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DYNAMIC FREIGHT SELECTION FOR REDUCING LONG-HAUL ROUND TRIP COSTS

Arturo E. Pérez Rivera & Martijn Mes

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

VeRoLog 2015 – Vienna, Austria
Wednesday, June 10th, 2015

OUTLINE

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- Problem definition
- Solution approaches
  - *Markov Model*
  - *Approximate Dynamic Programming*
- Preliminary numerical results
- Conclusions


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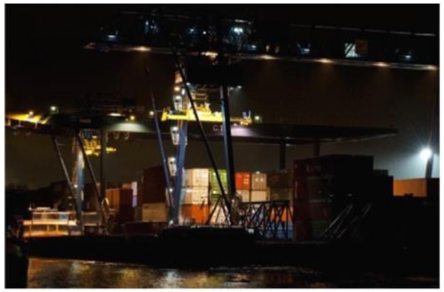
CHINA SHIPPING




FIGEE
LYS-LINE
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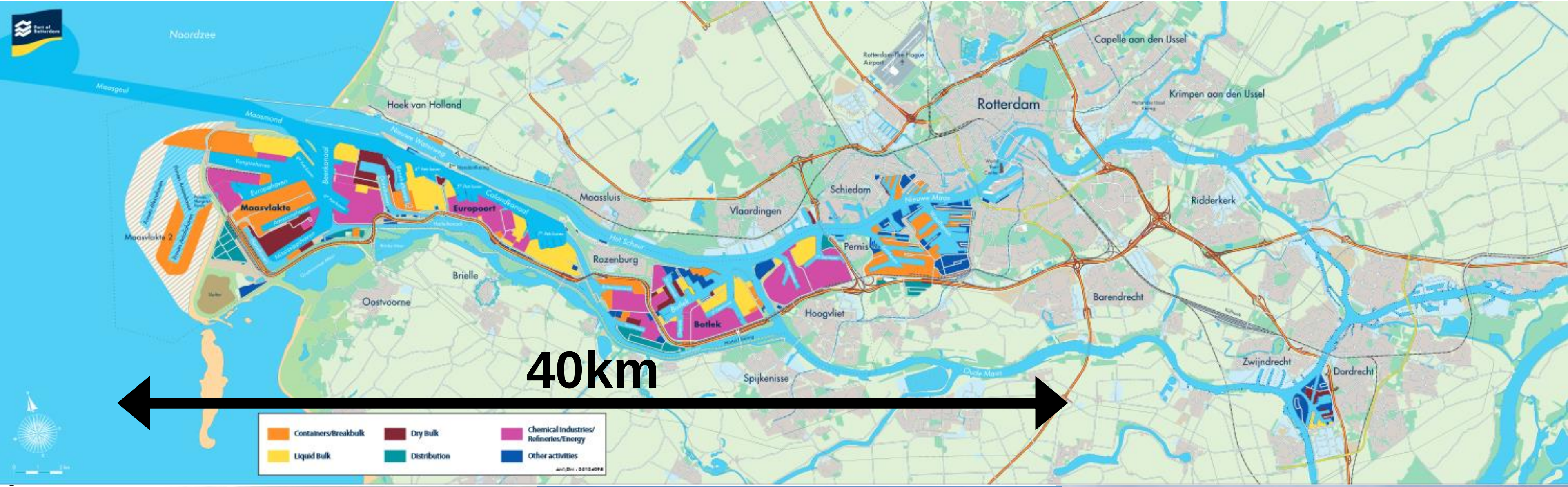
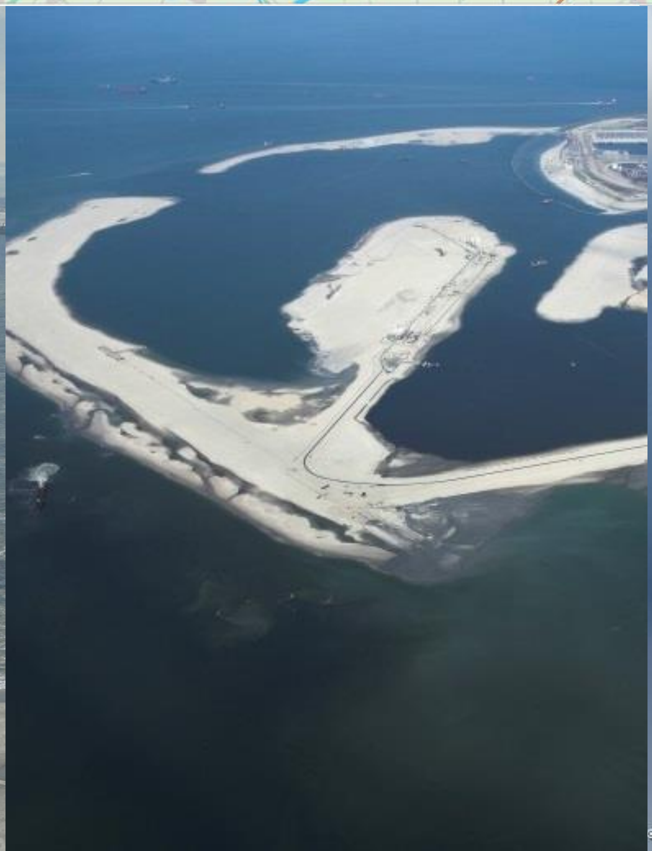
INTERMODAAL TRANSPORT

MOTIVATION
INDUSTRY IN TWENTE

CTT INTERMODAAL TRANSPORT

- Transportation of ***containers to and from Rotterdam***.
- Long-haul of the transportation is done ***using barges through Dutch waterways***.
- More than 150k containers per year (more than 300 per day).
- There are around 30 container terminals in Rotterdam.


