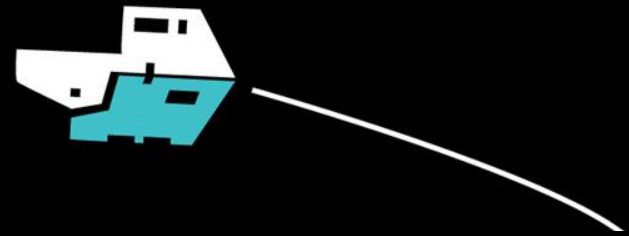
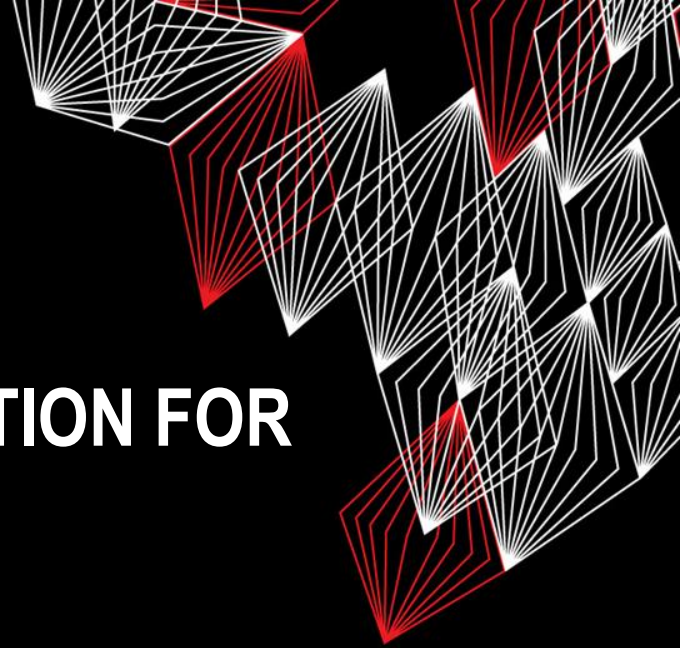


UNIVERSITY OF TWENTE.

LONG-HAUL FREIGHT SELECTION FOR LAST-MILE COST REDUCTION

Arturo E. Pérez Rivera & Martijn Mes

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

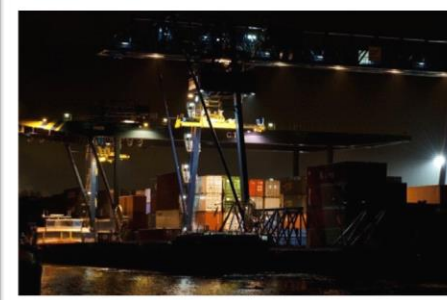


*INFORMS Annual Meeting 2014
Tuesday, November 11th, San Francisco, CA*



OUTLINE

- Case introduction
- ● The long-haul freight selection problem
- ● ● Solution approaches
 - *Mixed-Integer Linear Programming*
 - *Dynamic Programming*
 - *Approximate Dynamic Programming*
- ● ● ● Our approach
- What to remember

