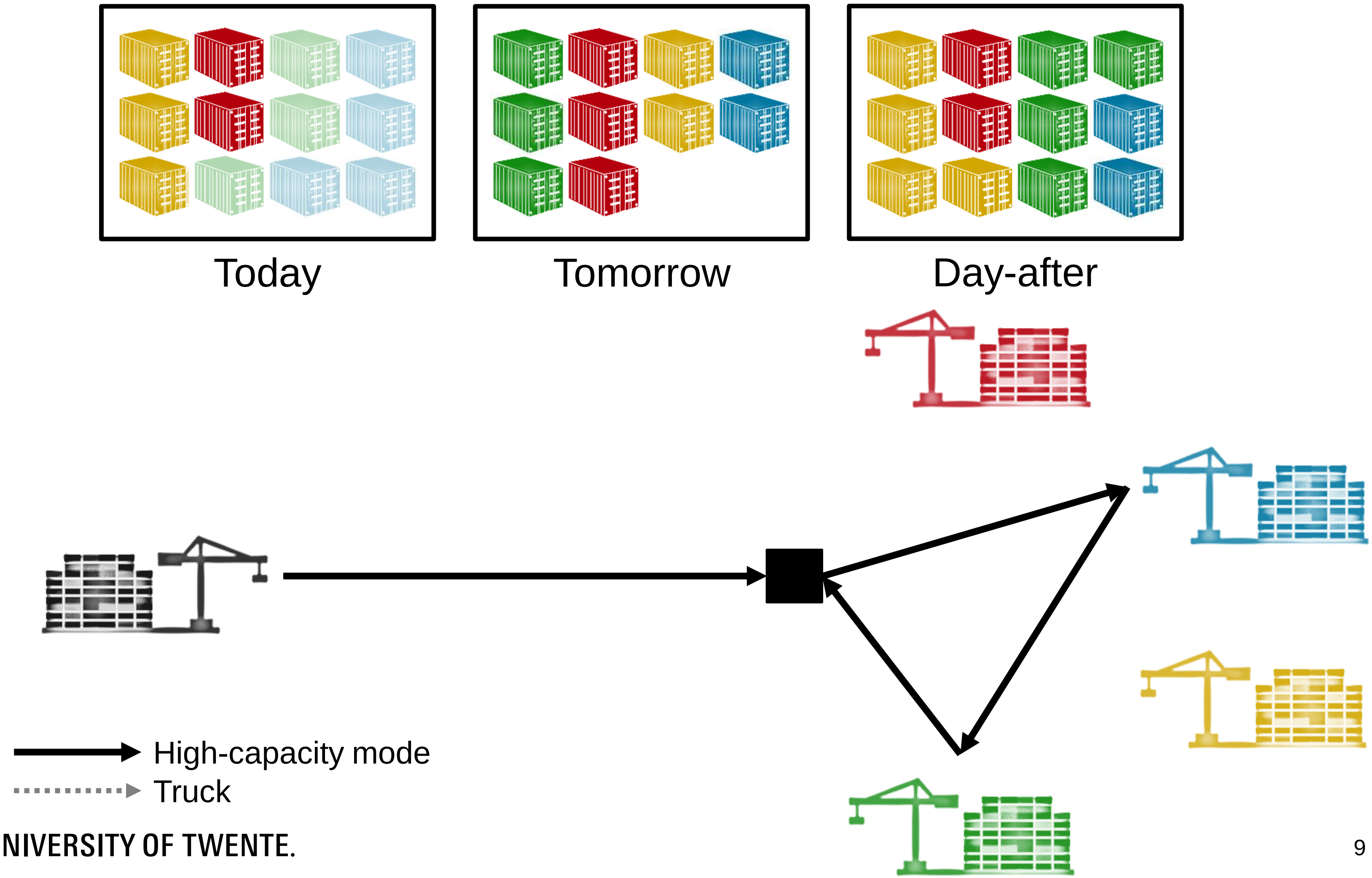
FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

