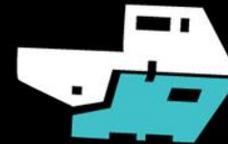




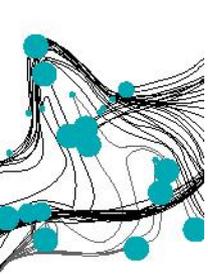
INTEGRATED SCHEDULING OF DRAYAGE AND LONG-HAUL TRANSPORTATION IN SYNCHROMODALITY

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

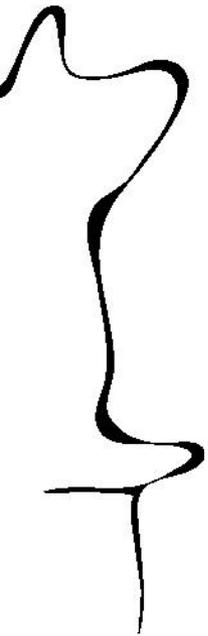
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*Odysseus 2018 - Thursday, June 7th
Cagliari, Italy*



CONTENTS



Background



Problem and model description



Heuristic approach



Numerical experiments



Conclusions





INTERMODAL TRANSPORTATION CHAIN

TWO PROCESSES: DRAYAGE AND LONG-HAUL TRANSPORTATION

“In an intermodal transportation chain, the initial and final trips represent **40% of total transport costs.”**

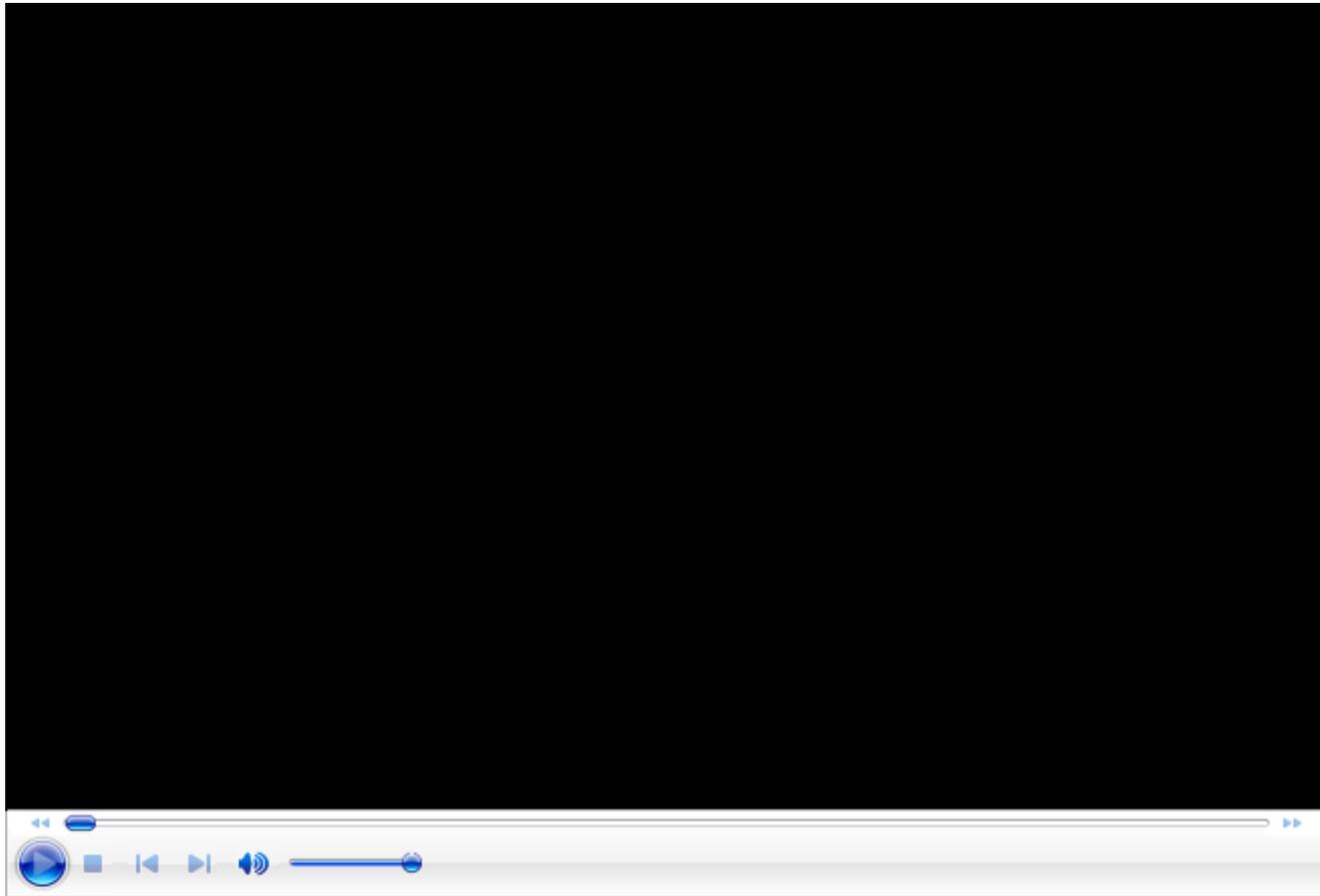
Escudero, A.; Muñuzuri, J.; Guadix, J. & Arango, C. (2013) Dynamic approach to solve the daily drayage problem with transit time uncertainty. *Computers in Industry*





SYNCHROMODALITY

WHAT IS SYNCHROMODAL TRANSPORTATION?



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

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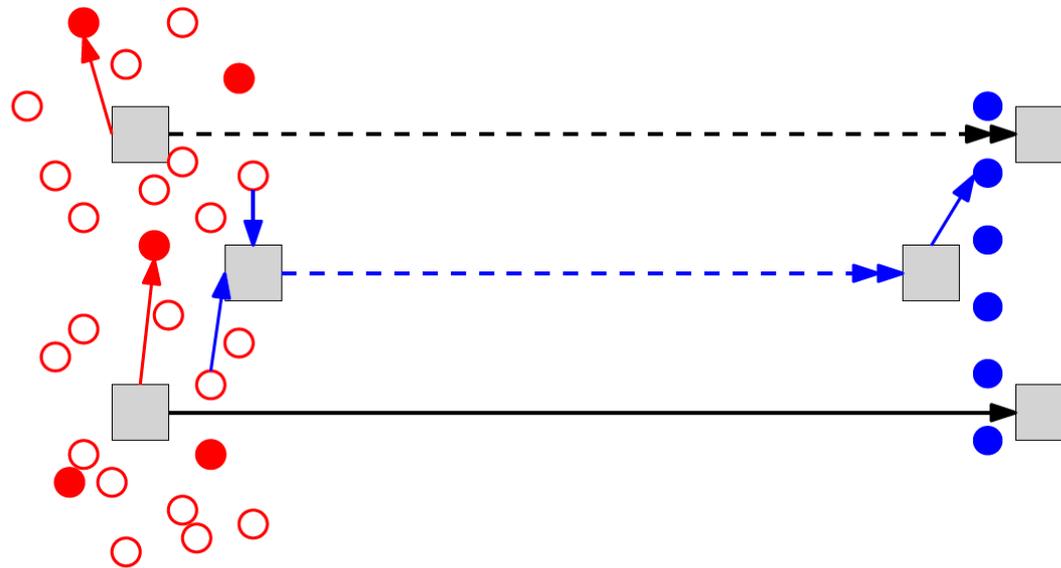
EXAMPLE TRADE-OFF