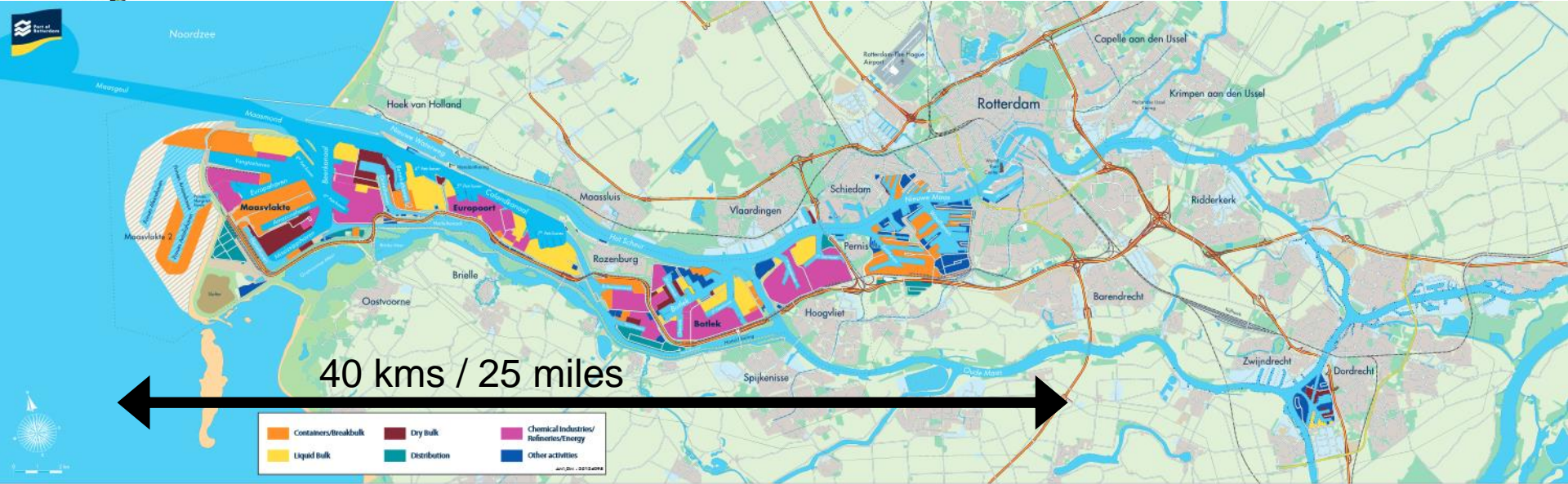


THE COMPANY



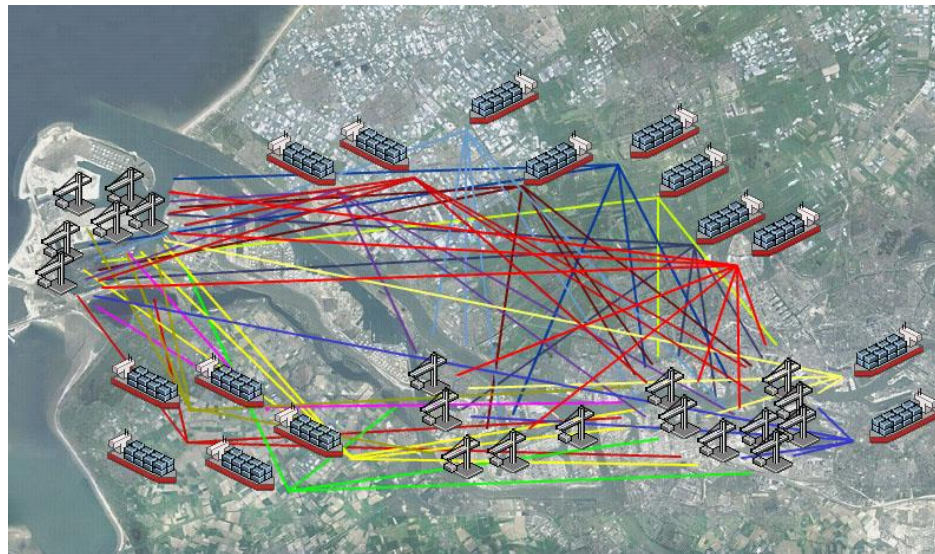
- Core business is the transportation of *containers to and from Rotterdam*.
- Long-haul of the transportation is done *using barges through Dutch waterways*.
- More than 150k containers per year (more than 300 per day).
- There are 30 terminals regularly visited in Rotterdam.



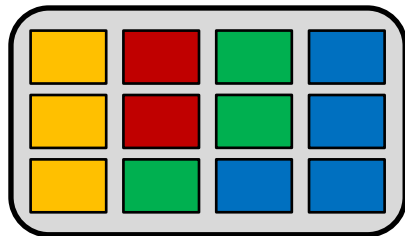


THE COMPANY'S COMPLAINT

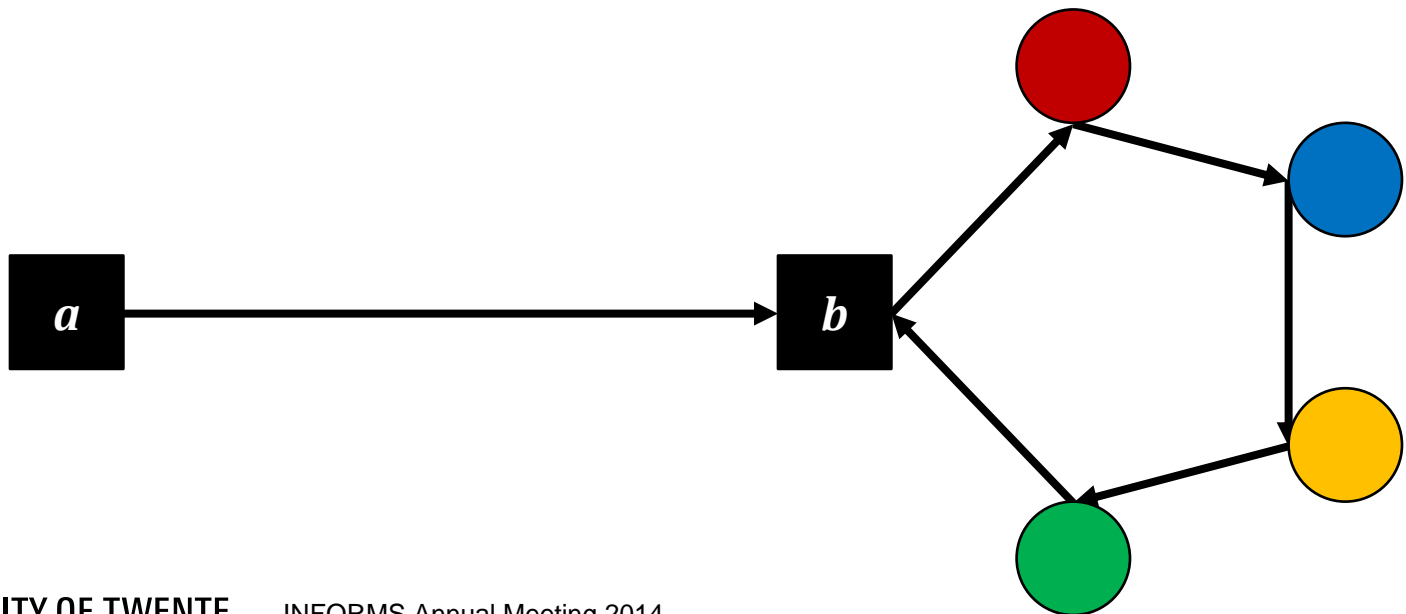
- Barges spend around two days *waiting and sailing between terminals in Rotterdam* due to changes in appointments (e.g., unavailable berths, deep sea vessel arrival, etc.)