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

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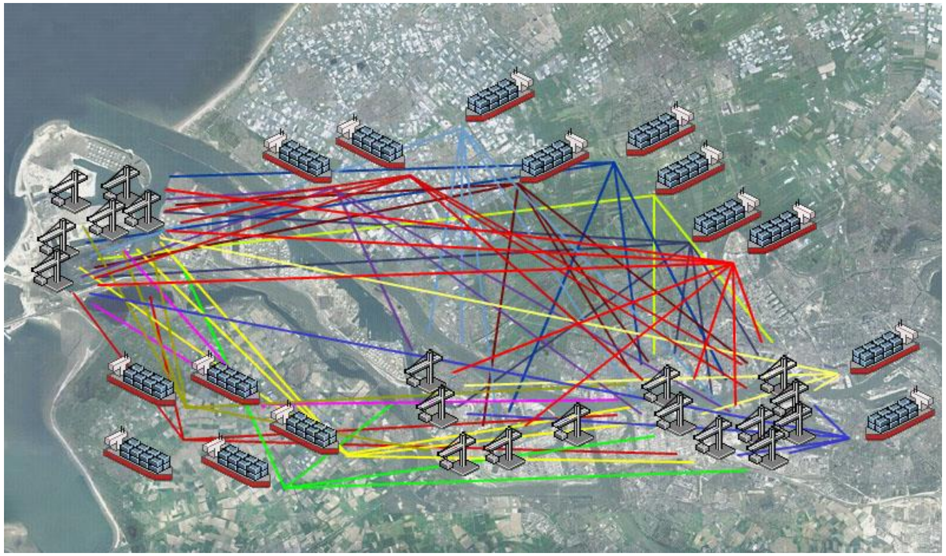
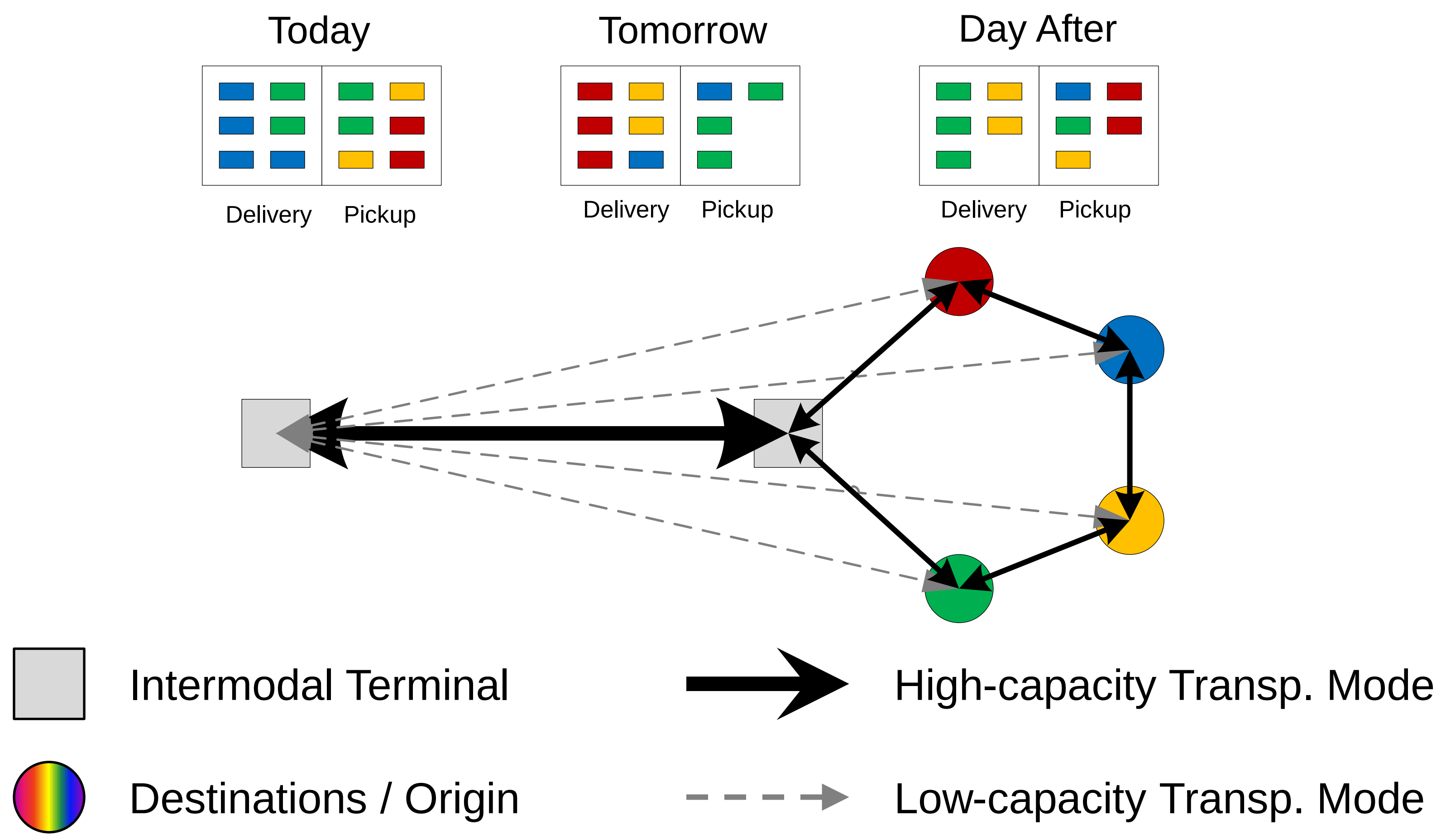
MOTIVATION

THE PROBLEM IN ROTTERDAM

- Barges spend around two days ***waiting and sailing between terminals in Rotterdam*** due to changes in appointments (e.g., unavailable berths, deep sea vessel arrival, etc.)