TRANSPORTATION OF CONTAINERS FROM TWENTE TO ROTTERDAM



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

PROBLEM DESCRIPTION



Legend:

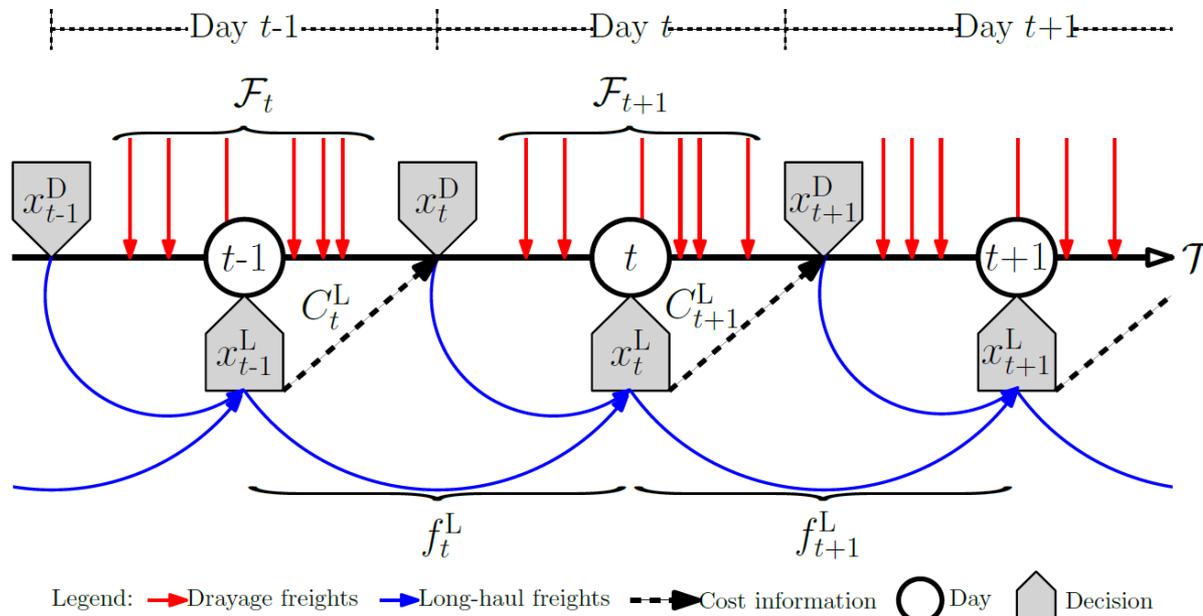
- Drayage origins \mathcal{O} ● Drayage destinations \mathcal{D}^D ● Long-haul destinations \mathcal{D}^L □ Terminals \mathcal{H}
- ➔ Train ➔ Barge ➔ Path end-haulage freight ➔ Path pre-haulage freight

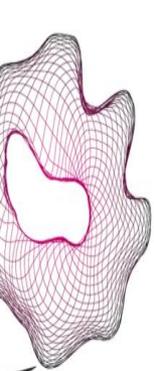
- **Schedule when (and where) to transport each freight** to achieve minimum costs over the network and over time.

PROBLEM DESCRIPTION

A stochastic optimization problem over a finite horizon where:

- **Random freights arrive**
- **Sequential schedules are made**





SCHEDULING DRAYAGE TRANSPORTATION

Full-Truckload Pickup-and-Delivery Problem with Time-Windows (FTPDPTW) to route trucks and assign terminals:

- Assignment of initial terminal for the long-haul of freights

Scheduling Drayage Operations in Synchronomodal Transport

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Abstract. We study the problem of scheduling drayage operations in synchronomodal transport. Besides the usual decisions to time the pick-up and delivery of containers, and to route the vehicles that transport them, synchronomodal transport includes the assignment of terminals for empty and loaded containers. The challenge consists of simultaneously deciding on these three aspects while considering various resource and timing restrictions. We model the problem using mixed-integer linear programming (MILP) and design a metaheuristic to solve it. Our algorithm iteratively confines the solution space of the MILP using several adaptations, and based on the incumbent solutions, guides the subsequent iterations and solutions. We test our algorithm under different problem configurations and provide insights into their relation to the three aspects of scheduling drayage operations in synchronomodal transport.

Keywords: Drayage operation, synchronomodal transport, metaheuristic

1 Introduction

During the last years, intermodal transport has received increased attention from academic, industrial, and governmental stakeholders due to potential reductions in cost and environmental impact [10]. To achieve such benefits, these stakeholders have proposed new forms of organizing intermodal transport. One of these new initiatives is synchronomodality, which aims to improve the efficiency and sustainability of intermodal transport through flexibility in the choice of mode and in the design of transport plans [12]. However, the potential benefits of any new form of intermodal transport depend to a great extent on the proper planning of drayage operations, also known as pre- and mid-haulage or first and last-mile trucking. Drayage operations, which account for 40% of the total transport costs in an intermodal transport chain [5], are the first step where the synchronomodal flexibility in transport mode can be taken advantage of. In this paper, we study the scheduling of drayage operations of intermodal transport considering terminal assignment (i.e., long-haul mode) decisions.

Drayage operations in intermodal transport include delivery and pick-up requests of either empty or loaded containers, to and from a terminal where long-haul modes arrive and depart. These operations occur, for example, at a Logistic

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T. Beking et al. (Eds.), KCI, 2017, LNCS 10572, pp. 404-419, 2017.
https://doi.org/10.1007/978-3-319-48066-3_27

8 A.E. Pérez Rivera, M.R.K. Mes

In addition to the bound on the number of arcs between all terminal nodes V^D , we can bound the traversed arcs between replicated nodes of a terminal using a similar logic. We define the set $V^{Dk} \subseteq V^D$ as the set containing all duplicated nodes of terminal $d \in U^D$. We put a bound M^{Dk} for each unique terminal node $d \in U^D$ as shown in (4).

$$\sum_{i \in K} \sum_{j \in V^{Dk}} x_{i,j,k} \leq M^{Dk}, \forall d \in U^D \quad (4a)$$

$$M^{Dk} = \sum_{d \in U^D} B_{d,k} \quad B_{d,k} = \begin{cases} 1 & \text{if } d \in F^k(r) \\ 0 & \text{otherwise} \end{cases}, \forall d \in U^D \quad (4b)$$

Taking advantage that our problem deals with jobs that have at most one origin and at most one destination, we can compute a minimum traveling distance and traveling time to fulfill all jobs by choosing the origin and destination with the shortest distance and time, respectively. Using this information, we can calculate the minimum number M^{LK} of trucks needed (since trucks have a maximum working time) and a lower bound on the routing costs M^{LC} . Furthermore, using a constructive heuristic (e.g., the one we handmade to in Sect. 6), we can find upper bounds M^{UK} and M^{UC} for the number of trucks needed and the routing costs, respectively. Thus, we can limit the number of trucks as shown in (5) and the routing costs as shown in (6).

