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SERVICE AND TRANSFER SELECTION FOR FREIGHTS IN A SYNCHROMODAL NETWORK

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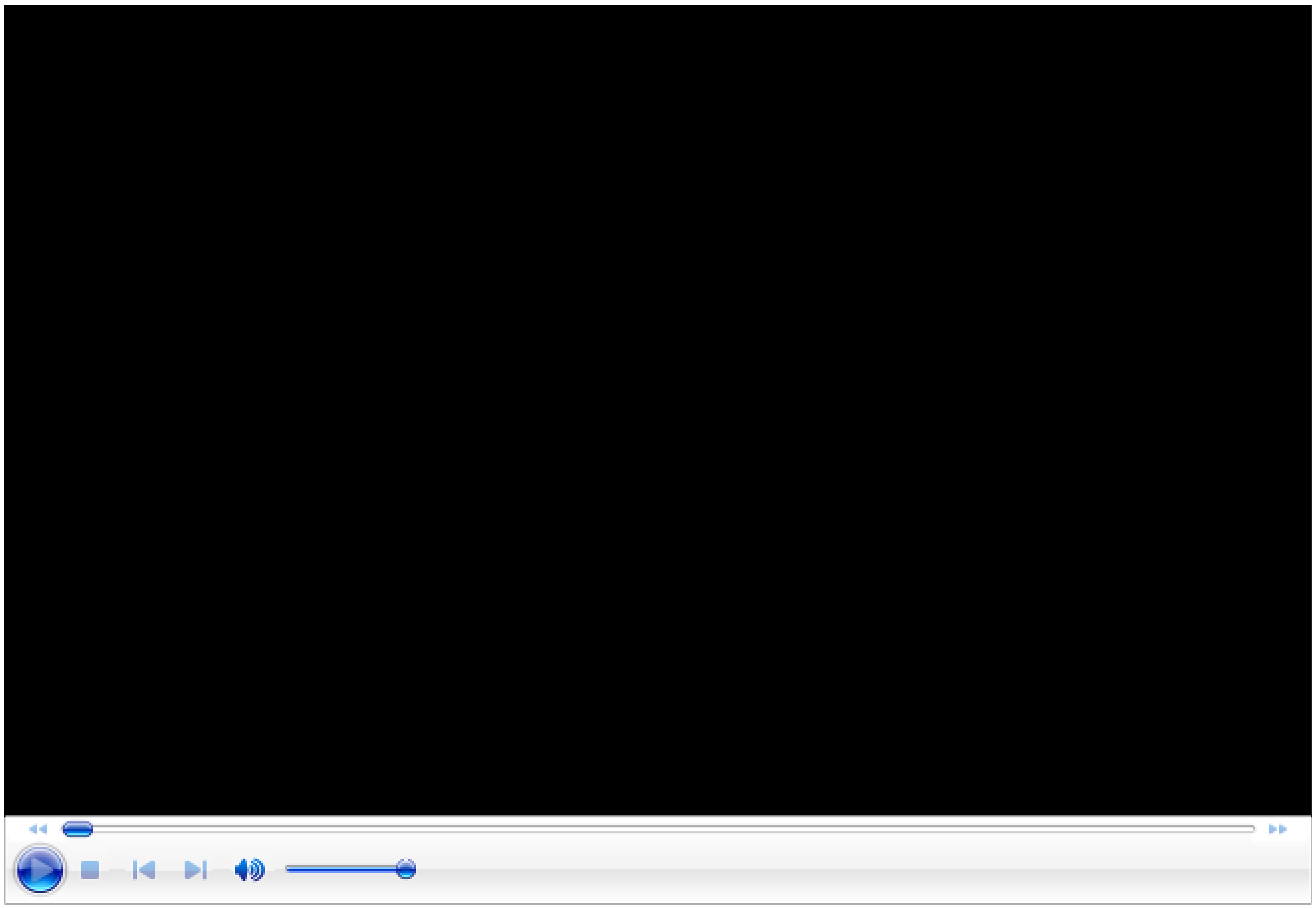
MOTIVATION
TRANSPORTATION OF CONTAINERS IN THE HINTERLAND