PROBLEM DEFINITION
DYNAMIC FREIGHT SELECTION



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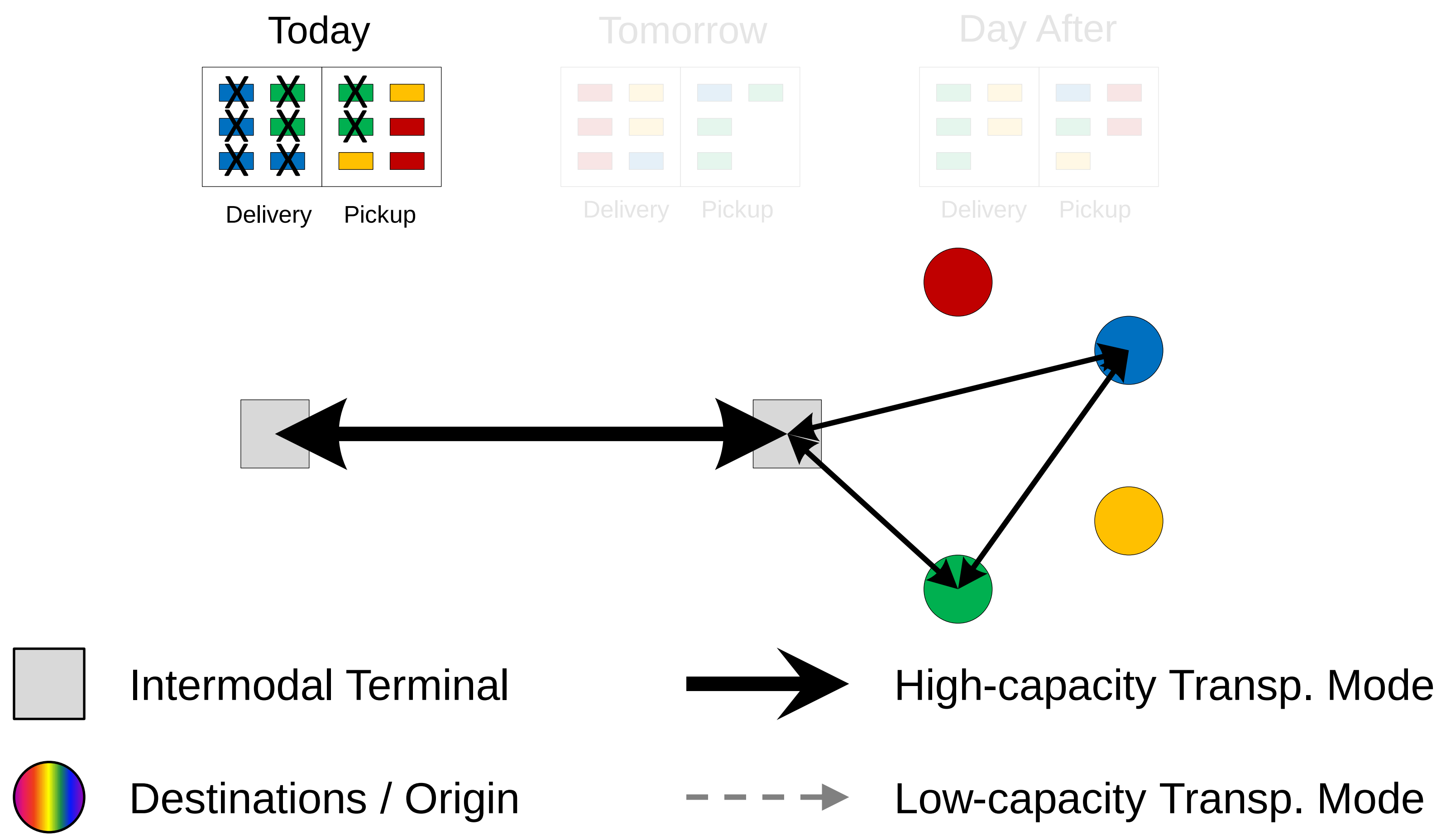
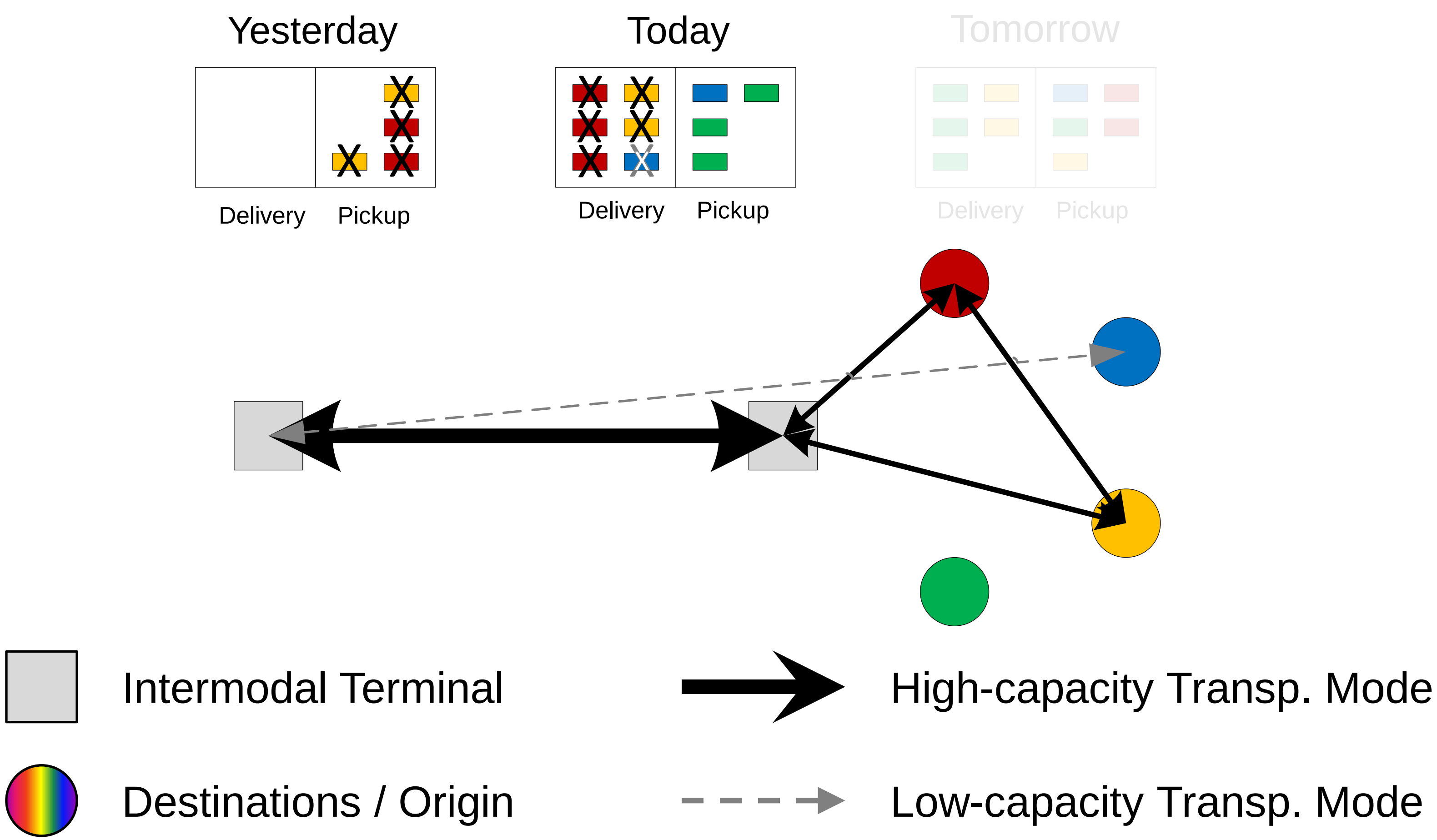
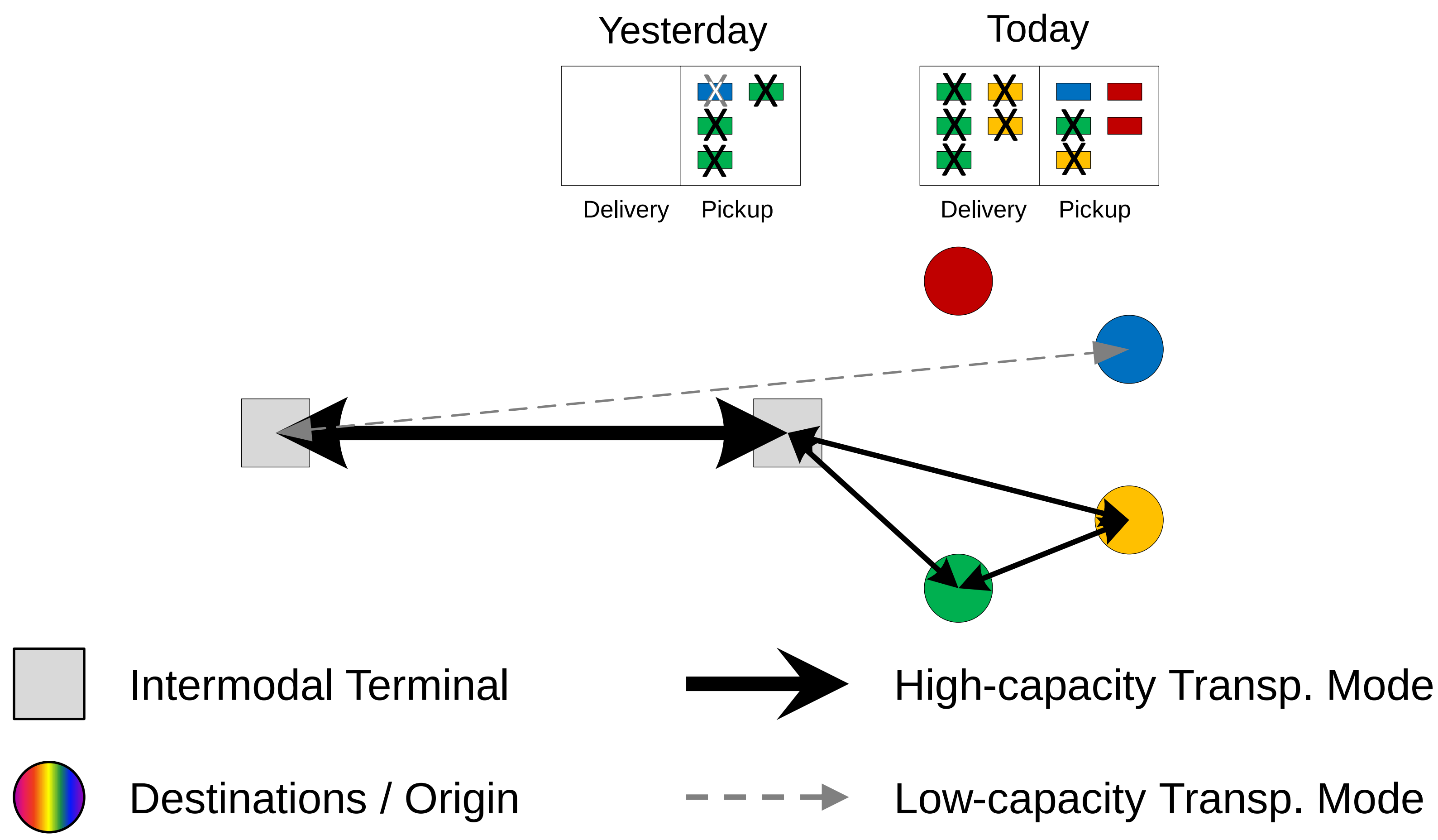