DYNAMIC MULTI-PERIOD PLANNING



FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

DYNAMIC MULTI-PERIOD PLANNING



FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

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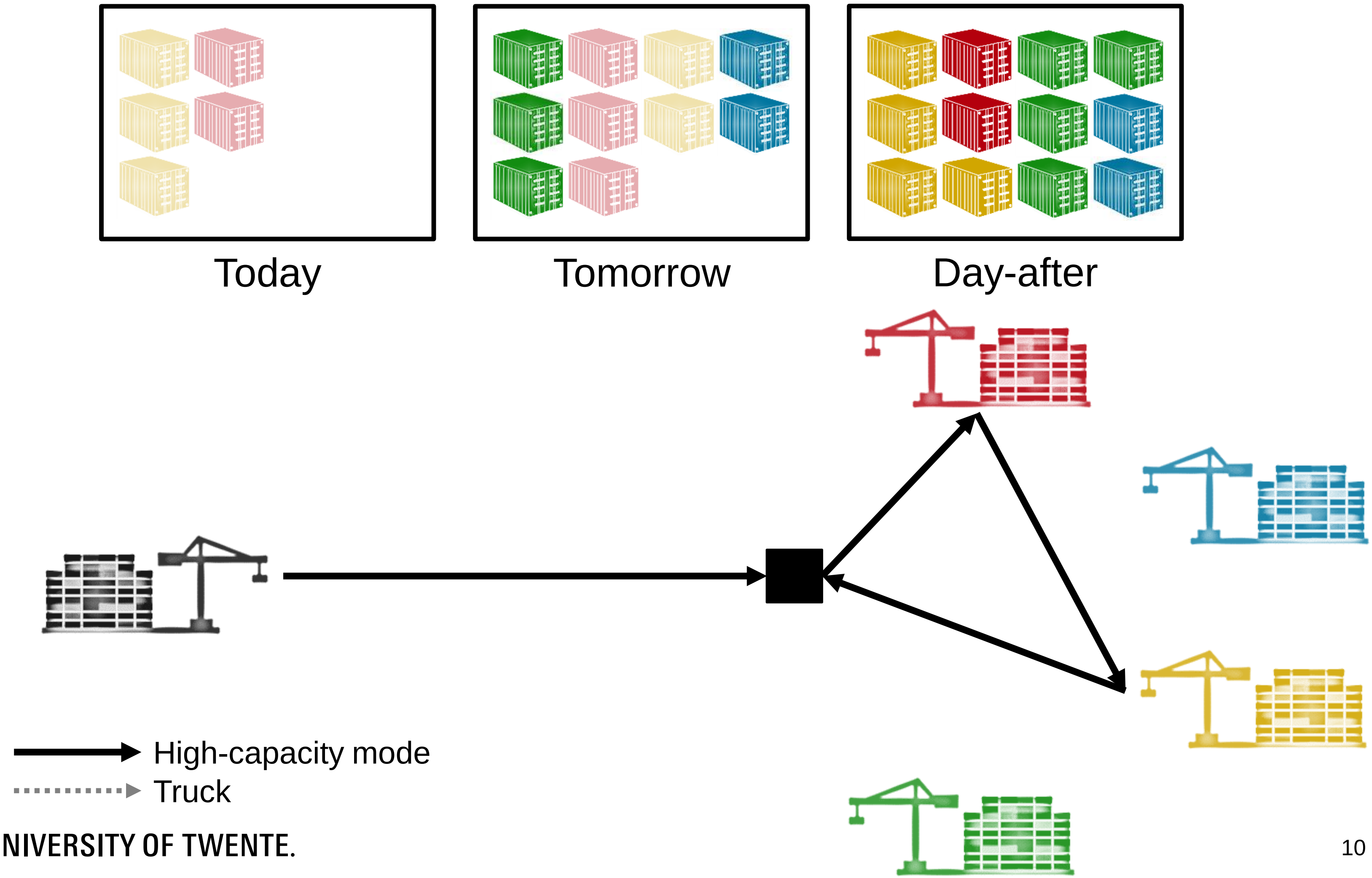
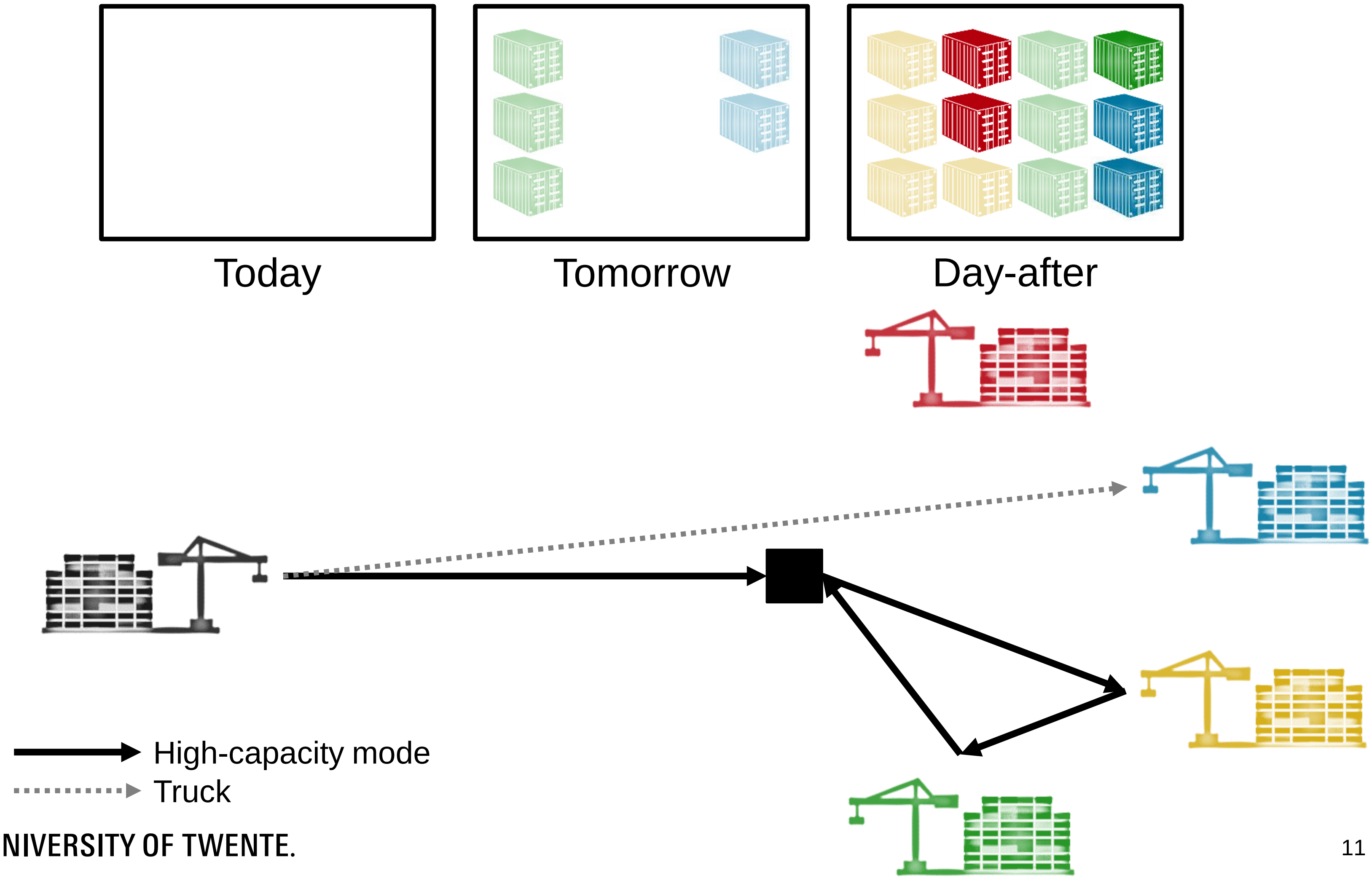


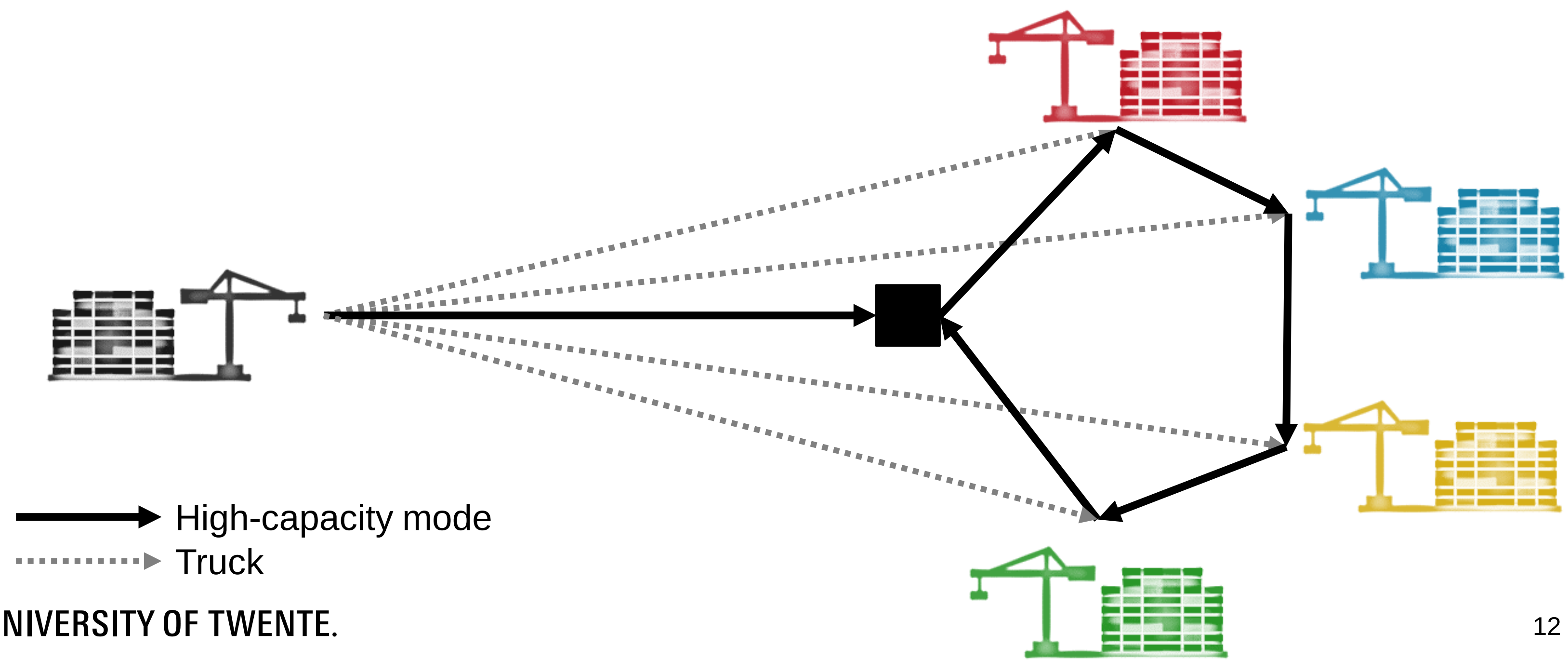
FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