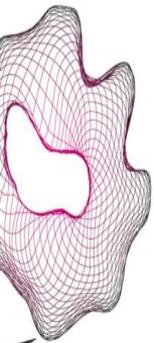
$$M^{LK} \leq \sum_{k \in K} \sum_{r \in F^k(r_k)} x_{m,r,k} \leq M^{UK} \quad (5)$$

$$M^{LC} \leq \sum_{k \in K} \left(c_k^e \cdot \sum_{r \in F^k(r_k)} x_{m,r,k} \right) + \sum_{k \in K} \sum_{d \in U^D} c_{d,k}^d \cdot x_{d,k} \leq M^{UC} \quad (6)$$

The last adaptation we introduce is the pre-processing of time-windows. In our model, there are duplicated nodes (i.e., same location, service time, and time-window) for each terminal to keep track of time. However, such duplicated terminal node can only be used for one job. Since we duplicate a terminal for each job that might use that terminal, we can use the time-window of the job to reduce the time-window of the duplicated node for that terminal. As an example, consider Fig. 2. In this figure, we see a job of Type 1 that requires a full container from terminal d and delivers an empty container to terminal d' . In order to carry out this job within its time-window $[E_r, L_r]$, the full container must be put on a truck and

Fig. 2. Example of pre-processing of time-windows for a job Type 1

Pérez Rivera, A.E., Mes, M.R.K. (2017). Scheduling Drayage Operations in Synchronomodal Transport. *Lecture Notes in Computer Science*, Volume 10572, pp. 404-419. Springer. DOI 10.1007/978-3-319-68496-3_27



SCHEDULING LONG-HAUL TRANSPORTATION

Markov Decision Process (MDP) to consolidate freights in daily barges or postpone their transport:

- **Arrival of freight is stochastic and dependent on drayage decisions**



Although freights are known only after they arrive, the LSP has probabilistic knowledge about them in the form of sight probability distribution. In between two consecutive days $t \in \mathcal{D}$ delivery freights and $g \in \mathcal{D}$ pickup freights arrive with probability p_t^d and p_t^g , respectively. A freight has destination $d \in \mathcal{D}$ with probability $p_t^{d|t}$ in case of delivery, and $p_t^{g|t}$ in case of pickup. A freight has release-day $r \in \mathcal{R}$ with probability $p_t^{r|t}$ in case of delivery, and $p_t^{g|t}$ in case of pickup. A freight has time-window length $k \in \mathcal{K}$ with probability $p_t^{k|t}$ in case of delivery, and $p_t^{g|t}$ in case of pickup.

In each period, intermodal transportation modes are available. First, there is one high-capacity vehicle along the round-trip with capacity of Q delivery freights and Q pickup freights. The costs C_{ij} of this vehicle depend on the group of destination k via $\mathcal{D} \subseteq \mathcal{D}$. In addition to C_{ij} , there is a cost β per freight with destination d considered in this vehicle. Second, we assume there is an unlimited number of alternative vehicles (e.g., trucks) for urgent freights, i.e., freights whose due-day is immediate at a cost A_{ij} per freight to be from destination d . The restriction of using alternative vehicles only for urgent freights does not impact the decision making process since there are no holding costs and transportation costs do not change over time. We introduce this restriction to reduce the size of the decision space, and thus the computational complexity of the model. We do not consider holding (i.e., inventory costs) since our focus is on the long-haul round-trip decisions, not on the pre- and end-haulage operations, and the time-window lengths are a tighter restriction on the postponement decisions than the physical space.

3.2. Formulation

Each day corresponds to a stage in the MDP. This stage is discrete, consecutive, and denoted by L at each stage L . There are $F_{L,t}$ delivery freights and $G_{L,t}$ pickup freights with destination d , release-day r , and time-window length k . The size of the system S_L consists of all freight variables at stage L , as seen in (1). We denote the state space of the system by \mathcal{S}_L , $\mathcal{S} \subseteq \mathcal{S}_L$.

$$S_L = \{ (C_{ij}, A_{ij}, Q_{ij}, \beta_{ij}, \mathcal{D}_{ij}, \mathcal{R}_{ij}, \mathcal{K}_{ij}) \}_{ij \in \mathcal{D} \times \mathcal{D}} \quad (1)$$

At each stage L , the decision consists of which delivery and pickup freights from S_L to consolidate in the high-capacity vehicle. This decision is restricted by the release-day of freights and by the capacity of the vehicle. We use the non-negative integer variables x_{ij}^d and x_{ij}^g to represent the number of related freights with destination d and time-window length k consolidated for delivery and pickup freights respectively. The decision x consists of d decision variables at stage L as seen in (2a), subject to constraints 2b, 2c, 2d, 2e, 2f, which define the feasible decision space \mathcal{X}_L .

$$x = \{ (x_{ij}^d, x_{ij}^g) \}_{ij \in \mathcal{D} \times \mathcal{D}} \quad (2a)$$

$$x_{ij}^d \leq \lfloor \frac{Q_{ij}}{k_{ij}} \rfloor, \quad \forall ij \in \mathcal{D} \times \mathcal{D} \quad (2b)$$

$$x_{ij}^g \leq \lfloor \frac{Q_{ij}}{k_{ij}} \rfloor, \quad \forall ij \in \mathcal{D} \times \mathcal{D} \quad (2c)$$

$$x_{ij}^d \leq C_{ij}, \quad \forall ij \in \mathcal{D} \times \mathcal{D} \quad (2d)$$

$$x_{ij}^g \leq G_{ij}, \quad \forall ij \in \mathcal{D} \times \mathcal{D} \quad (2e)$$

$$x_{ij}^d \leq A_{ij}, \quad \forall ij \in \mathcal{D} \times \mathcal{D} \quad (2f)$$

The costs of a decision depend on the destinations visited with the high-capacity vehicle and the use of the alternative transportation mode. We define $z_{ij} \in \{0, 1\}$ as the binary variable that gets a value of 1 if destination d is visited by the high-capacity vehicle at stage L and 0 otherwise. We define z_{ij} as the variable representing the number of freights to destination d that were transported with the alternative mode. These variables depend on the state and decision variables, as seen in (3a), (3c). Using these variables, the cost at stage L can be defined as a function of x and z , as shown in (3a).