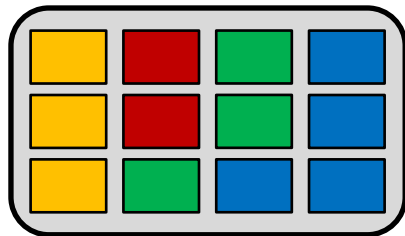
THE LONG-HAUL FREIGHT SELECTION PROBLEM



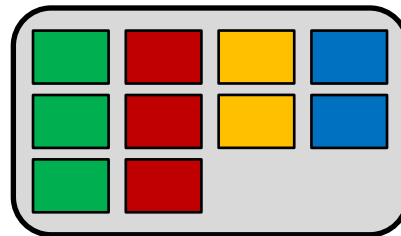
Today



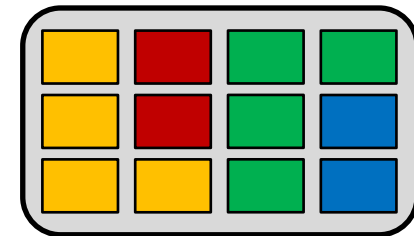
THE LONG-HAUL FREIGHT SELECTION PROBLEM



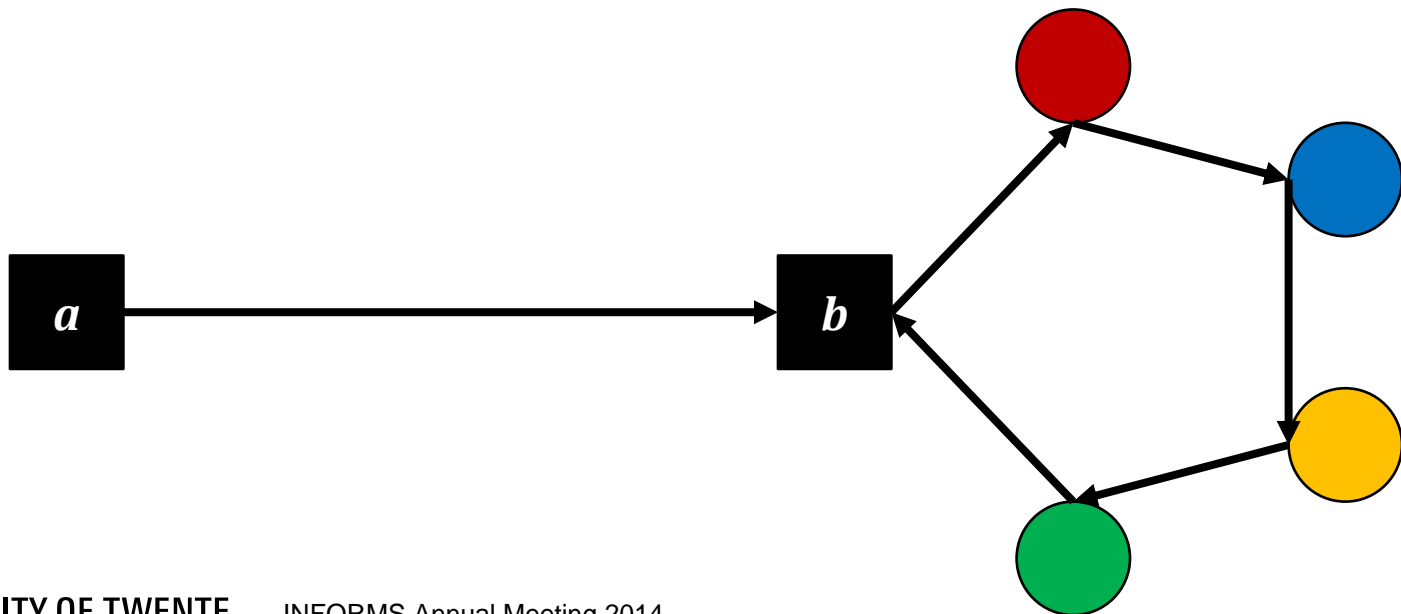
Today



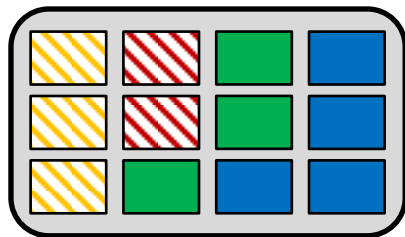
Tomorrow



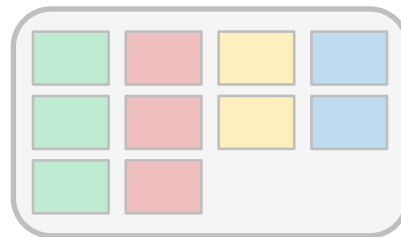
Day after



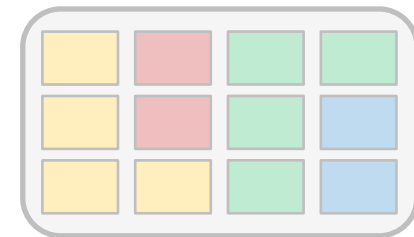
THE LONG-HAUL FREIGHT SELECTION PROBLEM



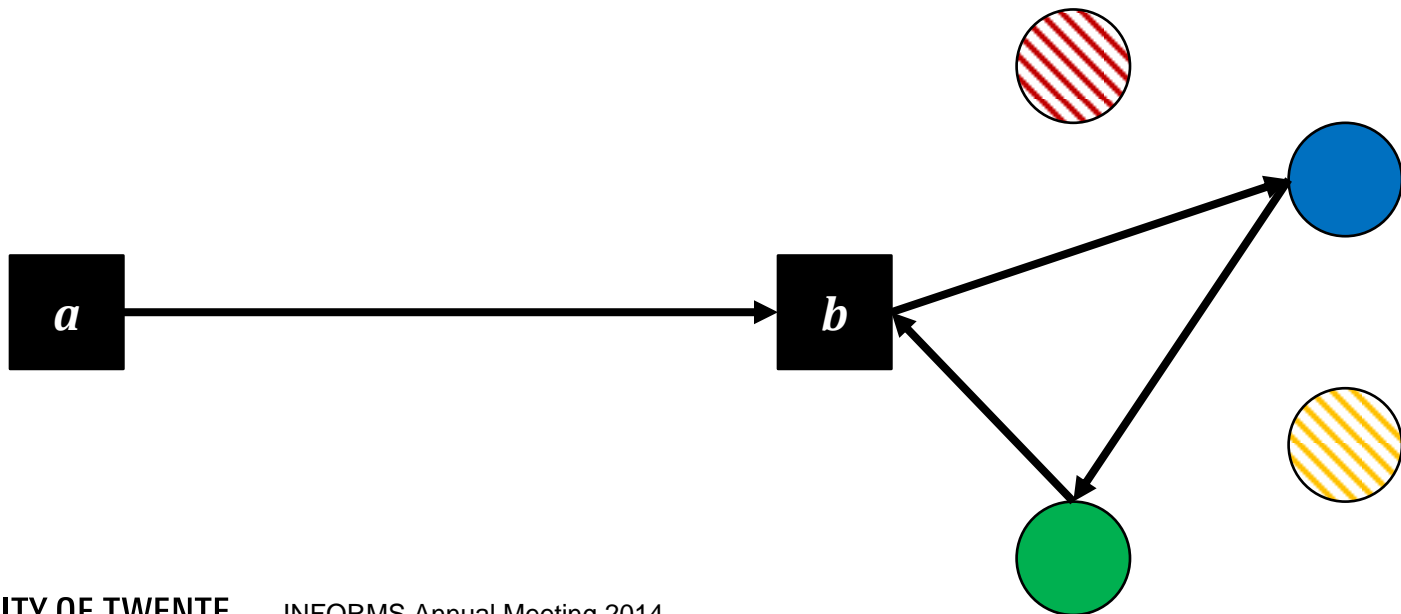
Today



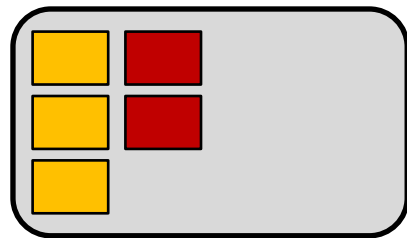
Tomorrow



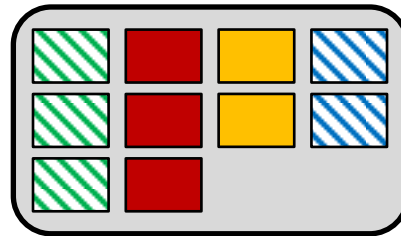
Day after



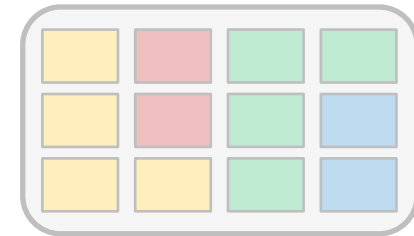