DYNAMIC MULTI-PERIOD PLANNING



FREIGHT CONSOLIDATION IN INTERMODAL NETWORKS

DYNAMIC MULTI-PERIOD PLANNING



MARKOV DECISION PROCESS (MDP) MODEL

STOCHASTIC PROCESS UNDER CONTROL

Stochasticity: Arrival of freights and their characteristics:

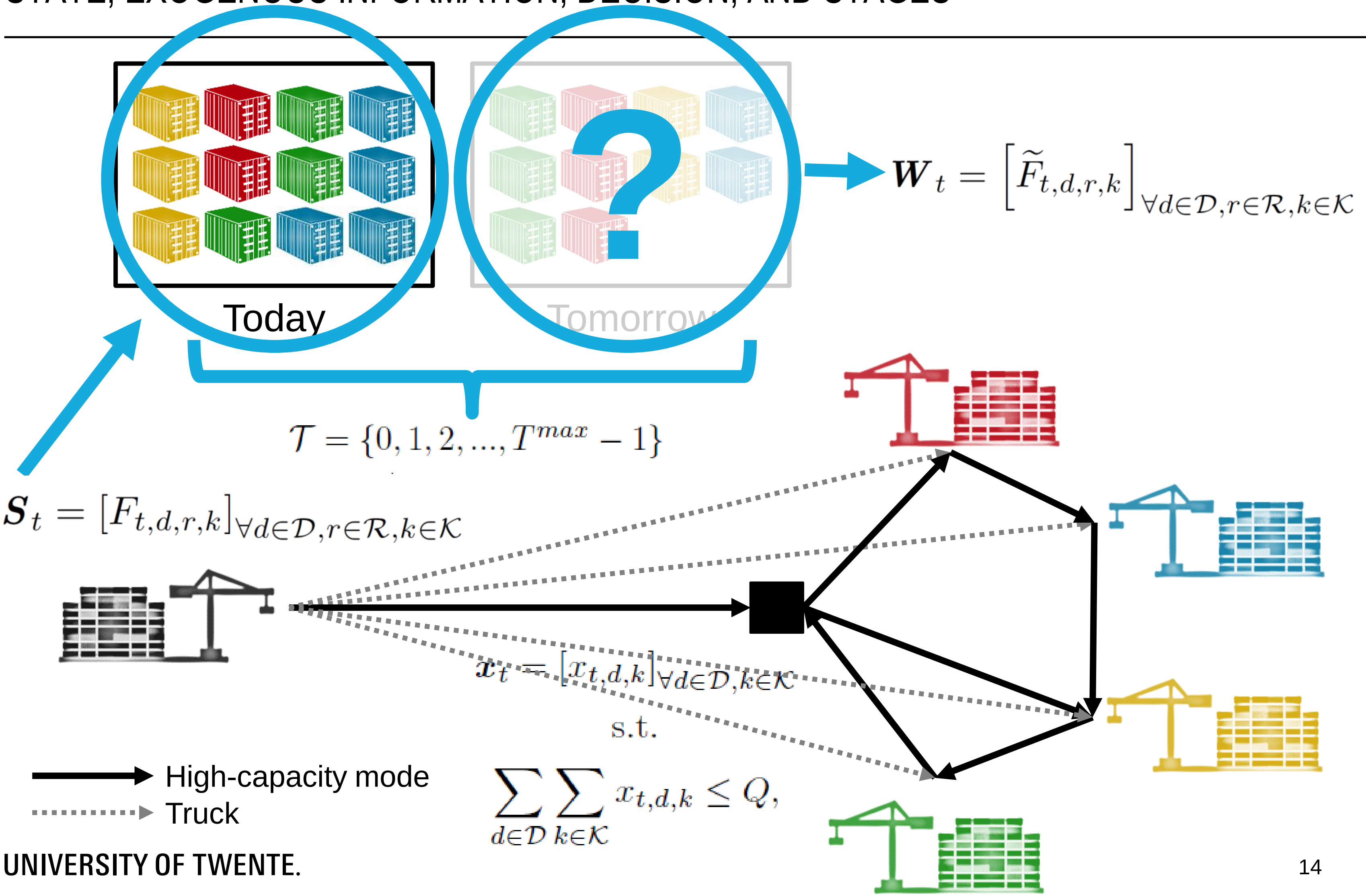
- Number of freights $\mathcal{F} \subseteq \mathbb{Z}^{+}$ p_f^F
- Destinations $\mathcal{D}$ p_d^{FD}
- Release day $\mathcal{R} = \{0, 1, 2, ..., R^{max}\}$ p_r^{FR}
- Time-window length $\mathcal{K} = \{0, 1, 2, ..., K^{max}\}$ p_k^{FK}

Control: Freights to consolidate/postpone every day.

Objective: Minimize the costs over the planning horizon.

MARKOV DECISION PROCESS (MDP) MODEL

STATE, EXOGENOUS INFORMATION, DECISION, AND STAGES



MARKOV DECISION PROCESS (MDP) MODEL

TRANSITION BETWEEN STAGES

Transition: Today's state depends on (1) yesterday's state, (2) yesterday's decision, and (3) the realizations of the random variables:

$$\boldsymbol{S}_t = S^M\left(\boldsymbol{S}_{t-1}, \boldsymbol{x}_{t-1}, \boldsymbol{W}_t\right), \ \forall t \in \mathcal{T} | t > 0$$

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

$$F_{t,d,0,k} = F_{t-1,d,0,k+1} - x_{t-1,d,k+1} + F_{t-1,d,1,k} + \widetilde{F}_{t,d,0,k}, \ |k < K^{max}$$

$$F_{t,d,r,k} = F_{t-1,d,r+1,k} + \widetilde{F}_{t,d,r,k}, \ |r \geq 1$$

$$F_{t,d,r,K^{max}} = \widetilde{F}_{t,d,r,K^{max}},$$

$$\forall d \in \mathcal{D}, \ r \in \mathcal{R}, \ r+1 \in \mathcal{R}, \ k \in \mathcal{K}, \ k+1 \in \mathcal{K}$$

Time-window length decreases once a freight is released.