$$C(x, z) = \sum_{ij \in \mathcal{D} \times \mathcal{D}} (C_{ij} \sum_{k \in \mathcal{K}} x_{ij}^d \prod_{r \in \mathcal{R}} (1 - \beta_{ij}^r)^{x_{ij}^d} + \sum_{k \in \mathcal{K}} \beta_{ij}^k (x_{ij}^d + x_{ij}^g)) + \sum_{ij \in \mathcal{D} \times \mathcal{D}} (A_{ij} z_{ij}) \quad (3a)$$

where

$$z_{ij} = \begin{cases} 1, & \text{if } \sum_{k \in \mathcal{K}} (x_{ij}^d + x_{ij}^g) > 0, \quad \forall ij \in \mathcal{D} \\ 0, & \text{otherwise} \end{cases} \quad (3b)$$

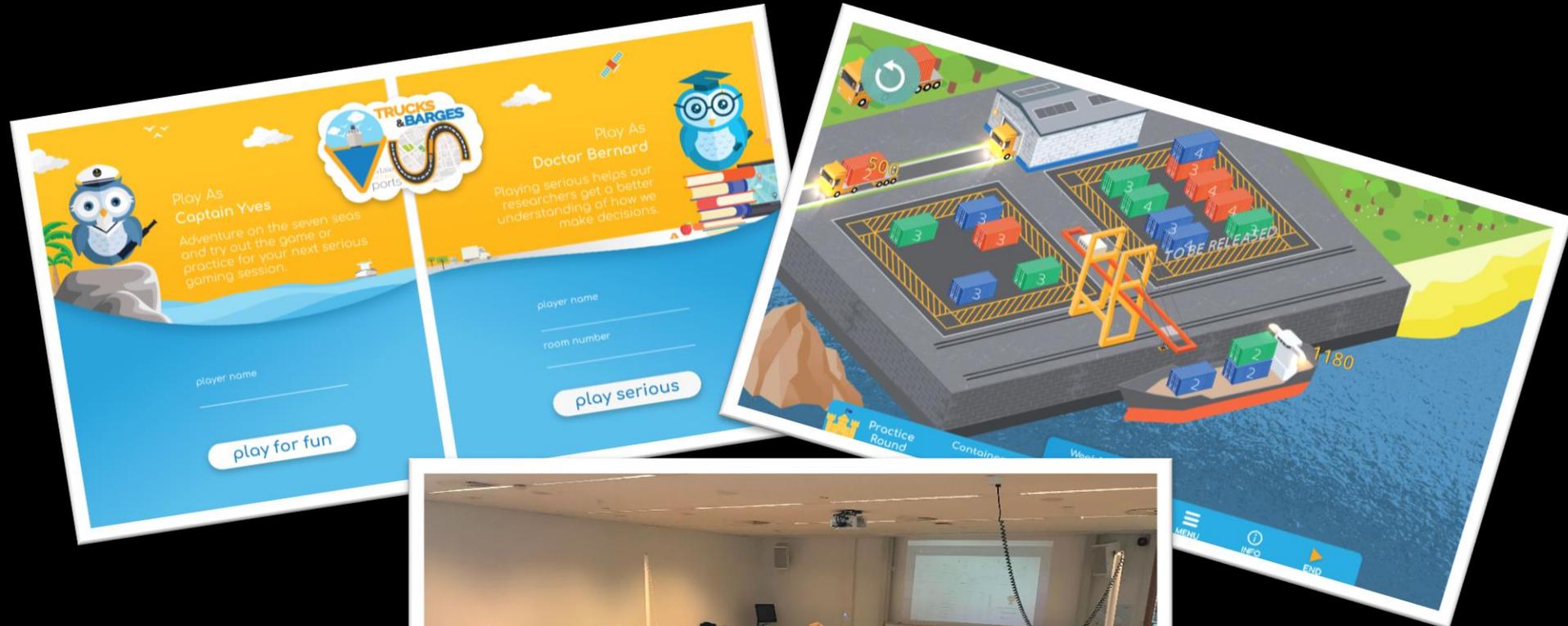
$$z_{ij} = x_{ij}^d + x_{ij}^g + C_{ij} - A_{ij}, \quad \forall ij \in \mathcal{D} \quad (3c)$$

The objective is to minimize the costs over the entire planning horizon, i.e., the sum of (3a) over all $L \in \mathcal{T}$. However, there is uncertainty in the arrival of freights within this horizon, and thus in the state. Consequently, the formal objective is to minimize the expected costs over the horizon. Since for every possible state there is an optimal decision, the output has

Pérez Rivera, A.E., Mes, M.R.K. (2016). Anticipatory Freight Selection in Intermodal Long-haul Round-trips. *Transportation Research Part E: Logistics and Transportation Review*. Volume 105: pp. 176-194. Elsevier. DOI 10.1016/j.tre.2016.09.002

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INTEGRATED SCHEDULING

UNIFIED CONTROL OF DRAYAGE AND LONG-HAUL TRANSPORTATION

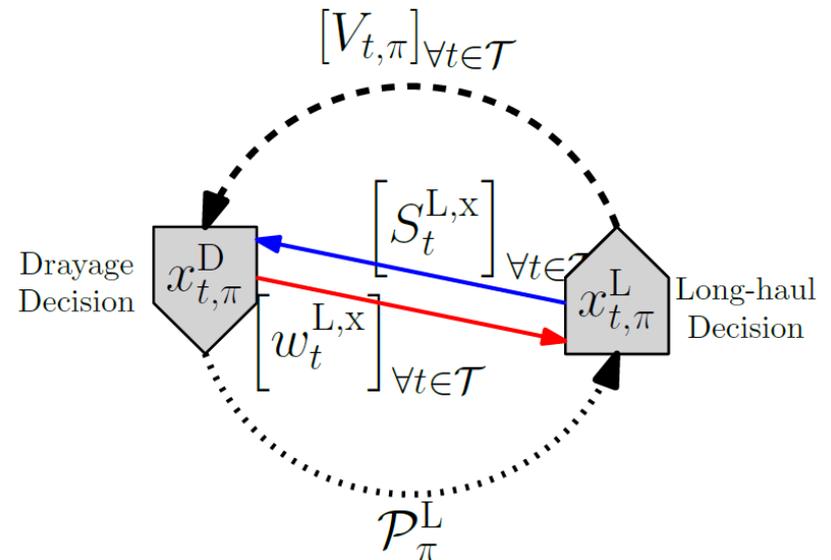
The goal is to **minimize the total expected network-wide costs**, where the drayage schedule depends on the long-haul policy, and where the long-haul policy depends on the arrivals from the drayage schedule.