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

MOTIVATION
SYNCHROMODALITY



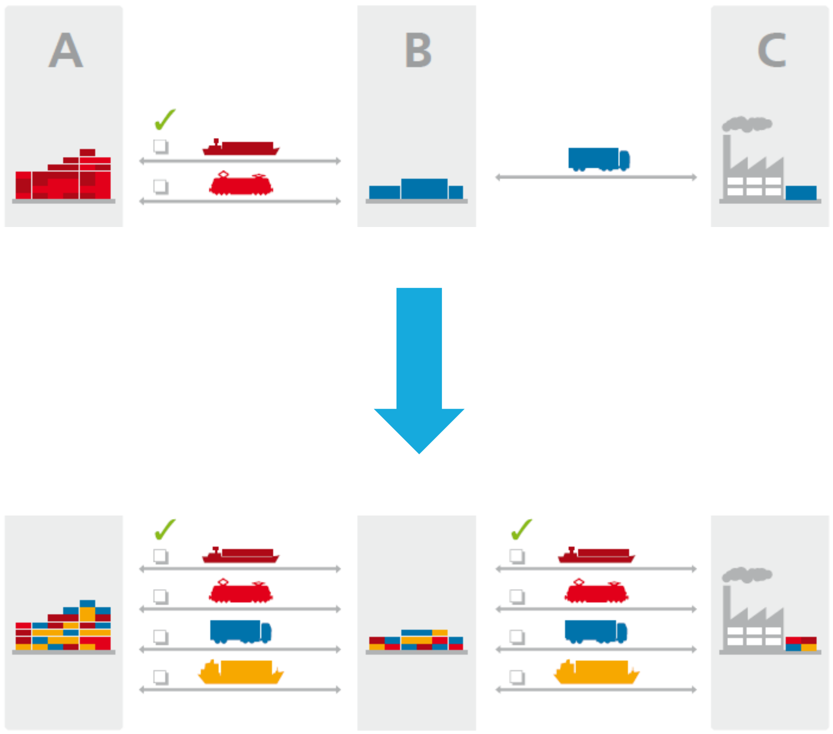
**Source of video: Dutch Institute for Advanced Logistics (DINALOG) www.dinalog.nl*

MOTIVATION

SYNCHROMODALITY

The characteristics of synchromodality:

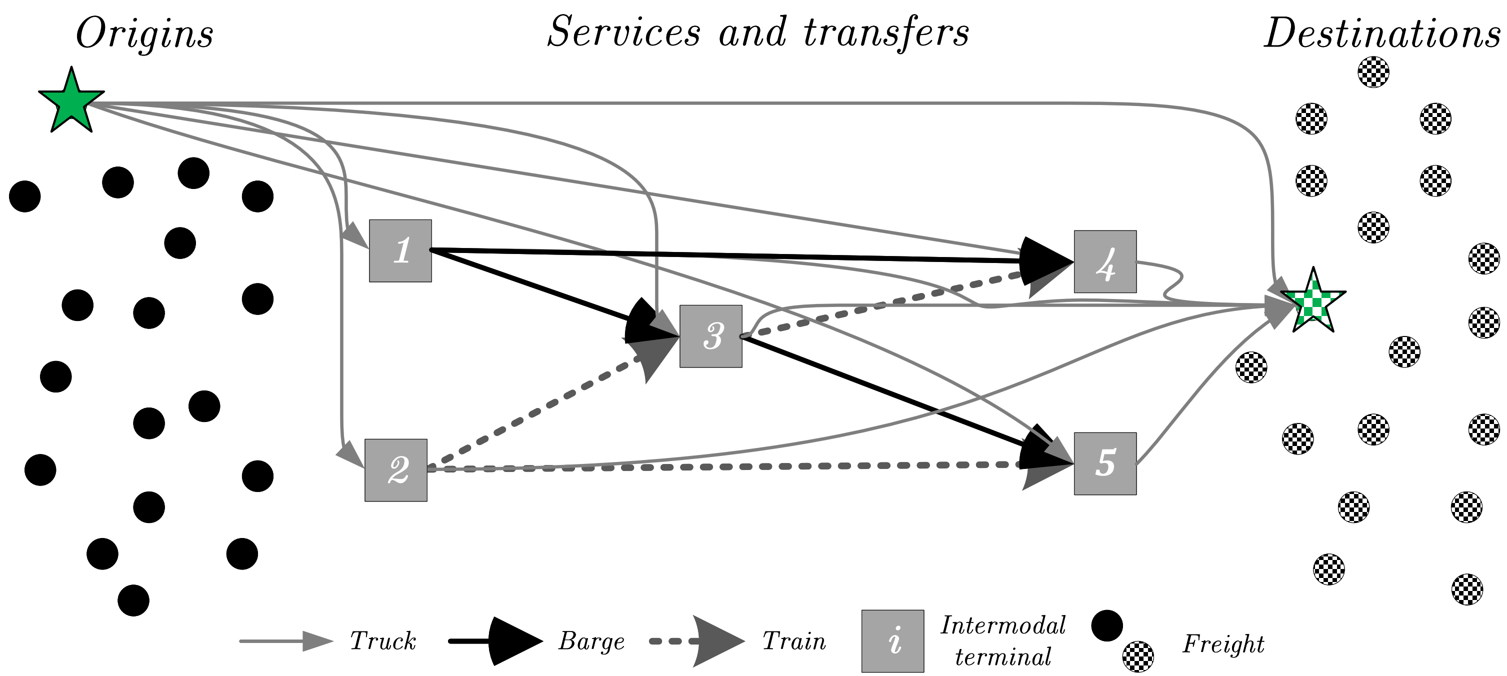
- ***Mode-free booking*** for all freights.
- ***Network-wise decisions*** at any point in time.
- ***Real-time information*** about the state of the network.
- ***Overall performance*** in the network and in time.