MARKOV DECISION PROCESS (MDP) MODEL

COST DEFINITION AND OBJECTIVE

Costs: Visiting a subset of destinations with the high-capacity mode and using trucks:

$$C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) = \sum_{\mathcal{D}' \subseteq \mathcal{D}} \left(C_{\mathcal{D}'} \cdot \prod_{d' \in \mathcal{D}'} y_{t,d'} \cdot \prod_{d'' \in \mathcal{D} \setminus \mathcal{D}'} \left(1 - y_{t,d''}\right) \right) + \sum_{d \in \mathcal{D}} \left(B_d \cdot z_{t,d}\right)$$

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

$$y_{t,d} = \begin{cases} 1, & \text{if } \sum_{k \in \mathcal{K}} x_{t,d,k} > 0 \\ 0, & \text{otherwise} \end{cases}, \ \forall d \in \mathcal{D}$$

$$z_{t,d} = F_{t,d,0,0} - x_{t,d,0}, \ \forall d \in \mathcal{D}$$

Objective: Find the policy $\pi : \boldsymbol{S}_t \rightarrow \boldsymbol{x}_t^{\pi}$ that minimizes the expected costs over the horizon.

$$\min_{\pi \in \Pi} \mathbb{E} \left\{ \sum_{t \in \mathcal{T}} C\left(\boldsymbol{S}_t, \boldsymbol{x}_t^{\pi}\right) \middle| \boldsymbol{S}_0 \right\}$$

MARKOV DECISION PROCESS (MDP) MODEL

HOW TO FIND THE OPTIMAL POLICY?

Using Bellman's recursion (dynamic programming), which balance ***daily*** and ***future*** costs :

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

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

All possible decisions in a state!

All possible realizations of the random variables!

All possible states!

MARKOV DECISION PROCESS (MDP) MODEL

PROS: The MDP model outputs a dynamic decision making function that achieves the lowest expected costs over the horizon.

$$\pi : \boldsymbol{S}_t \rightarrow \boldsymbol{x}_t^{\pi}$$

CONS: The MDP model can only be solved (e.g., using the Bellman's recursion) for small instances of the problem.

- ***However:*** the building blocks of the MDP model can be used within the approximate dynamic programming framework to solve the MDP model heuristically for large instances.

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

FRAMEWORK FOR SOLVING LARGE MDP 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

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

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

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

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

  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 (ADP)

THE NEW CONSTRUCTS BASED ON THE MDP MODEL

The ***post-decision state*** $\boldsymbol{S}_t^{n,x}$ describes the system "estimating" all possible realizations of the random variables.

$$\boldsymbol{S}_t^{n,x} = S^{M,x}\left(\boldsymbol{S}_t^n, \boldsymbol{x}_t^n\right), \ \forall t \in \mathcal{T}$$

The ***Value Function Approximation (VFA)*** $\bar{V}_t^n(\boldsymbol{S}_t^{n,x})$ approximates the future costs of the post-decision state:

$$\bar{V}_t^n(\boldsymbol{S}_t^{n,x}) = \mathbb{E}\left\{V_{t+1}\left(\boldsymbol{S}_{t+1}\right) | \boldsymbol{S}_t^x\right\}$$

RESULT: It is not necessary to consider all realizations of the random variables in the new Bellman's recursion:

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

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

THE VALUE FUNCTION APPROXIMATION

We use the concept of ***basis functions***, or post-decision characteristics, where the value of a post-decision state is a weighted combination of its characteristics:

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

RESULT: It is not necessary to consider all post-decision states (and hence states), since there is a function $\phi_a(\boldsymbol{S}_t^{n,x})$ that returns its characteristic $a \in \mathcal{A}$ and the weights θ_a depend only on the characteristic considered.

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

THE VALUE FUNCTION APPROXIMATION

Examples of basis functions or post-decision characteristics:

1. Number of freights that are not yet released for transport, per destination ***(i.e. future freights)***.
2. Number of freights that are released for transport and whose due-day is not immediate, per destination ***(i.e., may-go freights)***.
3. Binary indicator of a destination having urgent freights ***(i.e., must-visit destination)***.
4. Some power function (e.g., ^2) of each state variable ***(i.e., non-linear components in costs)*** .

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

UPDATING THE VALUE FUNCTION APPROXIMATION

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

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

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

$$\theta^{n}_{a} = \theta^{n-1}_{a} - (G^{n})^{-1}\phi_{a}(\boldsymbol{S}^{n,x}_{t})\left(\bar{V}^{n-1}_{t-1}(\boldsymbol{S}^{n,x}_{t-1}) - \hat{v}^{n}_{t}\right)$$