$$\min_{\pi \in \Pi} \mathbb{E} \left[\sum_{t \in \mathcal{T}} (z_t^D(x_{t,\pi}^D) + z_t^L(x_{t,\pi}^L)) \mid s_0^L, \mathcal{P}^D, \Gamma \right]$$

where

$$x_{t,\pi}^D = \operatorname{argmin}_{x_t^D \in \mathcal{X}_t^D} [\tilde{z}_{t,\pi}^D(x_t^D)]$$

$$\Gamma(\mathcal{P}^D, [x_{t,\pi}^D]_{\forall t \in \mathcal{T}}) = \mathcal{P}_\pi^L$$



Legend:

→ Drayage freights

→ Long-haul freights

---→ Long-haul costs

....→ Freight arrivals probabilities

HEURISTIC APPROACH

HEURISTICS FOR THE DRAYAGE SCHEDULE AND LONG-HAUL POLICY

- We use a **Matheuristic (MH)** for scheduling drayage transportation, which uses various cuts based on the ‘terminal assignment cost’ resulting from the long-haul policy.

- We use an **Approximate Dynamic Programming (ADP)** algorithm for learning a long-haul policy, i.e., Value Function Approximation (VFA), based on the observed distributions from a simulation of the MH.

Scheduling Drayage Operations in Synchronomodal Transport 9

travel from terminal d anywhere between $[E_r - (S_r + T_{d,r}), L_r - (S_r + T_{d,r})]$. Similarly, after unloading the container, the empty container can arrive to terminal d' anywhere between $[E_r + (S_r + T_{r,d}), L_r + (S_r + T_{r,d})]$. We can repeat this logic with all jobs, their associated (possible) terminals, and the duplicated nodes for those terminals.

The benefit of the aforementioned enhancements of the MILP is twofold. First, the valid inequalities tighten the feasible solution. Second, the time-window preprocessing breaks the asymmetry in MILP solutions introduced by the duplicated terminal nodes. However, these modifications are sufficient to solve only small problems. In the following section, we elaborate on further adaptations of the MILP that can allow it to be applied to larger problems.

5 Matheuristics

In our problem, MILP solvers are able to find a good feasible solution fast, but struggle on improving it further or in proving its optimality. In this section, we design three adaptations to the MILP that are aimed to help a solver find good feasible solutions faster. Furthermore, we design two matheuristics: (i) a static matheuristic to solve a single instance of the problem using Math-Heuristic Operators (MHOs) and (ii) a dynamic matheuristic to solve a re-planning instance of the problem using Fixing Criteria (FCs), as shown in the pseudo-codes of Algorithms 1 and 2, respectively. We now elaborate on the MHOs, FCs, and parts of each algorithm.

Algorithm 1 Static Matheuristic	Algorithm 2 Dynamic Matheuristic
Requires: Cargo \mathcal{J} and unassigned parameters \mathcal{U}	Requires: Unplanning trigger and current schedule
1. Initialize best solution	1. Initialize current state
2. While Stopping criterion not met do	2. Fix trucks with FCs (10) and (11)
3. Get MHOs \mathcal{H} , \mathcal{U} , and \mathcal{D}	3. Determine re-planning jobs
4. Build adapted MILP	4. Build \mathcal{J} and associated parameters
5. Solve adapted MILP	5. Run Algorithm 1
6. If Current solution \mathcal{C} best solution then	6. return: Solution
7. Else solution = Current Solution	
8. end if	
9. end while	
10. return: Best solution	

5.1 Static Matheuristic

Our static matheuristic uses three adaptations to the MILP, iteratively and in a local-search fashion. These adaptations, denoted by MHOs, are basically additional constraints in the MILP that can be seen as cutting planes that reduce the feasible space. Since our formulation results in a lot of arcs, our MHOs focus on fixing those arcs in an intuitive way. We now explain each MHO in more detail.

MHO 1: For N^{MHO} random jobs $e \in \mathcal{E}$, we limit the number of feasible jobs-arc to at most two, i.e., $|\delta^+(e)| \leq 2$ and $|\delta^-(e)| \leq 2$. These arcs are from (to) the

Al. Wan, M.A.K. Wu / Transportation Research Part B 112 (2018) 1–14

Algorithm 1. Approximate dynamic programming solution algorithm.

```

1: Initialize  $\mathcal{V}^n, \forall n \in \mathcal{T}$ 
2:  $n = 1$ 
3: while  $n \leq N$  do
4:    $\mathcal{S}^n = \mathcal{S}_0$ 
5:   for  $i = 1$  to  $n-1$  do
6:      $\mathcal{V}^i = \min_{\mathcal{K}^i} (C(\mathcal{S}^i, \mathcal{K}^i) + \mathcal{V}^i - (\delta^{\text{opt}}(\mathcal{S}^i, \mathcal{K}^i)))$ 
7:      $\mathcal{K}^i = \arg \min_{\mathcal{K}^i} (C(\mathcal{S}^i, \mathcal{K}^i) + \mathcal{V}^i - (\delta^{\text{opt}}(\mathcal{S}^i, \mathcal{K}^i)))$ 
8:      $\mathcal{W}^i = \mathcal{W}^i(\mathcal{S}^i, \mathcal{K}^i)$ 
9:      $\mathcal{W}^i = \text{RandomFrom}(\mathcal{W}^i)$ 
10:     $\mathcal{S}^i = \mathcal{S}^i(\mathcal{S}^i, \mathcal{K}^i, \mathcal{W}^i)$ 
11:   end for
12:   for  $i = 1$  to  $n-1$  do
13:      $\mathcal{V}^i, \mathcal{K}^i, \mathcal{W}^i = \mathcal{D}^i(\mathcal{V}^i, \mathcal{K}^i, \mathcal{W}^i, \mathcal{S}^i, \mathcal{S}^i, \mathcal{V}^i)$ 
14:   end for
15:    $n = n + 1$ 
16: end while
17: return  $\mathcal{V}^N$ 

```

4.1. Post-decision state and forward dynamic programming

To tackle the large set of realizations of the exogenous information Ω , we introduce two new components into the model: (i) a post-decision state \mathcal{S}^n , and (ii) an approximated next-stage cost $\mathcal{V}^n(\mathcal{S}^n)$. The post-decision state is the state of the system directly after a decision \mathcal{K}^n has been made but before the exogenous information \mathcal{W}^n becomes known, at iteration $n = 1, 2, \dots, N$ of the algorithm. The approximated next-stage cost $\mathcal{V}^n(\mathcal{S}^n)$ serves as an estimated measurement for the next-stage costs (i.e., $\mathcal{V}^n(\mathcal{S}^n) = \mathbb{E}[V_n(\mathcal{S}^n, \Omega_n)]$). We elaborate on this measurement later on. For now, we focus on the post-decision state. In a similar way to the freight variables of a state, the post-decision freight variables $\mathcal{F}_a^{\text{post}}, \mathcal{F}_a^{\text{pre}}, \mathcal{F}_a^{\text{pre}}$ from the post-decision state \mathcal{S}^n , as seen in (11). Note that these components are all indexed with a superscript n , which denotes the iteration in they correspond to.