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

SERVICE AND TRANSFER SELECTION IN A SYNCHROMODAL NETWORK

PROBLEM DESCRIPTION

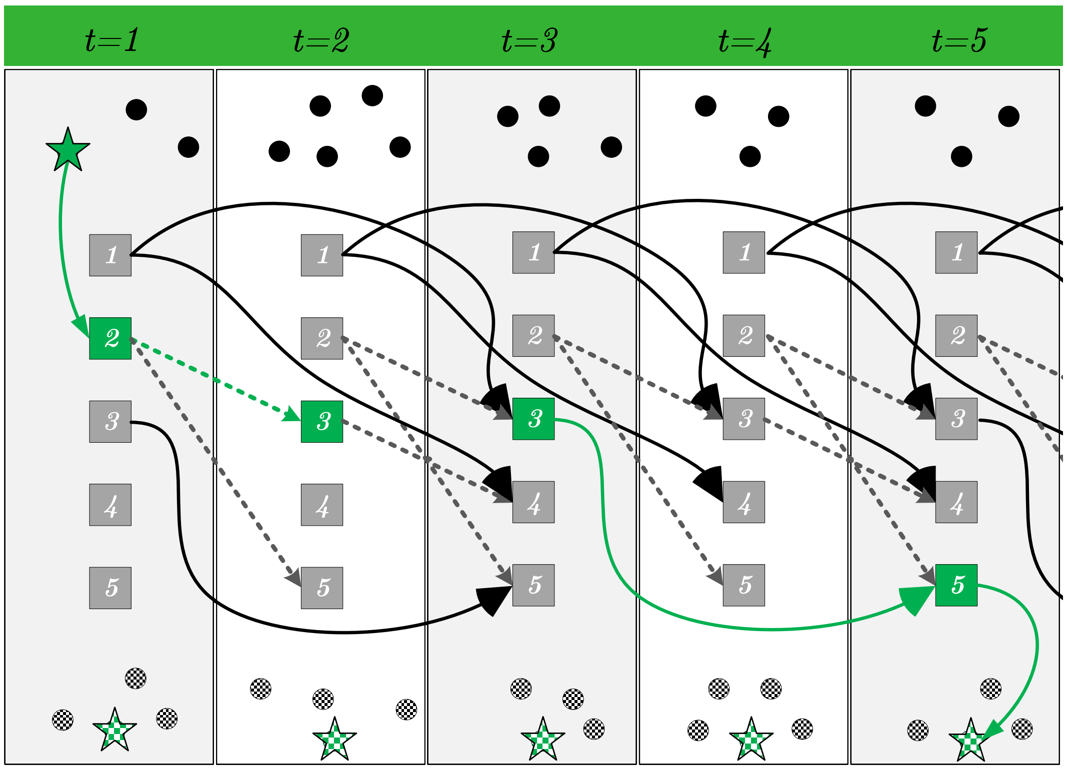


- Schedule
- Duration
- Capacity

- Origin
- Destination
- Time-window

SERVICE AND TRANSFER SELECTION IN A SYNCHROMODAL NETWORK

A SOLUTION EXAMPLE



Legend

- *Truck*
- *Barge*
- *Train*
- *Terminal*
- *Origins*
- *Destinations*

Plan for the Star freight

(t=1) Star Origin – Terminal 2.
(t=1) Terminal 2 – Terminal 3
(t=2) Waiting at Terminal 3
(t=3) Terminal 3 – Terminal 5
(t=4) Traveling by barge
(t=5) Terminal 5 – Star Destination

MARKOV DECISION PROCESS MODEL
STOCHASTIC PROCESS UNDER SEQUENTIAL DECISION MAKING

- ***Stages*** for sequential decisions: $t \in \mathcal{T} = \{0, 1, \ldots, T^{\max} - 1\}$
- ***Stochasticity*** in the arrival of freights:

Parameter	Notation	Probability
Number of freights	$f \in \mathcal{F} \subseteq \mathbb{N}$	$p^{\mathrm{F}}_{f,t}$
Origin	$i \in \mathcal{N}^{\mathrm{O}}_t$	$p^{\mathrm{O}}_{i,t}$
Destination	$d \in \mathcal{N}^{\mathrm{D}}_t$	$p^{\mathrm{D}}_{d,t}$
Release-day	$r \in \mathcal{R}_t = \{0, 1, 2, \ldots, R^{\max}_t\}$	$p^{\mathrm{R}}_{r,t}$
Time-window length	$k \in \mathcal{K}_t = \{0, 1, 2, \ldots, K^{\max}_t\}$	$p^{\mathrm{K}}_{k,t}$

- ***Decisions*** in which service to use for a freight, if any, at each stage.
- ***Objective*** to minimize a cost function over all stages.

MARKOV DECISION PROCESS MODEL

STATE AND DECISION AT EACH STAGE

- The ***state*** describes all freights known at a stage:

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

- The ***decision*** describes all freights assigned to the services at a stage:

$$x_t = [x_{i,j,d,k,t}]_{\forall (i,j) \in \mathcal{A}_t, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t} \tag{2a}$$

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

$$\sum_{j \in \mathcal{N}_t^{\mathrm{I}} \cup \{d\}} x_{i,j,d,k,t} \leq F_{i,d,0,k,t}, \quad \forall i \in \mathcal{N}_t^{\mathrm{O}} \cup \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t \tag{2b}$$

$$x_{i,d,d,L^{\mathrm{A}}_{i,d,t},t} \geq F_{i,d,0,L^{\mathrm{A}}_{i,d,t},t}, \quad \forall (i,d) \in \mathcal{A}_t^{\mathrm{D}}, k \in \mathcal{K}_t \tag{2c}$$

$$x_{i,j,d,k,t} = 0, \quad \forall (i,j) \in \mathcal{A}_t, d \in \mathcal{N}_t^{\mathrm{D}}, k \in \mathcal{K}_t | k < M_{i,j,t} + M_{j,d,t} \tag{2d}$$

$$\sum_{d \in \mathcal{N}_t^{\mathrm{D}}} \sum_{k \in \mathcal{K}_t} x_{i,j,d,k,t} \leq Q_{i,j,t}, \quad \forall (i,j) \in \mathcal{A}_t^{\mathrm{I}} \tag{2e}$$