PROBLEM DEFINITION

DYNAMIC FREIGHT SELECTION

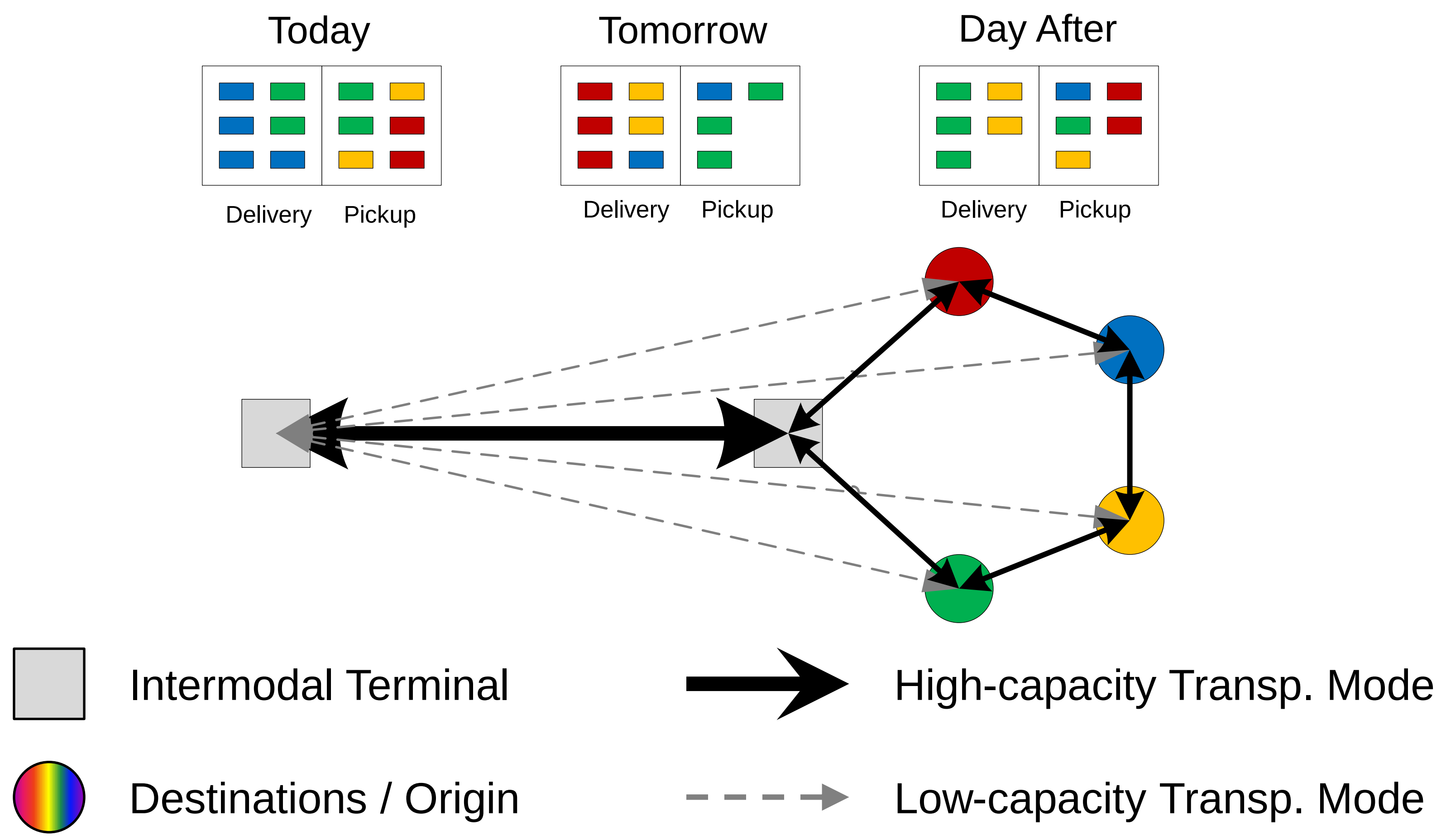


PROBLEM DEFINITION
DYNAMIC FREIGHT SELECTION



PROBLEM DEFINITION

DYNAMIC FREIGHT SELECTION



SOLUTION APPROACH
THE OPTIMIZATION PROBLEM

Main Parameters	Set	Probabilities
Planning horizon	$\mathcal{T} = \{0, 1, 2, ..., T^{max} - 1\}$	—
Number of delivery freights	$\mathcal{F} \subseteq \mathbb{Z}^+$	$p_f^F \; \forall f \in \mathcal{F}$
Number of pickup freights	$\mathcal{G} \subseteq \mathbb{Z}^+$	$p_g^G \; \forall g \in \mathcal{G}$
Last-mile destinations	$\mathcal{D}$	$p_d^{FD}, p_d^{GD} \; \forall d \in \mathcal{D}$
Release-days	$\mathcal{R} = \{0, 1, 2, ..., R^{max}\}$	$p_r^{FR}, p_r^{GR} \; \forall r \in \mathcal{R}$
Time-window lengths	$\mathcal{K} = \{0, 1, 2, ..., K^{max}\}$	$p_k^{FK}, p_k^{GK} \; \forall k \in \mathcal{K}$

Decision: Which freights to consolidate in the high-capacity vehicle each period of the horizon?