THE LONG-HAUL FREIGHT SELECTION PROBLEM



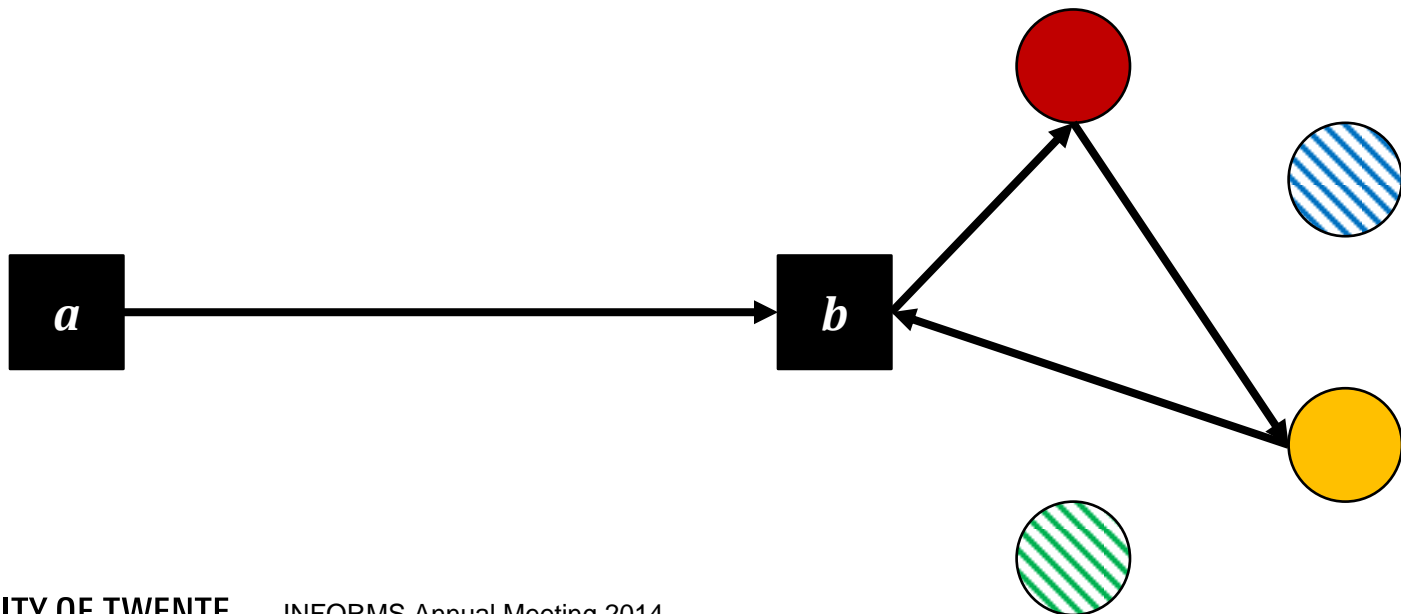
Today



Tomorrow



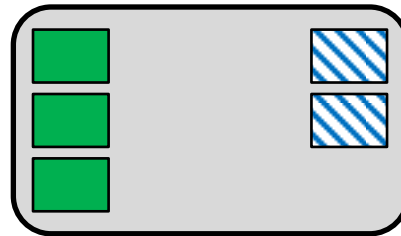
Day after



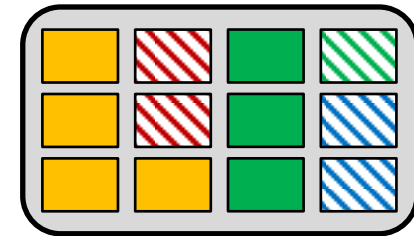
THE LONG-HAUL FREIGHT SELECTION PROBLEM



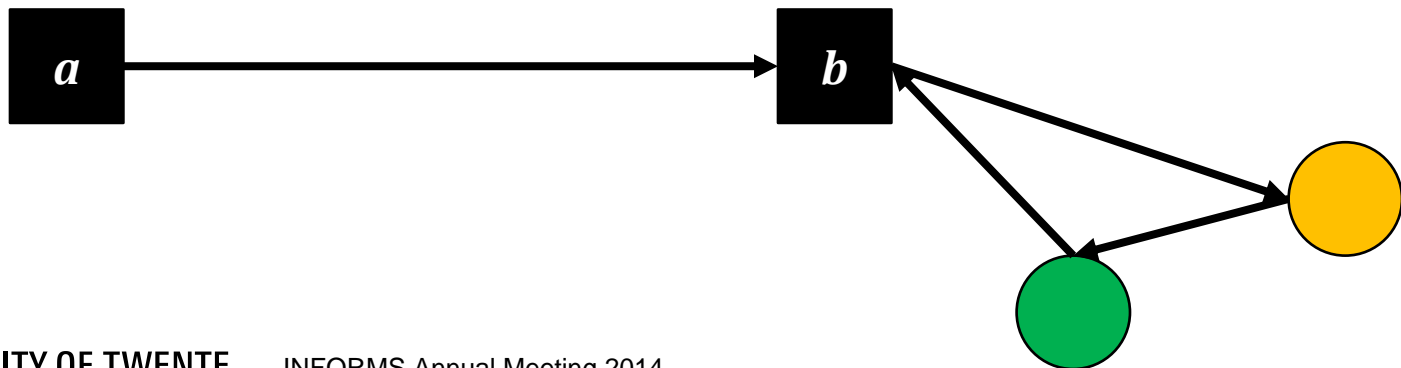
Today



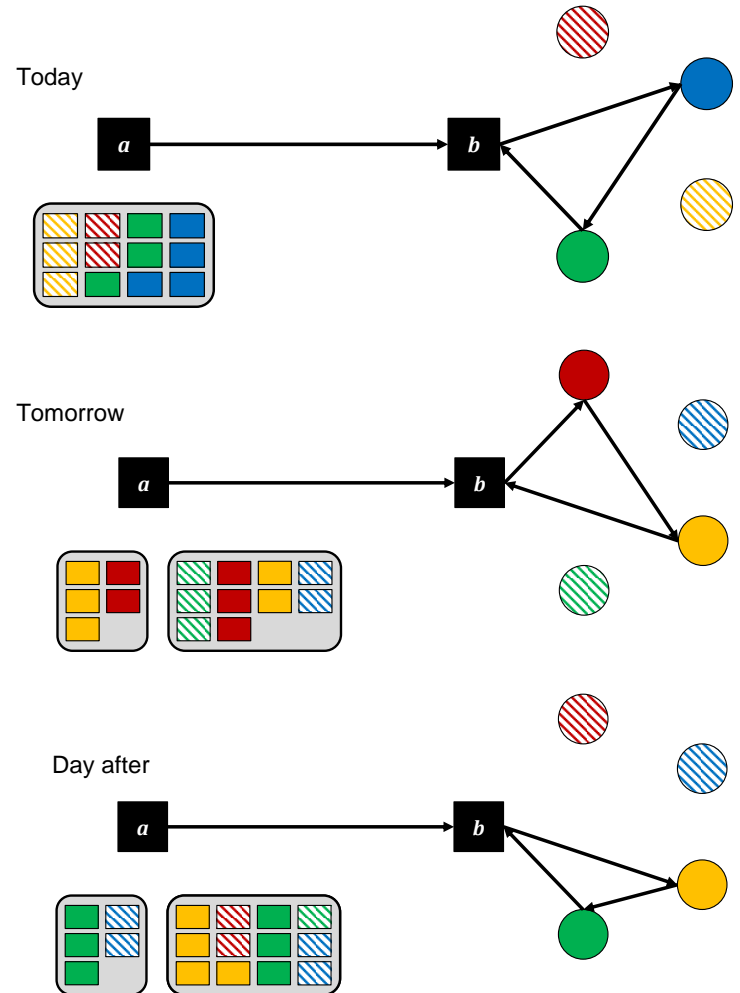
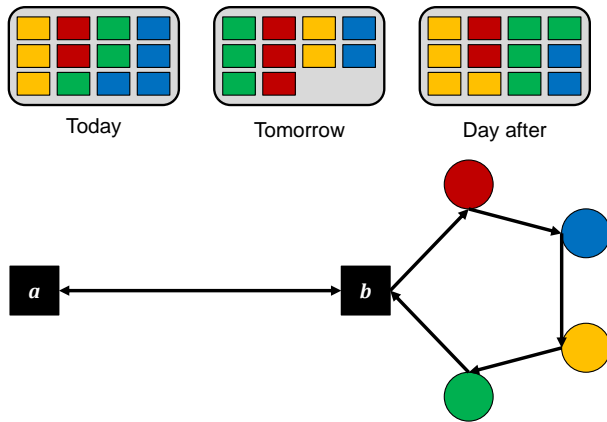
Tomorrow



Day after




THE LONG-HAUL FREIGHT SELECTION PROBLEM

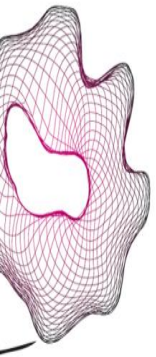




PROBLEM FORMULATION

What are our problem characteristics?

- Discrete and finite planning horizon $t \in \mathcal{T}$
 - Set of freights $f \in \mathcal{F}$
 - Release-date $r \in \mathcal{R}$
 - Due-date $k \in \mathcal{K}$
 - Destination $d \in \mathcal{D}$
 - Cost per subset of destinations via barge $C_{\mathcal{D}'} \in \mathbb{R}^+, \forall \mathcal{D}' \subseteq \mathcal{D}$
 - Cost of direct transport via truck $B_d \in \mathbb{R}^+, \forall d \in \mathcal{D}$
 - Capacity of the barge $Q \in \mathbb{N}$
- 



PROBLEM FORMULATION

Assumptions and constraints:

- One barge sails per time unit (decision moment)
- Barge has a maximum capacity.
- Each freight consists of one unit (i.e., container).
- Each freight must be transported after its release-date and before its due-date.
- There is an unlimited number of trucks for the direct option.