MARKOV DECISION PROCESS MODEL

EXOGENOUS INFORMATION AND TRANSITION FUNCTION

- The ***exogenous information*** describes all freights that arrived between the previous and the current stage:

$$W_t = \left[\widetilde{F}_{i,d,r,k,t}\right]_{\forall i \in \mathcal{N}_t^{\mathrm{O}}, d \in \mathcal{N}_t^{\mathrm{D}}, r \in \mathcal{R}_t, k \in \mathcal{K}_t} \quad (3)$$

- The ***transition function*** describes how the system evolves::

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

$$\vdots$$

$$\begin{aligned} F_{t,i,d,0,k} = F_{t-1,i,d,0,k+1} - \sum_{j \in \mathcal{A}_t} x_{t-1,i,j,d,k+1} + F_{t-1,i,d,1,k} \\ + \sum_{j \in \mathcal{A}_t | M_{j,i,t}=1} x_{t-1,j,i,d,k+M_{j,i,t}}, \\ \forall i \in \mathcal{N}_t^{\mathrm{I}}, d \in \mathcal{N}_t^{\mathrm{D}}, k+1 \in \mathcal{K}_t \end{aligned} \quad (4c)$$

$$\vdots$$

MARKOV DECISION PROCESS MODEL

TRANSITION FUNCTION – A SMALL EXAMPLE

- 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					$F_{d,d,0,0,11}$

MARKOV DECISION PROCESS MODEL

OBJECTIVE AND SOLUTION ALGORITHM

- The ***objective*** is to minimize the expected costs in the horizon:

$$\min_{\pi\in\Pi} \mathbb{E}\left[\sum_{t\in\mathcal{T}} C_t\left(x_t^\pi\right) = \sum_{t\in\mathcal{T}}\sum_{(i,j)\in\mathcal{A}_t}\left(C_{i,j,t}\cdot\sum_{d\in\mathcal{N}_t^{\mathrm{D}}}\sum_{k\in\mathcal{K}_t} x^\pi_{i,j,d,k,t}\right)\middle| S_0\right] \quad (5)$$

- The ***solution*** can be obtained using Bellman's principle of optimality and backward induction:

$$V_t\left(S_t\right) = \min_{x_t^\pi\in\mathcal{X}_t}\left(C_t\left(x_t^\pi\right) + \sum_{\omega\in\Omega_{t+1}} p_\omega^{\Omega_{t+1}}\cdot V_{t+1}\left(S^M\left(S_t, x_t^\pi, \omega\right)\right)\right), \forall S_t\in\mathcal{S} \quad (6)$$

All feasible decisions in a state!

All realizations of the random variables!

