

# Recovery-Robust Platforming by Network Buffering

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## Outline

### Train Platforming Problem

In and Out

TPP deterministic model

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## Problem definition

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The objective of train platforming is assigning trains to platforms in a railway station. Platforming is carried out:

- ▶ for a specific railway station
- ▶ after the timetable has been defined

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- ▶ Train schedule : arrival, departure times, directions and allowed shifts
- ▶ Railway station topology: platforms, paths and directions

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### Output

- ▶ Assign each train a platform and two paths for arrival and departure s.t. no operational constraint is violated

## Train schedule

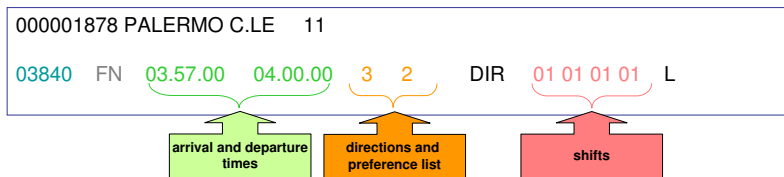


Figure: Train Schedule

The train schedule of a railway station contains info on arrival and departure times, directions and allowed shifts of each train passing through it.

## Railway station topology

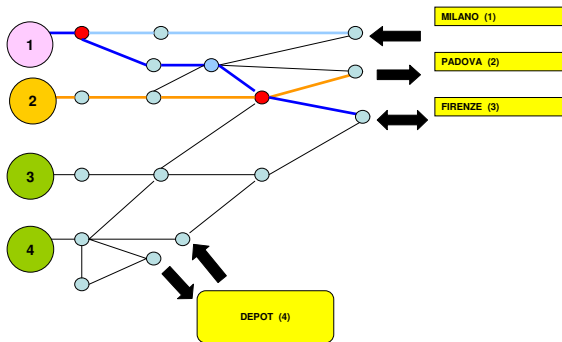


Figure: Topology

The topology of a railway station includes platforms, paths and directions.

## Resources and operational constraints

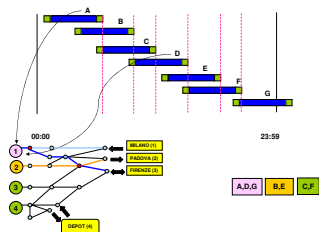


Figure: Platform and path.

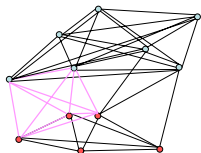


Figure: Incompatibility graph.

Platform conflicts are forbidden, path conflicts are allowed to some extent.

A pattern  $P$  for a train  $t$  is a 5-tuple defining: platform, arrival/departure paths and shifts. Operational constraints can be expressed using an incompatibility graph among patterns.

## TPP deterministic model

$$\min \sum_{t \in T} \sum_{P \in \mathcal{P}_t} c_{t,P} x_{t,P} \quad (1)$$

s.t.

$$\sum_{P \in \mathcal{P}_t} x_{t,P} = 1, \quad t \in T \quad (2)$$

$$\sum_{(t_1, P_1) \in K} x_{t_1, P_1} + \sum_{(t_2, P_2) \in K} x_{t_2, P_2} \leq 1, \quad (t_1, t_2) \in T^2, K \in \mathcal{K}(t_1, t_2) \quad (3)$$

$$x_{t,P} \in \{0, 1\}, \quad t \in T, P \in \mathcal{P}_t \quad (4)$$

**Details** in Caprara *et al.* 2007 [2].



## Robust Optimization

Robust Optimization finds best solutions, which are feasible for all likely scenarios.

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### Cons

*Strict robustness* is generally overconservative, because:

- ▶ solutions must cope with every likely scenarios without any recovery
- ▶ it is unable to account for limits to the sum of all disturbances

## Recoverable Robustness

Informally speaking, a solution to an optimization problem is called *recovery robust* if it can be adjusted to all likely scenarios by limited recovery action. Thus a recovery-robust solution provides a service guarantee (Liebchen *et al.* 2007 [3]).

## Robust Network Buffering

We are interested in the special case in which the recovery problem is a delay ( $y_i^a$ ) propagation in some directed graph  $N$ , which is buffered on the arcs by means of  $f$  against disturbances on the arcs  $a \in A(N)$ . Denoting by  $A(N)$  the set of arcs in  $N$ , we get:

$$\begin{aligned} & \min_{f \in P} c(f) \\ \text{s.t. } & \forall a \in A(N) \exists y^a \in \mathbb{R}^{|A(N)|} : \\ & f_{(i,j)} + y_i^a - y_j^a \geq \Delta \cdot \chi_a((i,j)), \quad a = (i,j) \in A(N) \\ & D - d^l y^a \geq 0 \end{aligned}$$

**Details** in Liebchen *et al.* 2007 [3].

## Delay propagation network

The platforming gives rise in a natural way to a network in which the delay caused by disturbances propagates. This *delay propagation network* is a directed acyclic graph in which each vertex represents the delay of a particular train for a particular resource.