MIXED-INTEGER LINEAR PROGRAMMING MODEL

$$\begin{aligned} & \min Z \\ & \text{s.t.} \\ Z = & \sum_{t \in \mathcal{T}} \sum_{\mathcal{D}' \subseteq \mathcal{D}} \left(C_{\mathcal{D}'} \cdot \prod_{d' \in \mathcal{D}'} y_{d',t} \cdot \prod_{d'' \in \mathcal{D}_t \setminus \mathcal{D}'} (1 - y_{d'',t}) \right) + \sum_{t \in \mathcal{T}} \sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} (B_d \cdot L_{f,d} \cdot v_{f,t}) \end{aligned} \quad (1)$$

$$\sum_{f \in \mathcal{F}} x_{f,t} \leq Q, \forall t \in \mathcal{T} \quad (2)$$

Non-linear!

$$\sum_{t \in \mathcal{T} | t < R_f} (x_{f,t} + v_{f,t}) = 0, \forall f \in \mathcal{F} \quad (3)$$

$$\sum_{t \in \mathcal{T} | R_f \leq t \leq K_f} (x_{f,t} + v_{f,t}) = 1, \forall f \in \mathcal{F} \quad (4)$$

$$\sum_{f \in \mathcal{F}} (L_{f,d} \cdot x_{f,t}) - M_d \cdot y_{d,t} \leq 0, \forall d \in \mathcal{D}_t, t \in \mathcal{T} \quad (5)$$

$$\mathcal{D}_t = \{d : L_{f,d} = 1 \text{ and } R_f \leq t, \forall d \in \mathcal{D}, f \in \mathcal{F}\}, \forall t \in \mathcal{T} \quad (6)$$

$$\text{Freight goes by barge} \rightarrow x_{f,t} \in \{0, 1\}, \forall f \in \mathcal{F}, t \in \mathcal{T} \quad (7)$$

$$\text{Destination is visited} \rightarrow y_{d,t} \in \{0, 1\}, \forall d \in \mathcal{D}_t, t \in \mathcal{T} \quad (8)$$

$$\text{Freight goes by truck} \rightarrow v_{f,t} \in \{0, 1\}, \forall f \in \mathcal{F}, t \in \mathcal{T} \quad (9)$$

MIXED-INTEGER LINEAR PROGRAMMING MODEL

- The objective can be linearized as follows:

$$Z = \sum_{t \in \mathcal{T}} \sum_{\mathcal{D}' \subseteq \mathcal{D}} (C_{\mathcal{D}'} \cdot w_{\mathcal{D}',t}) + \sum_{t \in \mathcal{T}} \sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} (B_d \cdot L_{f,d} \cdot v_{f,t}) \quad (10)$$

$$w_{\mathcal{D}',t} - y_{d',t} \leq 0, \quad \forall \mathcal{D}' \subseteq \mathcal{D}_t, d' \in \mathcal{D}', t \in \mathcal{T} \quad (11)$$

$$w_{\mathcal{D}',t} + y_{d',t} \leq 1, \quad \forall \mathcal{D}' \subseteq \mathcal{D}_t, d' \in \mathcal{D}_t \setminus \mathcal{D}', t \in \mathcal{T} \quad (12)$$

$$w_{\mathcal{D}',t} + (|\mathcal{D}'| - 1) - \sum_{d' \in \mathcal{D}'} y_{d',t} + \sum_{d'' \in \mathcal{D}' \setminus \mathcal{D}_t} y_{d'',t} \geq 0, \quad \forall \mathcal{D}' \subseteq \mathcal{D}_t, t \in \mathcal{T} \quad (13)$$

Subset of destinations is visited $\rightarrow w_{\mathcal{D}',t} \in [0, 1], \quad \forall \mathcal{D}' \subseteq \mathcal{D}_t, t \in \mathcal{T} \quad (14)$

All subsets of the set of destinations!

➤ **MILP does not include uncertainty in arrival of freights!**



DYNAMIC PROGRAMMING MODEL

- One **stage** for each time period $t \in \mathcal{T}$.

Model's Uncertainty in arrivals between stages:

- Number of freights $F : P(F = f), f \in \mathcal{F}$
- Release-day of each freight $R : P(R = r), r \in \mathcal{R}$
- Due-day of each freight $K : P(K = k), k \in \mathcal{K}$
- Destination of each freight $D : P(D = d), d \in \mathcal{D}$

All random variables are captured in an **exogenous information vector** W_t :

$$W_t = \left[\tilde{F}_{t,d,r,k} \right]_{\forall d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}}, \forall t \in \mathcal{T}$$



DYNAMIC PROGRAMMING MODEL

Model's states and decisions:

- A **state** S_t is the collection of freights, and their characteristics, that are known at a given stage:

$$S_t = [F_{t,d,r,k}]_{\forall d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}}, \forall t \in \mathcal{T}.$$

- A **decision** x_t is the collection of freights, which have been released, that we are going to transport via barge at a given stage:

$$x_t = [x_{t,d,k}]_{\forall d \in \mathcal{D}, k \in \mathcal{K}}, \forall t \in \mathcal{T}$$

s.t.

$$0 \leq x_{t,d,k} \leq F_{t,d,0,k}, \forall t \in \mathcal{T}, d \in \mathcal{D}, k \in \mathcal{K}$$

$$\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} x_{t,d,k} \leq Q, \forall t \in \mathcal{T}$$



DYNAMIC PROGRAMMING MODEL

Model's state transition between stages:

- A **transition function** S^M captures the evolution of the system over the stages as a result of the decisions and the stochastic arrivals.

$$S_t = S^M (S_{t-1}, x_{t-1}, W_t), \forall t \in \mathcal{T}$$

s.t.

$$F_{t,d,0,0} = F_{t-1,d,1,1} + \tilde{F}_{t,d,0,0},$$
$$\forall t \in \mathcal{T}, d \in \mathcal{D}$$

$$F_{t,d,0,k} = F_{t-1,d,0,k+1} - x_{t-1,d,k+1} + F_{t-1,d,1,k+1} + \tilde{F}_{t,d,0,k},$$
$$\forall t \in \mathcal{T}, d \in \mathcal{D}, k \in \mathcal{K} \setminus \{0, |\mathcal{K}|\}$$

$$F_{t,d,r,k} = F_{t-1,d,r+1,k+1} + \tilde{F}_{t,d,r,k},$$
$$\forall t \in \mathcal{T}, d \in \mathcal{D}, r \in \mathcal{R} \setminus \{0\}, k \in \mathcal{K} \setminus \{0, |\mathcal{K}|\}$$