$$\mathcal{S}^n = \left\{ (C_{a,b}^{\text{post}}, C_{a,b}^{\text{pre}}) \right\}_{a,b \in \mathcal{A}} \quad (11)$$

To define a post-decision state \mathcal{S}^n , we define a function δ^{opt} that relates the post-decision freight variables \mathcal{S}^n with the state \mathcal{S}^n and decision \mathcal{K}^n , as shown in (12a). The workings of this function are similar to the transition function \mathcal{S}^n defined in (7a), having out the exogenous information \mathcal{W}^n .

$$\mathcal{S}^n = \delta^{\text{opt}}(\mathcal{S}^n, \mathcal{K}^n), \forall n \in \mathcal{T} \quad (12a)$$

where

$$\mathcal{F}_a^{\text{post}} = \mathcal{F}_a^{\text{pre}} - \mathcal{F}_a^{\text{load}} + \mathcal{F}_a^{\text{unload}}, \forall d \in \mathcal{D}, k \in \mathcal{K}^n \quad (12b)$$

$$\mathcal{C}_{a,b}^{\text{post}} = \mathcal{C}_{a,b}^{\text{pre}} + \mathcal{C}_{a,b}^{\text{load}} - \mathcal{C}_{a,b}^{\text{unload}}, \forall d \in \mathcal{D}, k \in \mathcal{K}^n, k \neq d \quad (12c)$$

$$\mathcal{F}_a^{\text{pre}} = \mathcal{F}_a^{\text{pre}}, \forall d \in \mathcal{D} \quad (12d)$$

$$\mathcal{C}_{a,b}^{\text{pre}} = \mathcal{C}_{a,b}^{\text{pre}}, \forall d \in \mathcal{D} \quad (12e)$$

$$\mathcal{F}_a^{\text{pre}} = \mathcal{F}_a^{\text{pre}}, \forall d \in \mathcal{D}, e \in \mathcal{E} \cup \{1, \dots, N^{\text{MHO}}\}, k \in \mathcal{K} \quad (12f)$$

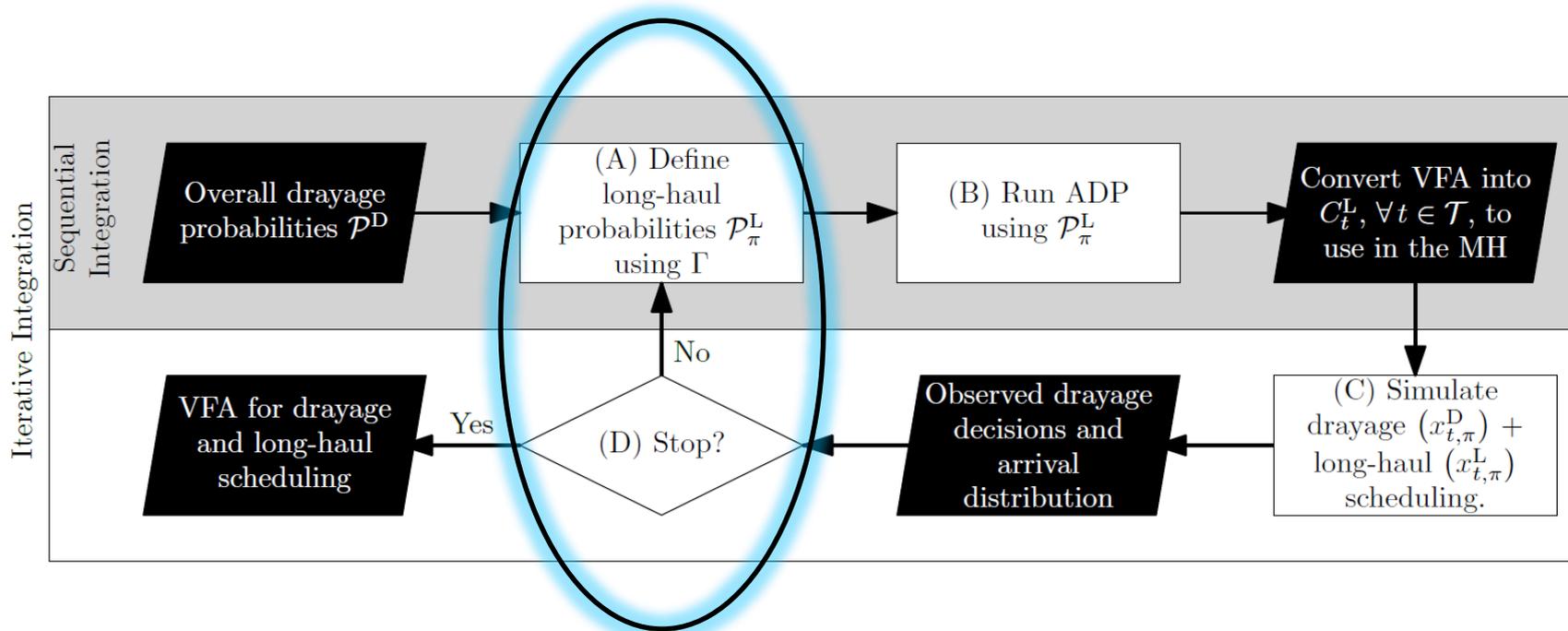
$$\mathcal{C}_{a,b}^{\text{pre}} = \mathcal{C}_{a,b}^{\text{pre}}, \forall d \in \mathcal{D}, e \in \mathcal{E} \cup \{1, \dots, N^{\text{MHO}}\}, k \in \mathcal{K} \quad (12g)$$

To tackle the large state space \mathcal{S} , we use the algorithmic manipulation of ‘forward dynamic programming’. In contrast to backward dynamic programming, forward dynamic programming starts at the first stage and, at each stage, solves an ‘optimality’ equation for only one state, as seen in (13). This equation follows the same meaning as the Bellman’s equation from (5), with two differences: (i) the next-stage costs are approximated and (ii) each feasible decision \mathcal{K}^n has only one corresponding post-decision state.

$$\mathcal{V}^n = \min_{\mathcal{K}^n} (C(\mathcal{S}^n, \mathcal{K}^n) + \mathcal{V}^n(\mathcal{S}^n)) - \min_{\mathcal{K}^n} (C(\mathcal{S}^n, \mathcal{K}^n) + \mathcal{V}^n(\delta^{\text{opt}}(\mathcal{S}^n, \mathcal{K}^n))) \quad (13)$$