## Delay propagation network

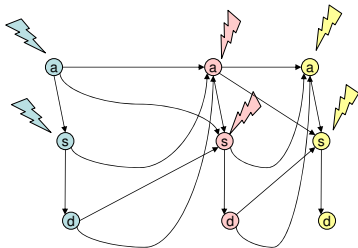


Figure: Delay propagation network

Each train has three associated vertices in this graph: (i)  $a$  for the arrival path, (ii)  $s$  for the stopping platform, and (iii)  $d$  for the departure path, corresponding to the delay (with respect to the nominal schedule) with which it will free up each of the three resources assigned to it.

## Example

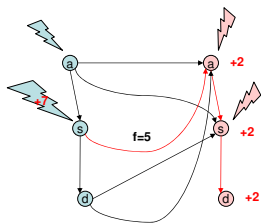


Figure: Example

Assume in the nominal schedule the first train frees up the platform at 10:00, the second train occupies it at 10:05 and frees it up at 10:10. Then a delay of more than 5 minutes for the first train results in a delay also for the second.



## Delay propagation network model

$$D \geq \sum_{t \in T} (a_t^\xi + s_t^\xi + d_t^\xi), \quad \xi \in \{\delta_t | t \in T\} \cup \{\delta'_t | t \in T\} \quad (5)$$

$$a_t^\xi \geq \delta_t^\xi, \quad t \in T \quad (6)$$

$$s_t^\xi \geq a_t^\xi + \delta_t^{\prime\xi}, \quad t \in T \quad (7)$$

$$d_t^\xi \geq s_t^\xi, \quad t \in T \quad (8)$$

$$m_{t_2}^\xi \geq h_{t_1}^\xi - f(h_{t_1}, m_{t_2}), \quad a = (h_{t_1}, m_{t_2}) \in A(N) \quad (9)$$

## Buffers linking constraints

A straightforward link between the buffer value of a given arc  $a \in A(N)$  associated with train pair  $(t_1, t_2) \in T^2$  and the choice of patterns for the given pair of trains is the following:

$$\sum_{P_1 \in \mathcal{P}_{t_1}} \sum_{P_2 \in \mathcal{P}_{t_2}} c_{P_1, P_2, a} x_{t_1, P_1} x_{t_2, P_2}$$

where  $c_{a, P_1, P_2}$  is a constant associated to arc  $a$  and to the corresponding choice of patterns  $(P_1, P_2)$  for trains  $(t_1, t_2)$ .

## Buffers linking constraints

$$f_a \leq \sum_{P_1 \in \mathcal{P}_{t_1}} \alpha_{P_1}^a x_{t_1, P_1} + \sum_{P_2 \in \mathcal{P}_{t_2}} \beta_{P_2}^a x_{t_2, P_2} - \gamma^a, \quad a \in A(N), (\alpha, \beta, \gamma) \in \mathcal{F}_a \quad (10)$$

Following Caprara *et al.* 2007 [2], the separation of Constraints (10) is done by a sort of polyhedral brute force, given that, for each pair of trains  $t_1, t_2$ , and for each arc  $a \in A(N)$  the number of vertices in  $Q_{t_1, t_2, a}$  is small. Specifically,  $Q_{t_1, t_2, a}$  has  $|\mathcal{P}_{t_1}| |\mathcal{P}_{t_2}|$  vertices and lies in  $\mathbb{R}^{|\mathcal{P}_{t_1}| + |\mathcal{P}_{t_2}| + 1}$ , so we can separate over it by solving an LP with  $|\mathcal{P}_{t_1}| |\mathcal{P}_{t_2}|$  variables and  $|\mathcal{P}_{t_1}| + |\mathcal{P}_{t_2}| + 1$  constraints.

## Computational results: Palermo C.Le.

time window	# trains n.p.	$D$ nom	CPU time nom (sec)	$D$ RR	CPU time RR (sec)	Diff. $D$	Diff. $D$ in %
A	0	646	7	479	46	167	25.85
B	2	729	7	579	3826	150	20.58
C	0	487	6	356	143	131	26.90
D	2	591	6	384	228	207	35.03
E	1	710	9	516	2217	194	27.32
F	1	560	7	480	18	80	14.29
G	3	465	11	378	64	87	18.71







Table: Results for Palermo Centrale

## Computational results: Genova P.Princ.

time window	# trains n.p.	$D$ nom	CPU time nom (sec)	$D$ RR	CPU time RR (sec)	Diff. $D$	Diff. $D$ in %
A	0	630	9	516	18190	114	18.10
B	0	838	11	624	3177	214	25.54
C	0	888	7	509	2495	379	42.68
D	4	895	8	657	9940	238	26.59
E	1	616	5	405	37	211	34.25
F	1	516	5	373	14	143	27.71
G	0	431	5	219	8	212	49.19

Table: Results for Genova Piazza Principe

## References

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