LSQ Optimization Matrix

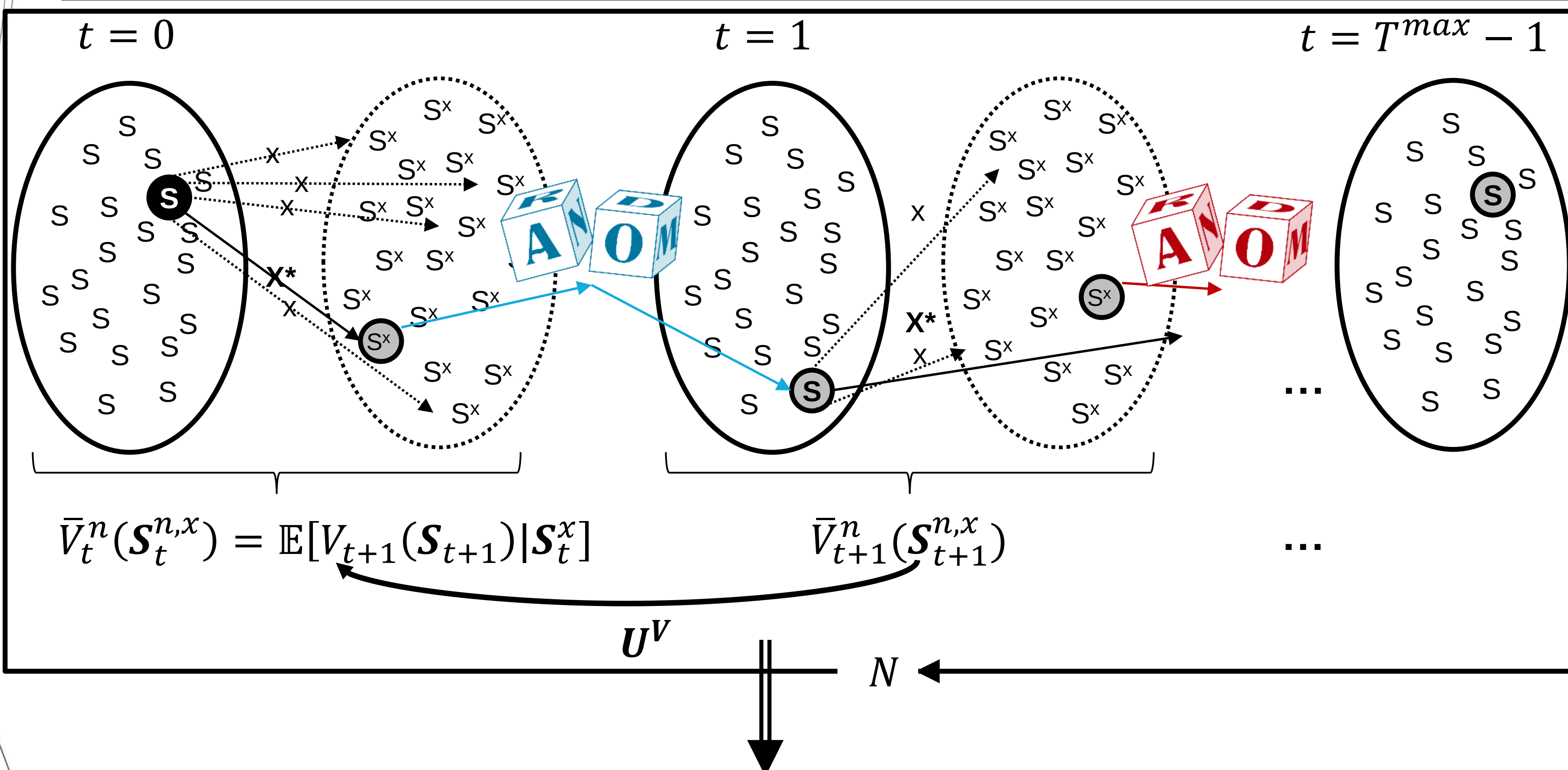
Observed Characteristic Value

Prediction Error

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

APPROXIMATE DYNAMIC PROGRAMMING (ADP)

A GRAPHICAL REPRESENTATION OF THE CONSTRUCTS AND THE ALGORITHM



$$\boldsymbol{x}_t^{\pi} = \arg\min \left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t^{\pi}\right) + \sum_{a \in \mathcal{A}} \theta_{a,t}^{N} \phi_a\left(\boldsymbol{S}_t^x\right) \right)$$

NUMERICAL EXPERIMENTS

1-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Two types of experiments:

A. *Convergence of the ADP approach* [1]

Convergence of the resulting ADP policy costs to the optimal costs obtained via the Markov model, for different initial states, in small instances. (≈ 3000 states)

B. *Performance of the resulting ADP policy* [2]

Comparison of the resulting ADP policy costs against the costs of a benchmark heuristic (myopic optimization), for different initial states, in larger instances. (> 8 x 10^{18} states)

For the experimental settings:

1. M.R.K. Mes, A.E. Pérez Rivera (2016). Approximate Dynamic Programming by Practical Examples. *Beta Working Paper 495*.
2. A.E. Pérez Rivera, M.R.K. Mes (2015). Dynamic Multi-period Freight Consolidation. *Lecture Notes in Computer Science*, Volume 9335: 370-385 .

NUMERICAL EXPERIMENTS

CONVERGENCE: 1-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

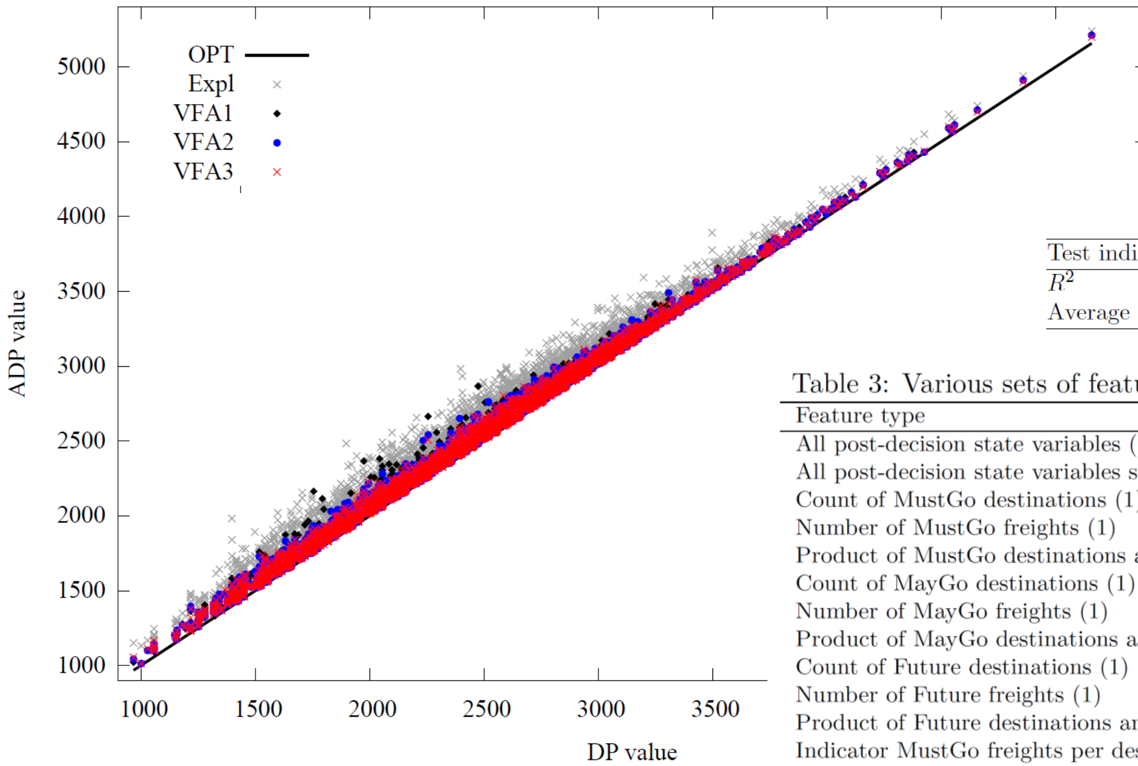


Table 2: Performance of the different VFAs

Test indicator	Lookup-table	VFA 1	VFA 2	VFA 3
R^2	-	0.8897	0.8915	0.8897
Average difference	7.50%	2.67%	2.45%	2.36%

Table 3: Various sets of features (basis functions of a post-decision state)