Objective: To reduce the expected total costs over the horizon.

SOLUTION APPROACH
THE MARKOV MODEL

The ***state*** $\boldsymbol{S}_t$ is the vector of delivery and pickup freights that are known at a given stage:

$$\boldsymbol{S}_t = [(F_{t,d,r,k}, G_{t,d,r,k})]_{\forall d\in\mathcal{D}, r\in\mathcal{R}, k\in\mathcal{K}}\,, \ \forall t \in \mathcal{T} \qquad (1)$$

The ***arriving information*** $\boldsymbol{W}_t$ is the vector of delivery and pickup freights that arrived from outside the system between periods $t-1$ and t :

$$\boldsymbol{W}_t = \left[\left(\widetilde{F}_{t,d,r,k}, \widetilde{G}_{t,d,r,k}\right)\right]_{\forall d\in\mathcal{D}, r\in\mathcal{R}, k\in\mathcal{K}}\,, \ \forall t \in \mathcal{T} \qquad (2)$$

SOLUTION APPROACH

THE MARKOV MODEL

The ***decision*** $\boldsymbol{x}_t$ is the vector of delivery and pickup freights, which have been released, that are consolidated in the high-capacity vehicle without exceeding its capacity Q:

$$\boldsymbol{x}_t = \left[\left(x^F_{t,d,k}, x^G_{t,d,k}\right)\right]_{\forall d \in \mathcal{D}, k \in \mathcal{K}} \Big| \boldsymbol{S}_t, \ \forall t \in \mathcal{T} \tag{3a}$$

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

$$0 \leq x^F_{t,d,k} \leq F_{t,d,0,k}, \ \forall d \in \mathcal{D}, k \in \mathcal{K} \tag{3b}$$

$$0 \leq x^G_{t,d,k} \leq G_{t,d,0,k}, \ \forall d \in \mathcal{D}, k \in \mathcal{K} \tag{3c}$$

$$\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} x^F_{t,d,k} \leq Q, \tag{3d}$$

$$\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} x^G_{t,d,k} \leq Q, \tag{3e}$$

$$x^F_{t,d,k}, x^G_{t,d,k} \in \mathbb{Z}^+ \tag{3f}$$

SOLUTION APPROACH

THE MARKOV MODEL

The ***transition function*** S^M captures the evolution of the system from one period of the horizon to the next one:

$$\boldsymbol{S}_t = S^M\left(\boldsymbol{S}_{t-1}, \boldsymbol{x}_{t-1}, \boldsymbol{W}_t\right), \ \forall t \in \mathcal{T} | t > 0 \tag{4a}$$

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

$$F_{t,d,0,k} = F_{t-1,d,0,k+1} - x^F_{t-1,d,k+1} + F_{t-1,d,1,k} + \widetilde{F}_{t,d,0,k}, \ \Big| k < K^{max} \tag{4b}$$

$$F_{t,d,r,k} = F_{t-1,d,r+1,k} + \widetilde{F}_{t,d,r,k}, \ \Big| r \geq 1 \tag{4c}$$

$$F_{t,d,r,K^{max}} = \widetilde{F}_{t,d,r,K^{max}}, \tag{4d}$$

$$G_{t,d,0,k} = G_{t-1,d,0,k+1} - x^G_{t-1,d,k+1} + G_{t-1,d,1,k} + \widetilde{G}_{t,d,0,k}, \ \Big| k < K^{max} \tag{4e}$$

$$G_{t,d,r,k} = G_{t-1,d,r+1,k} + \widetilde{G}_{t,d,r,k}, \ \Big| r \geq 1 \tag{4f}$$

$$G_{t,d,r,K^{max}} = \widetilde{G}_{t,d,r,K^{max}}, \tag{4g}$$

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

SOLUTION APPROACH

THE MARKOV MODEL

The ***cost function*** $C(S_t, x_t)$ defines the costs at a given period of the horizon as a function of the state and the decision taken:

$$C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) = \sum_{\mathcal{D}' \subseteq \mathcal{D}} \left(C_{\mathcal{D}'} \cdot \prod_{d' \in \mathcal{D}'} y_{t,d'} \cdot \prod_{d'' \in \mathcal{D} \setminus \mathcal{D}'} \left(1 - y_{t,d''}\right) \right) + \sum_{d \in \mathcal{D}} \left(B_d \cdot z_{t,d}\right) \tag{5a}$$

s.t.

$$y_{t,d} = \begin{cases} 1, & \text{if } \sum_{k \in \mathcal{K}} \left(x^F_{t,d,k} + x^G_{t,d,k} \right) > 0 \\ 0, & \text{otherwise} \end{cases}, \ \forall d \in \mathcal{D} \tag{5b}$$

$$z_{t,d} = F_{t,d,0,0} - x^F_{t,d,0} + G_{t,d,0,0} - x^G_{t,d,0}, \ \forall d \in \mathcal{D} \tag{5c}$$

SOLUTION APPROACH
THE MARKOV MODEL

The ***objective*** is to reduce the total expected costs over the horizon, given an initial state:

$$\min_{\pi \in \Pi} \mathbb{E} \left\{ \sum_{t \in \mathcal{T}} C\left(\boldsymbol{S}_t, \boldsymbol{x}_t^{\pi}\right) \middle| \boldsymbol{S}_0 \right\} \tag{6}$$