All 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

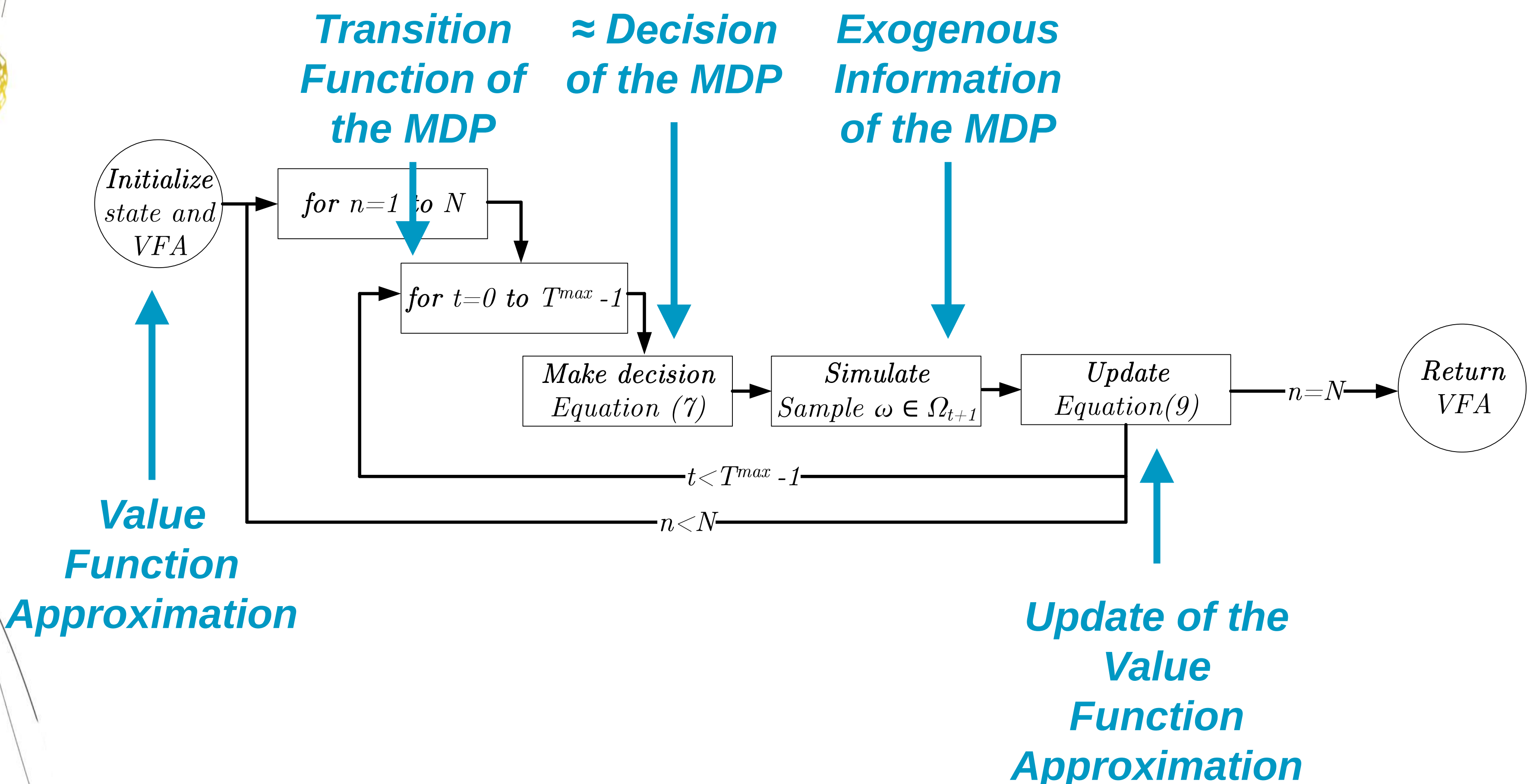
end while

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

A GRAPHICAL REPRESENTATION OF THE ALGORITHM



APPROXIMATE DYNAMIC PROGRAMMING

DECISIONS BASED ON THE VALUE FUNCTION APPROXIMATION

- The ***expected future costs*** are explained, to a certain extent, by the *post-decision state*:

$$V_t\left(S_t\right) = \min_{x_t^\pi \in \mathcal{X}_t} \left(C_t\left(x_t^\pi\right) + \underbrace{\sum_{\omega \in \Omega_{t+1}} p_\omega^{\Omega_{t+1}} \cdot V_{t+1}\left(S^M\left(S_t, x_t^\pi, \omega\right)\right)}\right), \forall S_t \in \mathcal{S} \quad (6)$$

$$V_t^n\left(S_t^n\right) = \min_{x_t^\pi \in \mathcal{X}_t} \left(C_t\left(x_t^\pi\right) + \overline{V}_t^n\left(S_t^{x,n}\right)\right) \quad (7)$$

- For the ***value function approximation*** we use the traditional basis functions approach (i.e., weighted features of a post-decision state):

$$\overline{V}_t^{x,n}\left(S_t^{x,n}\right) = \sum_{a \in \mathcal{A}} \theta_{a,t}^n \phi_a\left(S_t^{x,n}\right) \quad (8)$$