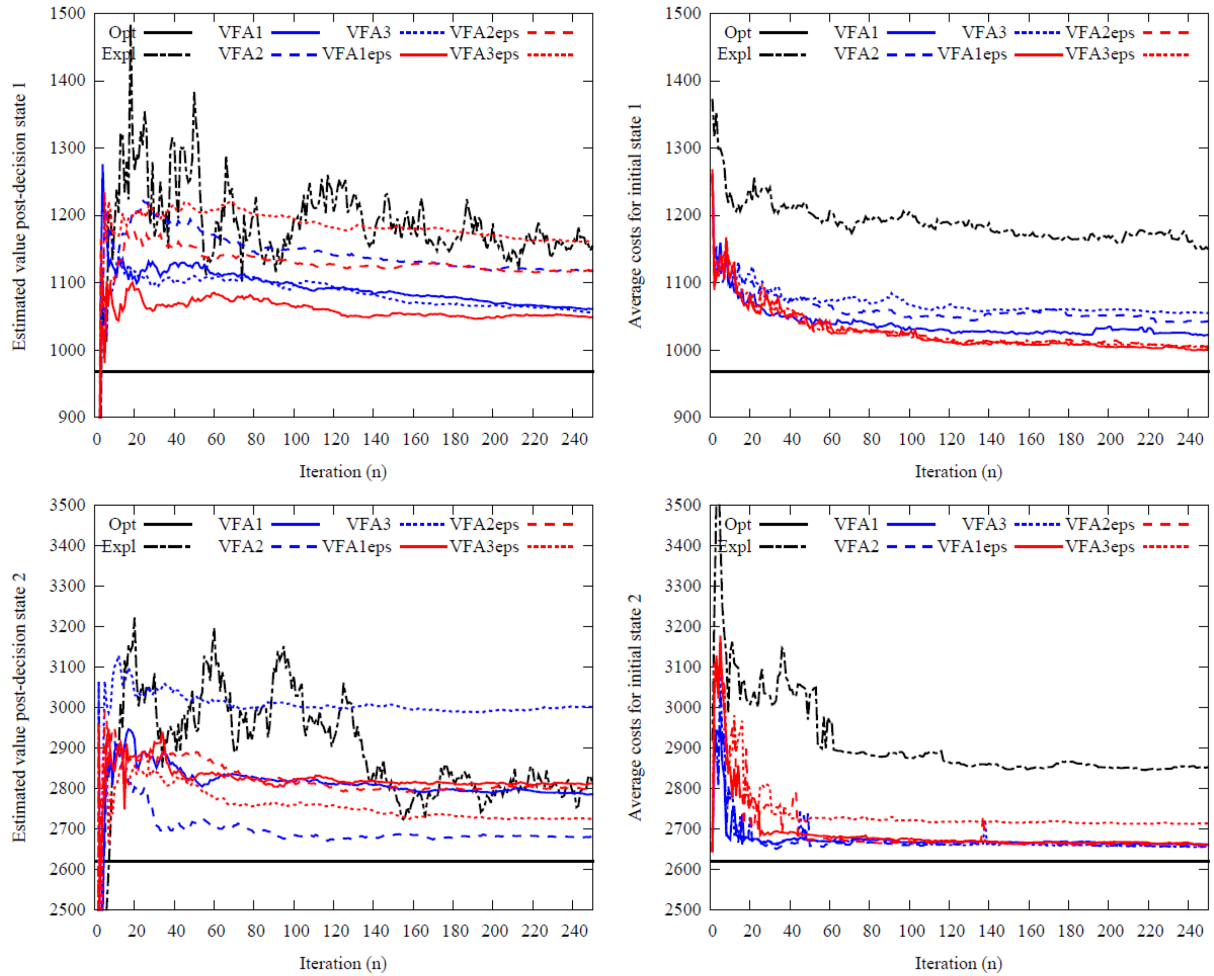
Feature type	VFA 1	VFA 2	VFA 3
All post-decision state variables (9)	*	*	*
All post-decision state variables squared (9)	*	-	-
Count of MustGo destinations (1)	*	*	*
Number of MustGo freights (1)	*	*	*
Product of MustGo destinations and MustGo freights (1)	*	-	-
Count of MayGo destinations (1)	*	*	*
Number of MayGo freights (1)	*	*	*
Product of MayGo destinations and MayGo freights (1)	*	-	-
Count of Future destinations (1)	*	*	*
Number of Future freights (1)	*	*	*
Product of Future destinations and Future freights (1)	*	-	-
Indicator MustGo freights per destination (3)	-	*	-
Indicator MayGo freights per destination (3)	-	*	-
Indicator Future freights per destination (3)	-	*	-
Number of all freights (1)	*	*	*
Constant (1)	*	*	*

NUMERICAL EXPERIMENTS

CONVERGENCE: 1-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

State 1:
$F_{0,2,0,2} = 1$

State 2:
$F_{0,2,0,0} = 1$
$F_{0,3,0,0} = 1$
$F_{0,2,0,1} = 3$
$F_{0,2,0,2} = 1$



NUMERICAL EXPERIMENTS

PERFORMANCE: 1-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

State	Normal Capacity Heuristic	Normal Capacity ADP	Normal Capacity Difference	Large Capacity Heuristic	Large Capacity ADP	Large Capacity 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%**

State A has no urgent freights ($F_{0,d,0,0}$) and State L has only urgent freights.

NUMERICAL EXPERIMENTS

PERFORMANCE: 1-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

	# 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

2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Extension: The high-capacity mode travels in round-trips, delivering some freights and picking-up some others: $\boldsymbol{S}_t = \left[\left(F_{t,d,r,k}, G_{t,d,r,k}\right)\right]_{\forall d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}}$

$$C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) = \sum_{\mathcal{D}' \subseteq \mathcal{D}} \left(C_{\mathcal{D}'} \cdot \prod_{d' \in \mathcal{D}'} y_{t,d'} \cdot \prod_{d'' \in \mathcal{D} \setminus \mathcal{D}'} \left(1 - y_{t,d''}\right) \right) + \sum_{d \in \mathcal{D}} \left(A_d \cdot z_{t,d}\right) + \sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} \left(B_d \cdot \left(x^F_{t,d,k} + x^G_{t,d,k}\right)\right)$$

s.t.

$$y_{t,d} = \begin{cases} 1, & \text{if } \sum_{k \in \mathcal{K}} \left(x^F_{t,d,k} + x^G_{t,d,k}\right) > 0 \\ 0, & \text{otherwise} \end{cases}, \ \forall d \in \mathcal{D}$$

$$z_{t,d} = F_{t,d,0,0} - x^F_{t,d,0} + G_{t,d,0,0} - x^G_{t,d,0}, \ \forall d \in \mathcal{D}$$

$$\boldsymbol{S}_t = S^M\left(\boldsymbol{S}_{t-1}, \boldsymbol{x}_{t-1}, \boldsymbol{W}_t\right), \ \forall t \in \mathcal{T} | t > 0$$

where

$$F_{t,d,0,k} = F_{t-1,d,0,k+1} - x^F_{t-1,d,k+1} + F_{t-1,d,1,k} + \widetilde{F}_{t,d,0,k},$$
$$G_{t,d,0,k} = G_{t-1,d,0,k+1} - x^G_{t-1,d,k+1} + G_{t-1,d,1,k} + \widetilde{G}_{t,d,0,k},$$
$$\forall d \in \mathcal{D}, \text{ and } k \in \mathcal{K} | k < K^{max} .$$

$$F_{t,d,0,K^{max}} = F_{t-1,d,1,K^{max}} + \widetilde{F}_{t,d,0,K^{max}},$$
$$G_{t,d,0,K^{max}} = G_{t-1,d,1,K^{max}} + \widetilde{G}_{t,d,0,K^{max}},$$
$$\forall d \in \mathcal{D}.$$

$$F_{t,d,r,k} = F_{t-1,d,r+1,k} + \widetilde{F}_{t,d,r,k},$$
$$G_{t,d,r,k} = G_{t-1,d,r+1,k} + \widetilde{G}_{t,d,r,k}$$
$$\forall d \in \mathcal{D}, \ r \in \mathcal{R} | 0 < r < R^{max}, \text{ and } k \in \mathcal{K} .$$

$$F_{t,d,R^{max},k} = \widetilde{F}_{t,d,R^{max},k}$$
$$G_{t,d,R^{max},k} = \widetilde{G}_{t,d,R^{max},k}$$
$$\forall d \in \mathcal{D}, \text{ and } k \in \mathcal{K} .$$

NUMERICAL EXPERIMENTS

2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Two types of experiments:

A. *Convergence of the ADP approach* [3]

Convergence of the resulting ADP policy costs to the optimal costs obtained via the Markov model, for different initial states, in small instances. (≈19000 states)

B. *Performance of the resulting ADP policy* [3]

Comparison of the resulting ADP policy costs against the costs of a benchmark heuristic (myopic optimization), for different initial states, in large instances. (>> 8 x 10^{27} states)

For the experimental settings:

3. A.E. Pérez Rivera, M.R.K. Mes (2015). Anticipatory Freight Selection in Intermodal Long-haul Round-trips. *Beta Working Paper 492*.