Using Bellman's principal of optimality, the Markov model can be solved with the backward recursion:

$$\begin{aligned} V_t\left(\boldsymbol{S}_t\right) &= \min_{\boldsymbol{x}_t} \left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) + \mathbb{E}\left\{V_{t+1}\left(\boldsymbol{S}_{t+1}\right)\right\}\right), \forall t \in \mathcal{T} \\ &= \min_{\boldsymbol{x}_t} \left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) + \mathbb{E}\left\{V_{t+1}\left(S^M\left(\boldsymbol{S}_t, \boldsymbol{x}_t, \boldsymbol{W}_{t+1}\right)\right)\right\}\right) \\ &= \min_{\boldsymbol{x}_t} \left(C\left(\boldsymbol{S}_t, \boldsymbol{x}_t\right) + \sum_{\omega \in \Omega} \left(p_\omega^\Omega \cdot V_{t+1}\left(S^M\left(\boldsymbol{S}_t, \boldsymbol{x}_t, \omega\right)\right)\right) \right) \end{aligned} \tag{7}$$

1

2

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SOLUTION APPROACH

APPROXIMATE DYNAMIC PROGRAMMING

Approximate Dynamic Programming (ADP) is an approach that uses algorithmic manipulations to solve 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.

SOLUTION APPROACH

APPROXIMATE DYNAMIC PROGRAMMING

A ***post-decision state*** $\boldsymbol{S}_t^{n,x}$ is used as a single estimator for all possible realizations of the random variables.

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

A ***Value Function Approximation (VFA)*** $\bar{V}_t^n(\boldsymbol{S}_t^{n,x})$ for the post-decision state is used to capture the future costs:

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

The approximation of Bellman's equations in ADP:

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

SOLUTION APPROACH

APPROXIMATE DYNAMIC PROGRAMMING

Use a weighted combination of ***state-features*** for approximating the value of a state (i.e., VFA function).

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

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

Assumption: There are specific characteristics of a post-decision state which significantly influence its future costs!

SOLUTION APPROACH

APPROXIMATE DYNAMIC PROGRAMMING

Examples of state-features:

1. Sum of delivery and pickup freights that are not yet released for transport, per destination ***(i.e. future freights)***.
2. Sum of delivery and pickup 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 delivery or pickup freights ***(i.e., must-visit destination)***.
4. Some power function (e.g., ^2) of each state variable ***(i.e., non-linear components in costs)*** .

SOLUTION APPROACH
APPROXIMATE DYNAMIC PROGRAMMING

The VFA must be ***updated*** after every iteration n with a function $U^V(\cdot)$.

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

In our case, the weights are updated through a recursive least squares method for non-stationary data[1]:

$$\theta^{n}_{a} = \theta^{n-1}_{a} \underbrace{- (G^{n})^{-1}}_{3} \underbrace{\phi_{a}(\boldsymbol{S}^{n,x}_{t})}_{2} \underbrace{\left(\bar{V}^{n-1}_{t-1}(\boldsymbol{S}^{n,x}_{t-1}) - \hat{v}^{n}_{t}\right)}_{1}$$

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

PRELIMINARY NUMERICAL RESULTS

ADP FOR THE DYNAMIC FREIGHT SELECTION IN ROUND-TRIPS

Two preliminary experiments:

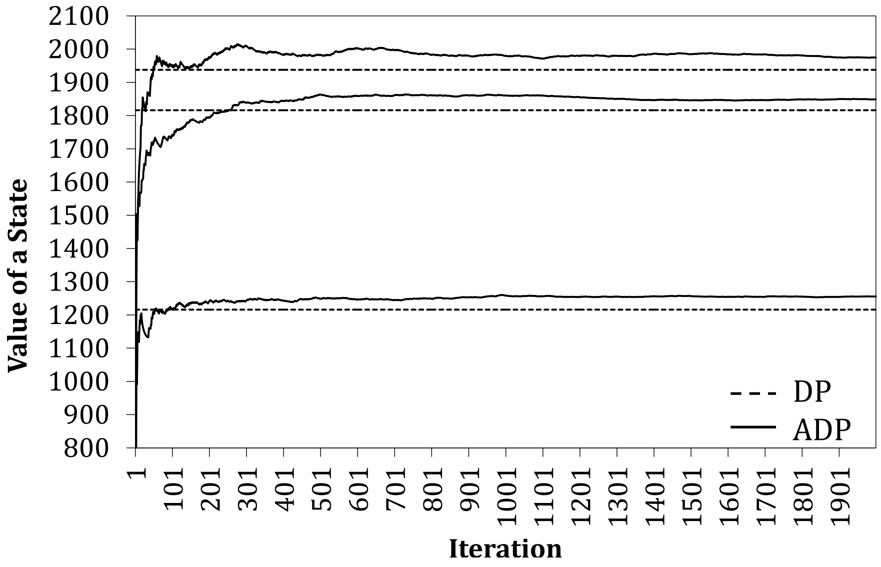
1. ***Convergence*** Test (one freight - 19,323 states)
2. ***Policy-performance*** Test (two freights - 8,317,456 states)