APPROXIMATE DYNAMIC PROGRAMMING

UPDATING THE VALUE FUNCTION APPROXIMATION

- In each iteration, we observe ***a realization of the future costs*** throughout the time horizon.
- We update (i.e., improve) the value function approximation using a ***recursive least squares (LSQ) method for non-stationary data*** method:

Observed Feature

$$\theta^{n}_{a,t} = \theta^{n-1}_{a,t} - H_n \phi_a\left(S^{x,n}_t\right)\left(\overline{V}^{n-1}_{t-1}\left(S^{x,n}_{t-1}\right) - \widehat{v}^{n}_t\right) \tag{9}$$

LSQ Optimization Matrix

Prediction Error

APPROXIMATE DYNAMIC PROGRAMMING

DECISIONS BASED ON A SECOND TYPE OF VALUE FUNCTION APPROXIMATION

- A second type of value function approximation ***using basis functions and sampling*** future costs of a fixed heuristic:

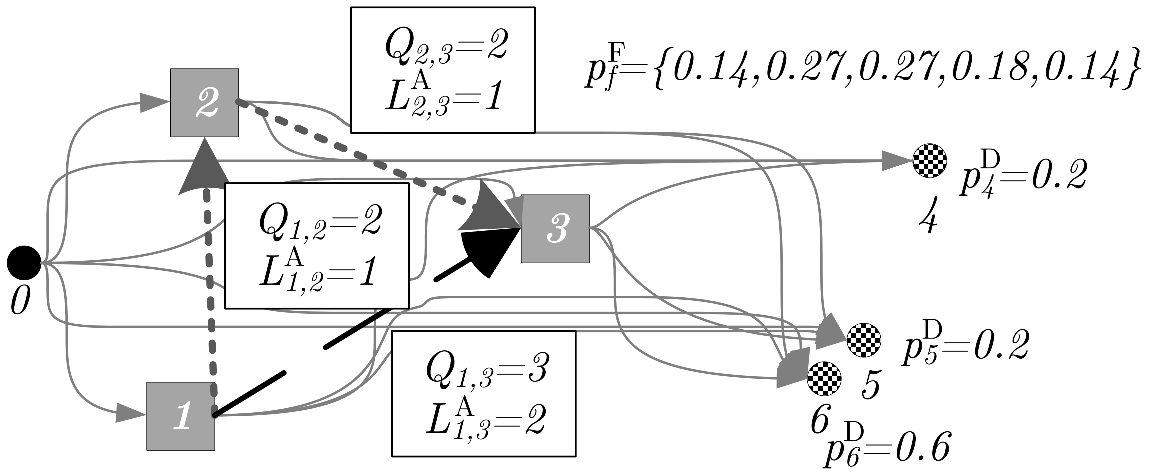
$$\overline{V}_t^{x,n}\left(S_t^{x,n}\right) = \alpha \sum_{a \in \mathcal{A}} \theta_{a,t}^{n} \phi_a\left(S_t^{x,n}\right) + (1-\alpha)\,\overline{C}_t^{n}\left(S_t^{x,n}\right) \tag{10}$$

- The ***policy*** resulting from both value function approximations is the function of the post-decision features with the weights of the last iteration:

$$x_t^{\pi} = \arg\min \left(C_t\left(x_t^{\pi}\right) + \sum_{a \in \mathcal{A}\left(S_t^{x}\right)} \theta_{a,t}^{N} \phi_a\left(S_t^{x}\right) \right) \tag{11}$$

NUMERICAL EXPERIMENTS

- ***Explore*** the value of our two ADP designs.
- Very small network in a 15 day horizon.
- Three time-window profiles: (1) long, (2) intermediate and (3) short.



	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

- Simulation study using 10 different initial states per instance.
- Four different planning policies:
  - ***Benchmark***: balance between consolidation and postponement using “savings” of intermodal services in the shortest path from origin to destination.
  - ***ADP 1***: weighted features using traditional learning of weights.
  - ***ADP 2***: weighted features using sampling while learning at early iterations.
  - ***Sampling***: using Monte Carlo simulation to estimate future costs of all feasible decisions.