NUMERICAL EXPERIMENTS

CONVERGENCE: 2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

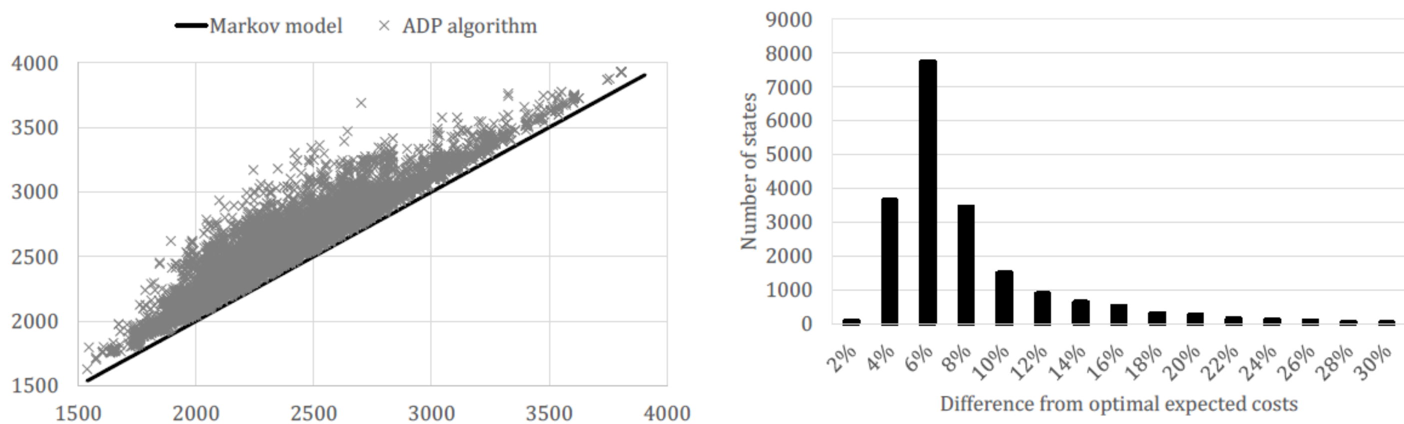


Figure 2: Accuracy of VFA 3 in Instance I_2

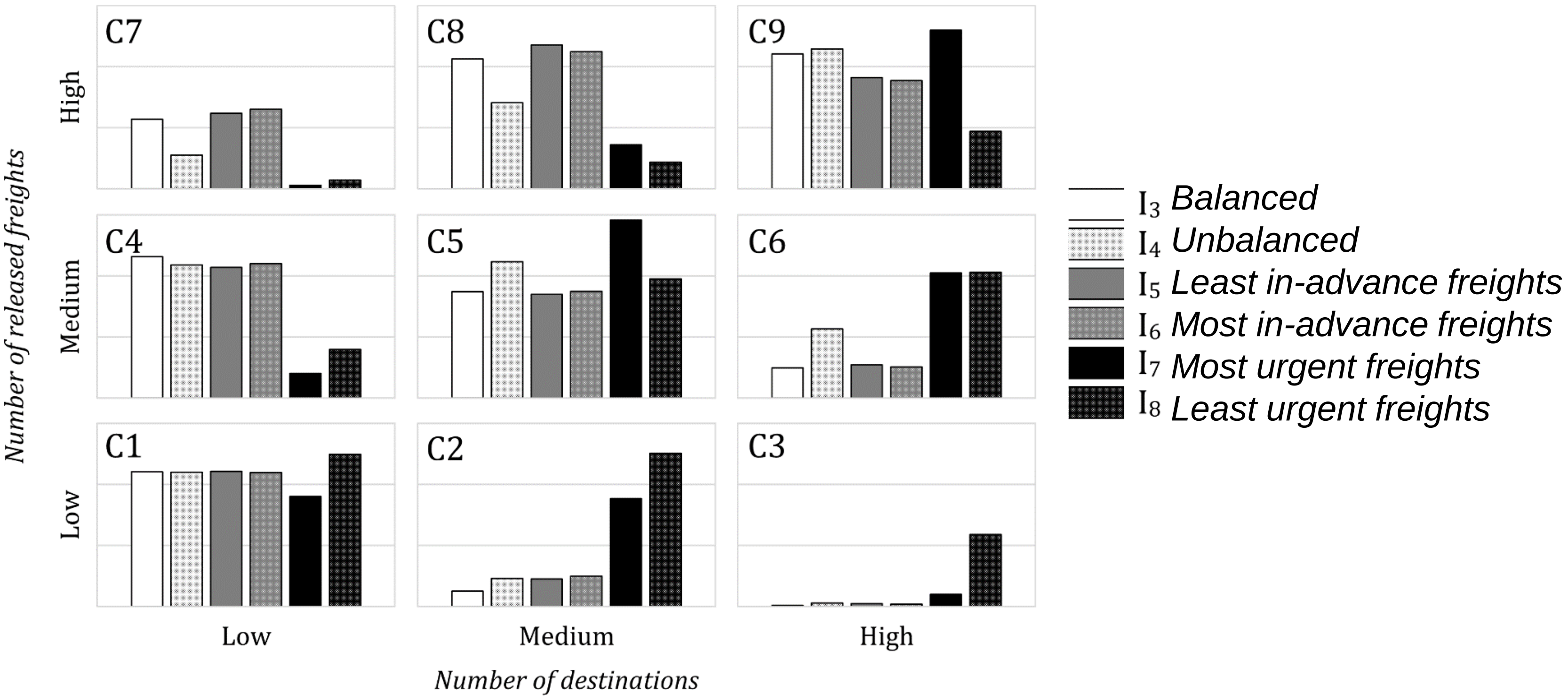
Table 4: Performance of the different VFAs in instances I_1 and I_2

Instance	VFA 1		VFA 2		VFA 3	
	R^2	Diff.	R^2	Diff.	R^2	Diff.
I_1	0.63	5.6%	0.69	5.9%	0.55	5.6%
I_2	0.64	6.6%	0.68	7.7%	0.55	6.8%
I_1-delivery	0.89	16%	0.89	14%	0.89	8%
I_2-delivery	0.89	8%	0.90	7%	0.90	7%

NUMERICAL EXPERIMENTS

CONVERGENCE: 2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Instances differ in their ***distribution of the random variables.***



NUMERICAL EXPERIMENTS

PERFORMANCE: 2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Table 5: Average cost difference between the ADP policy and the competing policy