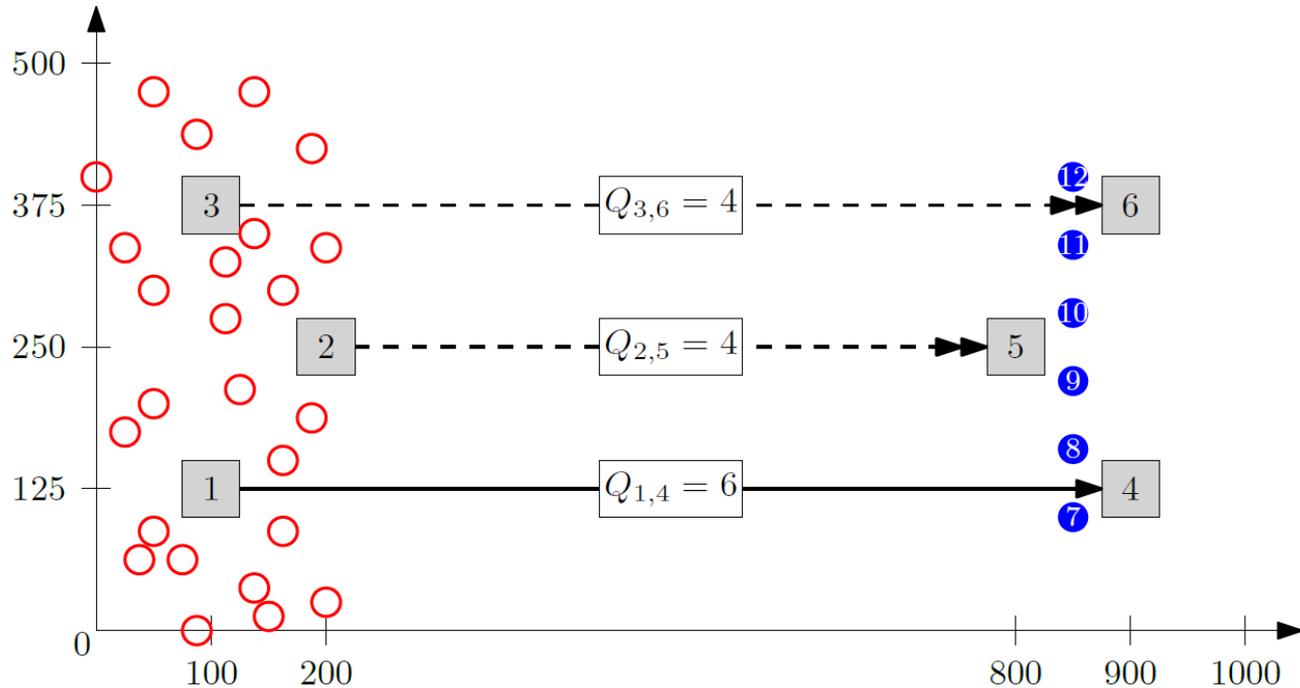
HEURISTIC APPROACH

INTEGRATION OF THE TWO HEURISTICS



NUMERICAL EXPERIMENTS

INSTANCES SETUP



Legend: ○ Drayage location ● Long-haul destination □ Terminal ->> Train -> Barge

Freight demand:

20 freights per day
(\approx Poisson dist.)

Drayage location:

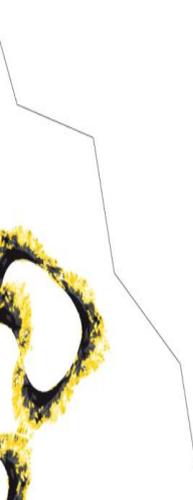
Random (R) or
Clustered (C).

Drayage type:

Pre-haulage (P) or
End-haulage (E).

Long-haul Destinations:

Balanced (B) or
Unbalanced (U).



NUMERICAL EXPERIMENTS

EXPERIMENTAL PHASES

We divide the experiments in two phases:

1. Calibration phase:

- Settings for heuristic parameters.
- Influence in drayage and long-haul schedules.

2. Evaluation phase:

- Savings with respect to a benchmark approach commonly found in practice.
- Sensitivity to different cost setups.