NUMERICAL EXPERIMENTS

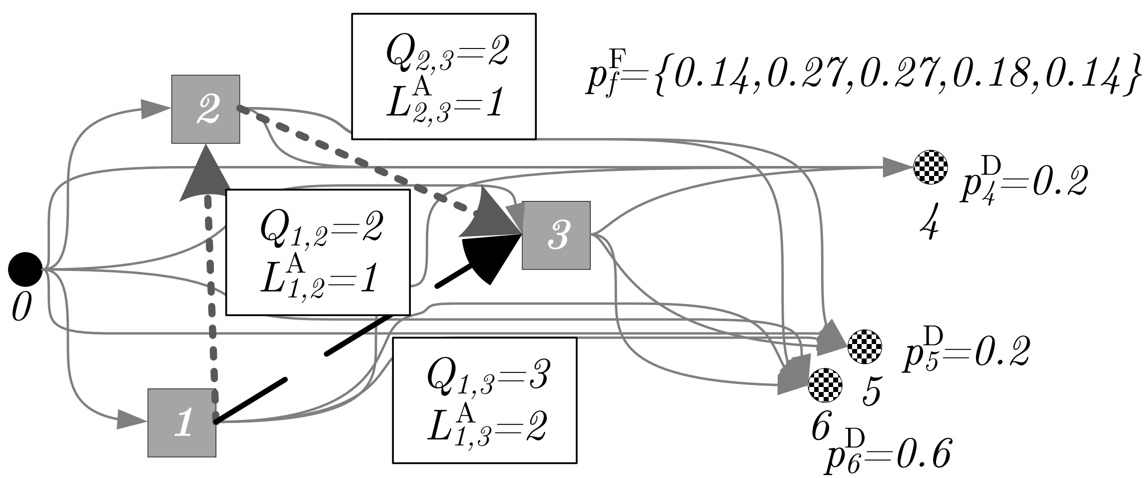
Table 1. Results for Instance I_1

State	Total Freights	Benchmark Solution	Time (s)	ADP 1 Solution	Time (s)	ADP 2 Solution	Time (s)	Sampling Solution	Time (s)
1	4	12221	0.92	-13.6%	29.94	-33.0%	101.31	-43.3%	688.29
2	7	14684	0.94	-12.8%	52.06	-32.7%	96.67	-39.9%	1687.18
3	5	13042	0.92	-13.1%	31.68	-27.5%	81.46	-41.5%	827.15
4	6	13863	0.94	-12.3%	32.99	-25.9%	81.42	-39.0%	832.67
5	6	13863	0.91	-12.0%	108.62	-30.0%	111.21	-42.3%	1356.80
6	6	13863	0.94	-10.4%	102.12	-31.3%	67.58	-42.9%	1317.73
7	5	13042	0.94	-12.6%	40.26	-23.4%	81.99	-41.5%	893.59
8	4	12221	0.92	-14.7%	37.44	-25.0%	78.41	-38.9%	547.66
9	2	10579	0.94	-14.9%	31.72	-29.9%	45.13	-42.4%	611.18
10	5	13042	1.01	-11.2%	30.81	-32.9%	42.92	-40.6%	727.28

NUMERICAL EXPERIMENTS

Table 2. Average results for Instance I_2 and I_3

Instance	Benchmark Solution	Time (s)	ADP 1 Solution	Time (s)	ADP 2 Solution	Time (s)	Sampling Solution	Time (s)
I_2	11078	0.88	-5.2%	10.52	-9.8%	13.89	-31.2%	217.19
I_3	12874	1.01	2.9%	3.19	0.4%	2.31	-3.3%	36.95



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

WHAT TO REMEMBER

- We developed an ***MDP model and ADP algorithm to select services for freights in a synchromodal network*** that consider stochastic freight arrival and performance over time.

- The policy performance of the weighted features ***is improved using sampling during the learning phase*** of the ADP algorithm.

- For realistic networks, further research in the ***value function approximation and decision making*** within the ADP algorithm is necessary for guaranteeing the best policies.

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THANKS FOR YOUR ATTENTION!

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