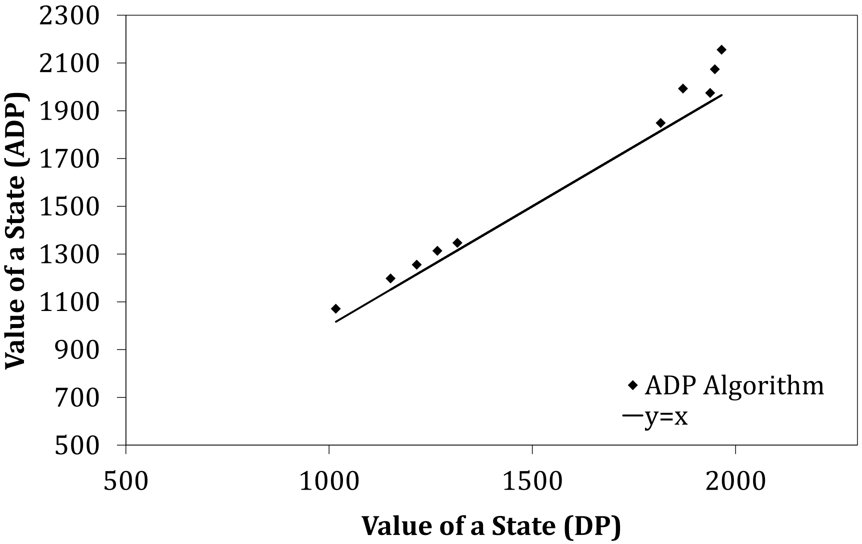
Input Parameter	Values
Freights arriving per day (F, G)	$\{1, 2\}$
$\rightarrow$Probability (p_f^F, p_g^G)	$\{0.8, 0.2\}$
Destinations (D)	$\{1, 2, 3\}$
$\rightarrow$Probability (p_d^{FD}, p_d^{GD})	$\{0.1, 0.8, 0.1\}$
Release-days (R)	$\{0\}$
$\rightarrow$Probability (p_r^{FR}, p_r^{GR})	$\{1\}$
Time-window lengths (K)	$\{0, 1, 2\}$
$\rightarrow$Probability (p_k^{FK}, p_k^{GK})	$\{0.2, 0.3, 0.5\}$
Planning horizon (T^{Max})	5
Long-haul capacity (Q)	2

PRELIMINARY NUMERICAL RESULTS

ADP FOR THE DYNAMIC FREIGHT SELECTION IN ROUND-TRIPS

Convergence Test:

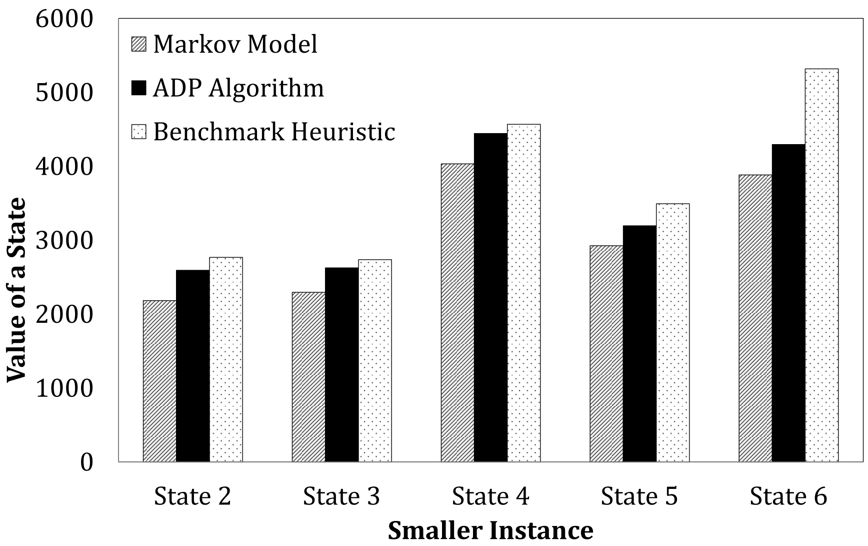


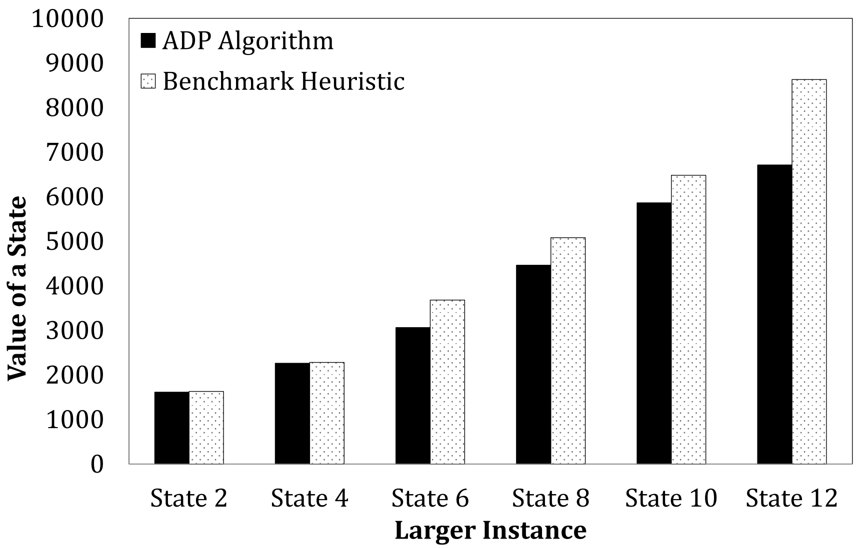


PRELIMINARY NUMERICAL RESULTS

ADP FOR THE DYNAMIC FREIGHT SELECTION IN ROUND-TRIPS

Policy-performance Test:





CONCLUSIONS

- “Looking” into future freight consolidation, through a Markov model, pays off when costs depend on the combination of destinations and the transport capacity is limited.

- Approximate Dynamic Programming (ADP) is an appropriate method for solving large Markov models as long as future costs can be estimated accurately.

- ADP can be used to obtain managerial insights in how destination-combination costs and time-windows influence overall performance.

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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