NUMERICAL EXPERIMENTS

CALIBRATION PHASE – PARAMETERS FOCUS ON DRAYAGE OR LONG-HAUL

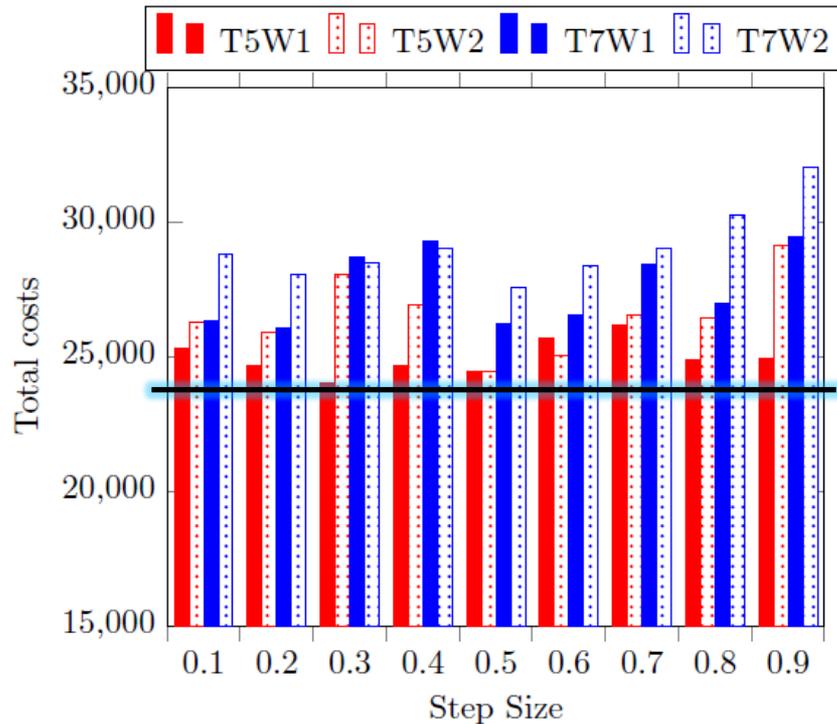


Figure 6.10: Total Costs $C-P-U$

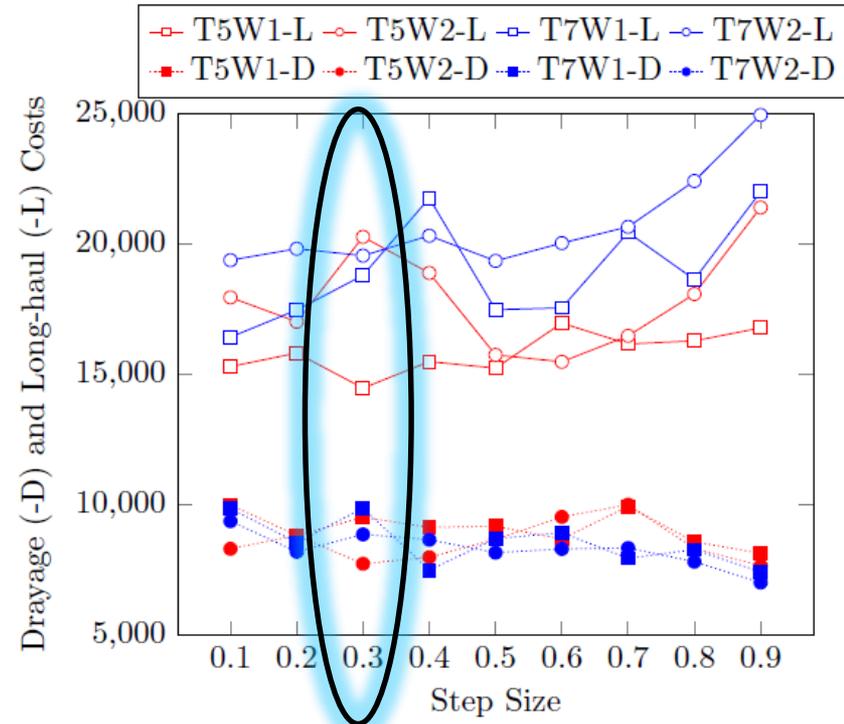


Figure 6.11: Individual Costs $C-P-U$

NUMERICAL EXPERIMENTS

EVALUATION PHASE – NORMAL COST SETUP

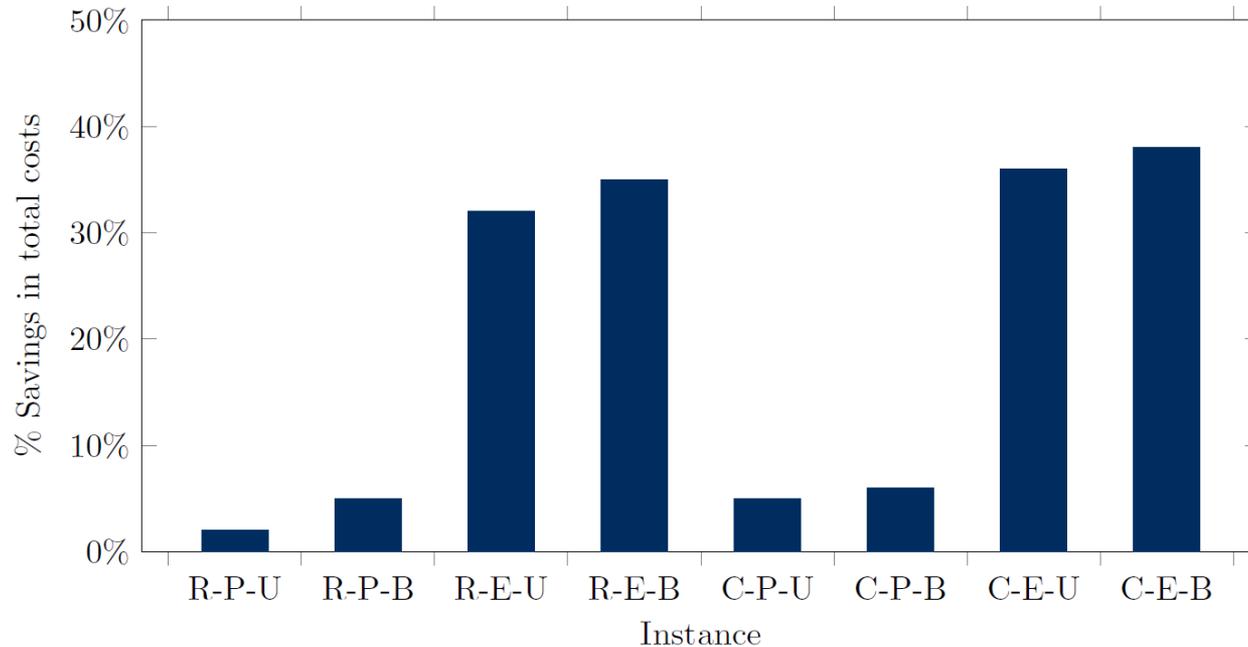


Table 1: Percentage difference with the benchmark in normal drayage-cost setup

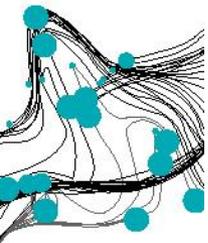
Instance	R-P-U	R-P-B	R-E-U	R-E-B	C-P-U	C-P-B	C-E-U	C-E-B
Long-haulCosts	-10%	-14%	-63%	-65%	-14%	-13%	-63%	-65%
DrayageCosts	17%	18%	33%	32%	16%	12%	21%	22%
Long-haulUtilization	4%	1%	-55%	-55%	5%	0%	-56%	-55%
Pre-haulageClosest	-21%	-27%	-82%	-81%	-37%	-35%	-81%	-82%

NUMERICAL EXPERIMENTS

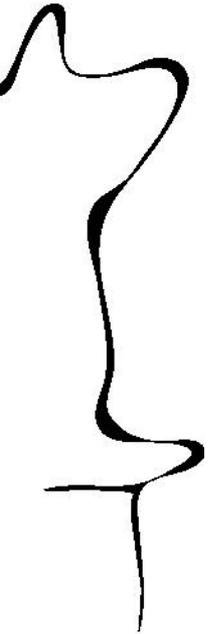
EVALUATION PHASE – COST SENSITIVITY

Table 6.5: *Percentage difference with the benchmark in high drayage-cost setup*

Instance	Costs			Long-haul Utilization	Pre-haulage to closest terminal
	Total	Long-haul	Drayage		
R-P-U	3%	-12%	6%	4%	5%
R-P-B	5%	-5%	7%	0%	4%
R-E-U	13%	-62%	29%	-55%	-72%
R-E-B	12%	-63%	30%	-55%	-74%
C-P-U	-9%	50%	-20%	-30%	18%
C-P-B	-12%	38%	-23%	-27%	21%
C-E-U	4%	-64%	19%	-55%	-71%
C-E-B	3%	-64%	18%	-55%	-73%



CONCLUSIONS



- We proposed the **integration of a MH for drayage scheduling and an ADP for long-haul scheduling** through (i) the inclusion of long-haul assignment costs in drayage decisions, and (ii) an improved VFA in the long-haul decisions.
- Numerical experiments show that **our integrated scheduling approach performs up to 38% better than separated scheduling** in terms of total network costs, with larger drayage costs.
- Further **research on the integration mechanisms of the MH and ADP, and their calibration**, is necessary to achieve the most of integrated scheduling in synchromodal transport.





THANKS FOR YOUR ATTENTION!

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