DYNAMIC PROGRAMMING MODEL

- A small example on how the *transition function* works:

$s_{t-1,d}$	$F_{t-1,d,0,0}$	$F_{t-1,d,0,1}$	$F_{t-1,d,0,2}$	$F_{t-1,d,1,2}$	$F_{t-1,d,1,3}$	$F_{t-1,d,2,3}$	$F_{t-1,d,3,4}$
	3	4	3	4	3	2	2
$x_{t-1,d}$	$F_{t-1,d,0,0}$	$F_{t-1,d,0,1}$	$F_{t-1,d,0,2}$				
	3	2	0				
$s_{t-1,d}^x$	$F_{t-1,d,0,0}$	$F_{t-1,d,0,1}$	$F_{t-1,d,0,2}$	$F_{t-1,d,1,2}$	$F_{t-1,d,1,3}$	$F_{t-1,d,2,3}$	$F_{t-1,d,2,4}$
	0	2	3	4	3	2	2
$w_{t,d}$	$F_{t,d,0,0}$	$F_{t,d,0,1}$	$r_{t,d,0,2}$	$r_{t,d,1,2}$	$F_{t,d,1,3}$	$F_{t,d,2,3}$	$F_{t,d,2,4}$
	0	0	0	1	2	0	1
$s_{t,d}$	$F_{t-1,d,0,0}$	$F_{t-1,d,0,1}$	$F_{t-1,d,0,2}$	$F_{t-1,d,1,2}$	$F_{t-1,d,1,3}$	$F_{t-1,d,2,3}$	$F_{t-1,d,2,4}$
	2	7	3	3	4	0	1



DYNAMIC PROGRAMMING MODEL

Model's costs and objective:

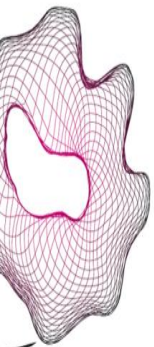
$$C(S_t, \mathbf{x}_t) = \sum_{\mathcal{D}' \subseteq \mathcal{D}} \left(C_{\mathcal{D}'} \cdot \prod_{d' \in \mathcal{D}'} y_{d',t} \cdot \prod_{d'' \in \mathcal{D} \setminus \mathcal{D}'} (1 - y_{d'',t}) \right) + \sum_{d \in \mathcal{D}} (B_d \cdot (F_{t,d,0,0} - x_{t,d,0}))$$

s.t.

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

- The objective is to find a **policy** π that minimizes the expected costs over the planning horizon given an initial state.

$$\min_{\pi \in \Pi} \mathbb{E} \left\{ \sum_{t \in \mathcal{T}} C(S_t, \mathbf{x}_t^\pi) \mid S_0 \right\}$$



DYNAMIC PROGRAMMING MODEL

How to find this policy?

Using Bellman's principle of optimality and backward induction:

$$V_t(S_t) = \min_{x_t} (C(S_t, x_t) + \mathbb{E} \{V_t(S^M(S_t, x_t, W_{t+1}))\})$$

$$V_t(S_t) = \min_{x_t} \left(C(S_t, x_t) + \sum_{\omega \in \Omega} (P(W_{t+1} = \omega) \cdot V_t(S^M(S_t, x_t, \omega))) \right)$$

$$\omega = [\hat{F}_{t,d,r,k}]_{\forall d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}}$$

$$P(W_t = \omega) = \frac{(\sum_{d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}} \hat{F}_{t,d,r,k})!}{\prod_{d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}} (\hat{F}_{t,d,r,k}!)}$$

All possible realizations of the random variables!
All possible decisions in a state!

All possible states!

$$\prod_{d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}} \left(P(F = \sum_{d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K}} \hat{F}_{t,d,r,k}) \cdot [P(D = d) \cdot P(R = r) \cdot P(K = k)]^{\hat{F}_{t,d,r,k}} \right)$$





APPROXIMATE DYNAMIC PROGRAMMING MODEL

Same cost and transition function as the DP model, however:

- A **post-decision state** S_t^x is used as a single estimator for all possible realization of the random variables.

$$S_t^x = S^{M,x} (S_{t-1}, x_{t-1})$$

- An **approximated value function** $V_t^x(S_t^x)$ for the post-decision state to capture the future costs:

$$V_t(S_t) = \min_{x_t} (C(S_t, x_t) + \mathbb{E} \{V_t(S^M(S_t, x_t, W_{t+1}))\})$$