Category	I_3	I_4	I_5	I_6	I_7	I_8	Average
C1	-5.9%	-8.6%	-9.4%	-5.5%	-0.6%	-5.2%	-5.9%
C2	-9.1%	-12.3%	-4.0%	-2.7%	-0.6%	-11.0%	-6.6%
C3	-1.9%	-6.7%	-8.2%	-3.1%	1.1%	-7.2%	-4.3%
C4	-14.9%	-25.5%	-5.2%	-11.8%	-1.5%	-8.0%	-11.2%
C5	-15.1%	-1.5%	-9.7%	-25.9%	-0.4%	-9.7%	-10.4%
C6	1.3%	-4.5%	-3.8%	-10.6%	-2.0%	-7.8%	-4.6%
C7	-4.4%	-3.7%	-24.2%	-0.1%	-11.0%	-7.3%	-8.4%
C8	2.3%	16.7%	2.1%	7.1%	0.6%	3.3%	5.3%
C9	-0.9%	2.3%	-4.4%	-11.0%	4.7%	-7.6%	-2.8%
Average	-5.9%	-8.6%	-7.9%	-8.6%	-1.2%	-7.5%	-6.6%
Weighted Average	-7.0%	-8.7%	-7.6%	-10.1%	0.3%	-8.0%	-6.9%

NUMERICAL EXPERIMENTS

1-WAY, MULTI-TERMINAL, MULTIPLE HIGH-CAPACITY MODES

Extension: There are multiple terminals with freight, and multiple high-capacity modes:

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

Decision becomes more complex due to the dynamic number of intermediate stops:

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

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

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

$$x_{i,d,d,L_{i,d,t}^{A},t} \geq F_{i,d,0,L_{i,d,t}^{A},t}, \quad \forall (i,d) \in \mathcal{A}_t^{\mathrm{D}}, k \in \mathcal{K}_t$$

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

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

NUMERICAL EXPERIMENTS

1-WAY, MULTI-TERMINAL, MULTIPLE HIGH-CAPACITY MODES

Transition: Multi-period traveling times and stops are captured in the state variables:

$$S_t = S^M\left(S_{t-1}, x_{t-1}, W_t\right)$$

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

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

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

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

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

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

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

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

$$F_{t,i,d,r,k} = F_{t-1,i,d,r+1,k} + \widetilde{F}_{t,i,d,r,k},$$

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

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

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

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

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

$$F_{t,i,d,R_t^{\max},k} = \widetilde{F}_{t,i,d,R_t^{\max},k},$$

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

NUMERICAL EXPERIMENTS

1-WAY, MULTI-TERMINAL, MULTIPLE HIGH-CAPACITY MODES

One type of experiments:

A. Performance of the resulting ADP policy [4]

Comparison of cost resulting from two different ADP policies against the costs of (1) myopic optimization and (2) sampling, for different initial states, in small instances.

ADP 1: $$\overline{V}_t^{x,n}\left(S_t^{x,n}\right)=\sum_{a\in\mathcal{A}}\theta_{a,t}^{n}\phi_a\left(S_t^{x,n}\right)$$

ADP 2: $$\overline{V}_t^{x,n}\left(S_t^{x,n}\right)=\alpha\sum_{a\in\mathcal{A}}\theta_{a,t}^{n}\phi_a\left(S_t^{x,n}\right)+(1-\alpha)\,\overline{C}_t^{n}\left(S_t^{x,n}\right)$$

ADP 1 and 2: $$\boldsymbol{x}_t^{\pi}=\arg\min\left(C\left(\boldsymbol{S}_t,\boldsymbol{x}_t^{\pi}\right)+\sum_{a\in\mathcal{A}}\theta_{a,t}^{N}\phi_a\left(\boldsymbol{S}_t^{x}\right)\right)$$

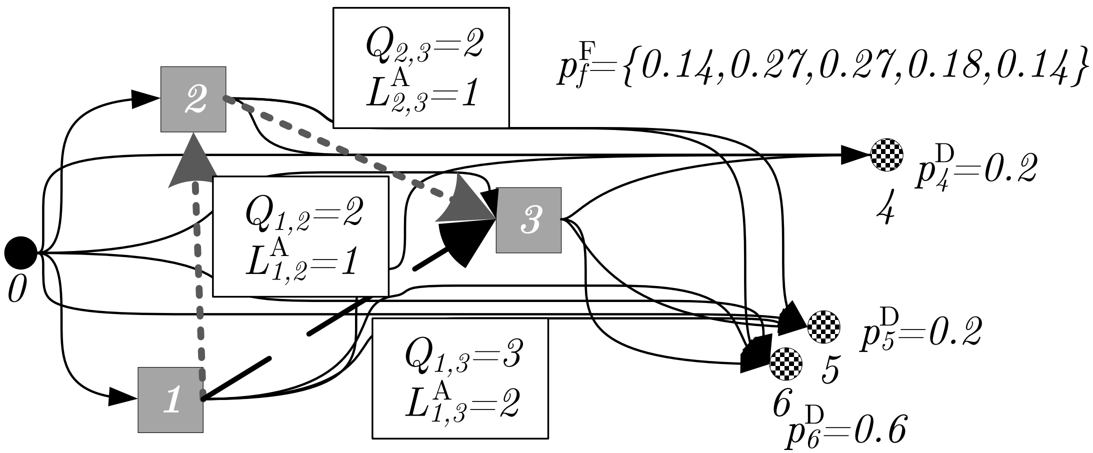
For the experimental settings:

4. A.E. Pérez Rivera, M.R.K. Mes (2016). Service and transfer selection for freights in a synchromodal network. *Beta Working Paper 504*.

NUMERICAL EXPERIMENTS

PERFORMANCE: 2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Instances differ in their ***distribution of the time-window length.***



	p^{K}_{k}		
k	I_1	I_2	I_3
0	0	0	0
1	0	0.05	0.4
2	0	0.05	0.3
3	0	0.2	0.2
4	0	0.3	0.05
5	1	0.4	0.05

NUMERICAL EXPERIMENTS

PERFORMANCE: 2-WAY, SINGLE TERMINAL, ONE HIGH-CAPACITY MODE

Table 1: Results for Instance I_1

State	Freights Total	Freights $k < 3$	Freights $k \geq 3$	Benchmark	ADP 1	ADP 2	Sampling
1	4	2	2	12221	-13.6%	-33.9%	-43.3%
2	7	3	4	14684	-12.8%	-32.7%	-39.9%
3	5	2	3	13042	-13.1%	-27.5%	-41.5%
4	6	3	3	13863	-12.3%	-25.9%	-39.0%
5	6	2	4	13863	-12.0%	-30.0%	-42.3%
6	6	2	4	13863	-10.4%	-31.3%	-42.9%
7	5	2	3	13042	-12.6%	-23.4%	-41.5%
8	4	3	1	12221	-14.7%	-25.0%	-38.9%
9	2	1	1	10579	-14.9%	-29.9%	-42.4%
10	5	3	2	13042	-11.2%	-32.9%	-40.6%

Table 2: Average results for Instance I_2 and I_3

Instance	Benchmark	ADP 1	ADP 2	Sampling
I_2	11078	-5.2%	-9.8%	-31.2%
I_3	12874	2.9%	0.4%	-3.3%

WHAT TO REMEMBER

- We propose an MDP model and ADP approach for dynamic and anticipatory decision making in intermodal transportation of freight.

- Through various VFA designs and problem structures, we show that the gap between the ADP and the optimal MDP (or other benchmark heuristics) solutions for is heavily instance/state dependent.

- In all different intermodal settings considered, the ADP approach seemed to perform better with more in-advance freight information and more complex transport networks.

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THANKS FOR YOUR ATTENTION!

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