$$V_t(S_t) = \min_{x_t} (C(S_t, x_t) + V_t^x(S_t^x))$$



APPROXIMATE DYNAMIC PROGRAMMING MODEL

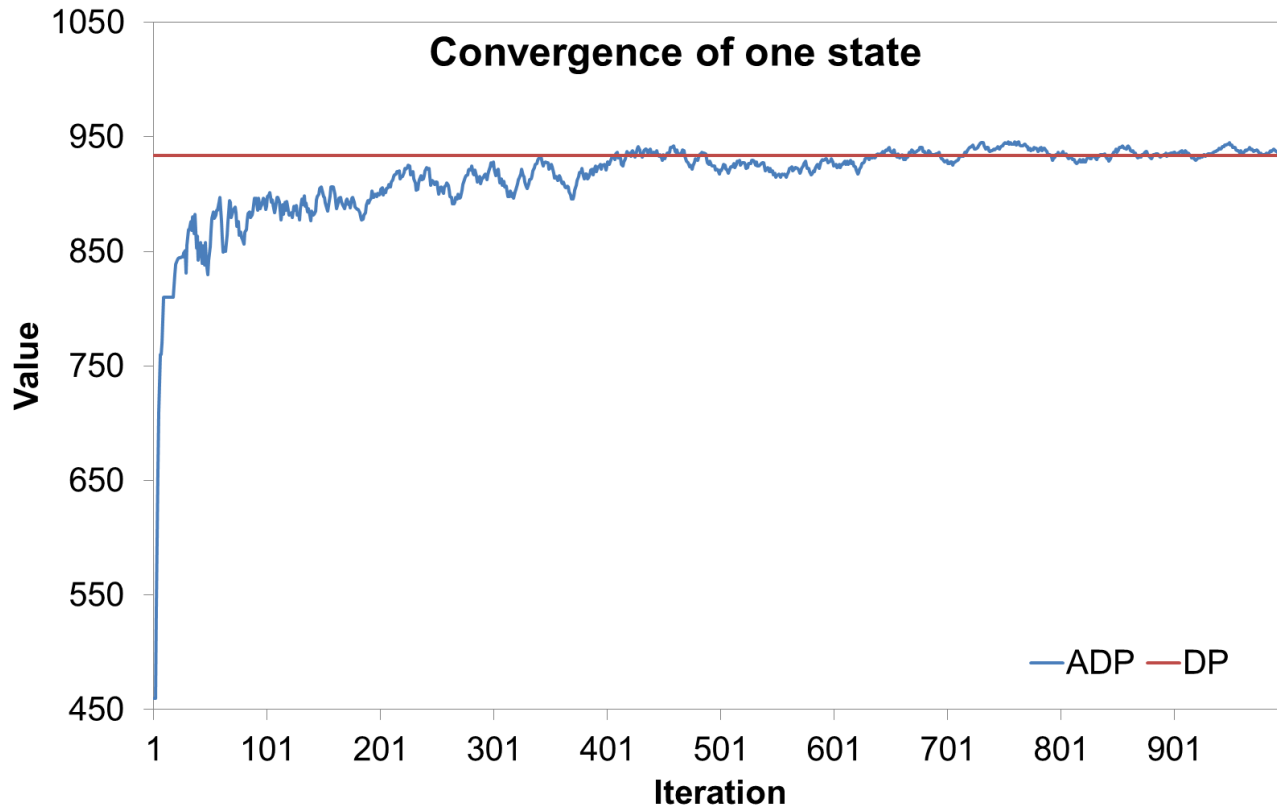
How to find the best decision for an initial state?¹

- By stepping forward in time:
 1. Find best decision for current state with current estimated value function of post-decision states.
 2. Update the estimated value of the previous post-decision state.
 3. Sample all exogenous information (in a Monte Carlo fashion), and get the new state.
- Repeat for a number of iterations until convergence.

1. For the comprehensive algorithm see Powell (2010) Approximate Dynamic Programming.

APPROXIMATE DYNAMIC PROGRAMMING MODEL

- Comparison between the DP and ADP (with lookup tables) models, for a small example with 7k states.



In 6% of the states the ADP decisions differ from optimal.

OUR APPROACH


- Based on the ADP model with post-decision state approximation.
- Use **basis functions** for approximating the value of a state. *Basis functions are specific features of a state which have a significant impact on its value.*

$$\bar{V}_t^n(S_t^x) = \sum_{f \in \mathcal{F}} \theta_f^n \phi_f(S_t^x), \quad \forall t \in \mathcal{T}.$$

- Where θ_f^n is a weight for each feature $f \in F$, and $\phi_f(S_t^x)$ is the value of the particular feature given the post-decision state S_t^x .



OUR APPROACH

- 
- With **regression analysis** we investigate which features have a significant impact on the value of a state.
 - *In an example instance (with approx. 78k states) the following choice of basis functions explain a large part of the variance in the computed values with the DP model ($R^2 = 0.94$):*
 - **All state variables.**
 - **Number of different destinations of all freights that have the same release-day (for each release-day).**
 - **Sum of all freights that that have the same release-day (for each release-day).**



WHAT TO REMEMBER

- Selecting which freights to consolidate today while considering consolidation of freights in future days is important when costs depend on the combination of freights consolidated.
- The DP model can easily handle costs as a function of the combination of freights and uncertainty in the arrival of freights, but solving it means facing “the curses of dimensionality”.
- The ADP model overcomes the DP model dimensionality issues through the use of a post-decision state and basis functions.

UNIVERSITY OF TWENTE.

THANKS FOR YOUR ATTENTION!

ARTURO E. PÉREZ RIVERA

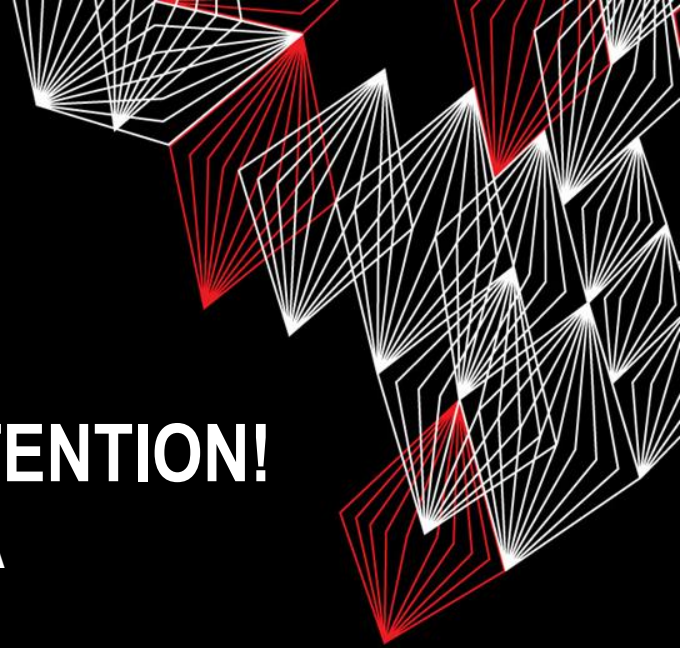
PhD Candidate

Department of Industrial Engineering and Business Information Systems

University of Twente, The Netherlands

<http://www.utwente.nl/mb/ieb/staff/perezrivera/>

a.e.perezrivera@utwente.nl



*INFORMS Annual Meeting 2014
Tuesday, November 11th, San Francisco, CA*