

# Towards Solving Very Large Scale Train Timetabling Problems by Lagrangian Relaxation

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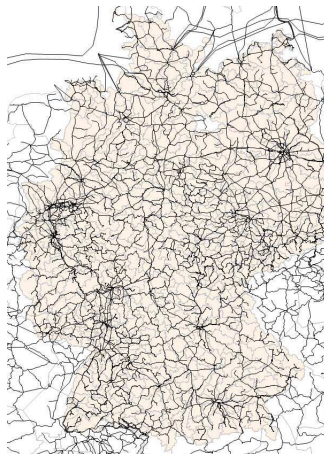
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## Problem description

Classical Train Timetabling Problem (TTP).

**Goal:** generate a timetable for the *whole German railway network* of Deutsche Bahn.



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Classical Train Timetabling Problem (TTP).

**Goal:** generate a timetable for the *whole German railway network* of Deutsche Bahn.

**Given:**

- railway network (stations, tracks, track switches ...)
- passenger and freight trains with predefined route

**Restrictions:**

- running times, headway times, capacities
- base timetable for passenger trains

**Goal:**

- feasible timetable with few delays

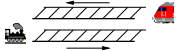
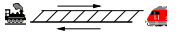
## Former work

The TTP is a well investigated problem:

- *periodic scheduling literature*
  - Serafini, Ukovich (1989)
  - Kroon, Dekker, Michiel, Vromans (2005)
  - Liebchen (2006)
- *non-periodic scheduling literature*
  - Schrijver, Steenbeck (1994)
  - Higgins, Kozan, Ferreira (1997)
  - Brännlund, Lindberg, Nõu, Nilsson (1998)
  - Caprara, Fischetti, Toth (2002)
  - Cacchiani, Caprara, Toth (2006)
  - Caprara, Kroon, Monaci, Peeters, Toth (2006)
  - Ingolotti, Baber, Tormos, Lova, Ealido, Abril (2006)
  - Borndörfer, Schlechte (2007)

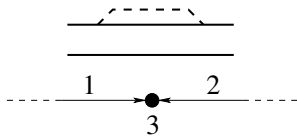
# Problem data

Given:

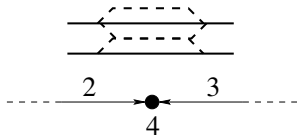
- *infrastructure digraph*  $D = (V, A)$  where
  - $V$  set of stations, track switches ...
  - $A$  set of tracks, may be
    - *double tracks* 
    - *single tracks* 
  - *absolute node capacities*
  - *directional capacities*

# Problem data

**Example:** absolute and directional capacities.



absolute	left dir.	right. dir.
3	1	2



absolute	left dir.	right. dir.
4	2	3

# Trains

For each train  $j \in T$ :

- *train type*  $m(j) \in M$
- *predefined route*: ordered sequence of nodes  
 $U(j) = (u_1^j, \dots, u_{n_j}^j), n_j \in \mathbb{N}$

Furthermore for each passenger train

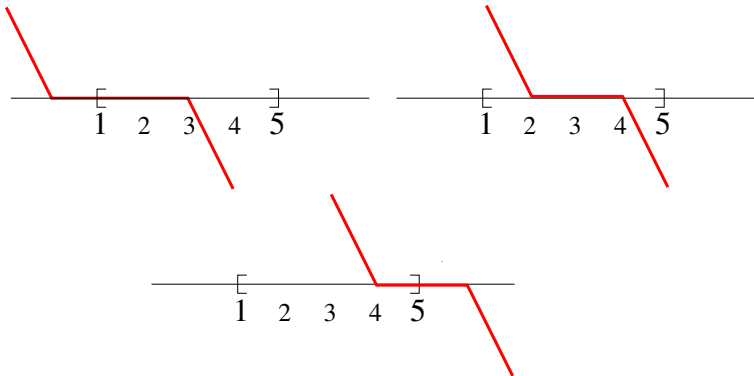
- *stopping interval*  $I_i^j = [t_i^{S,j}, t_i^{E,j}] \subset \mathbb{Z} \cup \{\pm\infty\}$   
“when the train has to wait”
- *minimal stopping time*  $d_i^j \in \mathbb{Z}_+$ .  
“how long the train has to wait”

train must arrive before  $t_i^{E,j}$  and must not leave before  $t_i^{S,j} + d_i^j$ .

# Stopping interval and minimal stopping time

Example: stopping interval =  $[1, 5]$ , minimal stopping time = 2 minutes

The following examples are valid:

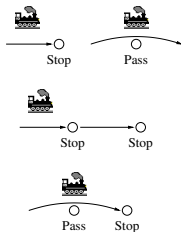




# Running times

A train needs some time from one station to the next, its *running time*.

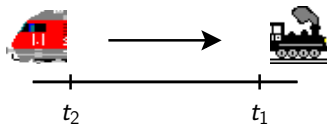
This depends on the train type ( $m \in M$ ) and on whether the train *stops* or *passes* at the stations:



$$t_a^R : M \times B_R \rightarrow \mathbb{Z}_+, a \in A, B_R = \{pass, stop\}$$

# Headway times

There must be a safety distance between two sequent trains on the same track, the *minimal headway times*.



$$t_1 + t_a^H \leq t_2$$

They depend on both train-types and stopping behaviours:

$$t_a^H: M \times B_R \times M \times B_R \rightarrow \mathbb{Z}_+.$$

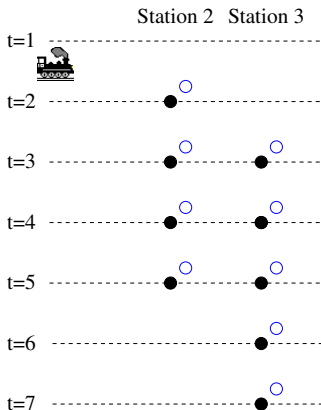
# Model

Classic model via *time discretised networks* for the single train routes (e.g. Caprara et al.):

For each train  $j \in T$  a graph  $G^j = (V^j, A^j)$  where

- $V^j$  contains
  - an artificial *start-node*  $\sigma^j$ ,
  - an artificial *end-node*  $\tau^j$ ,
  - a *wait-node* and a *stop-node* node for each *station, time-step*
- $A^j$  contains
  - *starting arcs* from  $\sigma^j$  to the first station's nodes,
  - *ending arcs* from the last station's nodes to  $\tau^j$ ,
  - *waiting arcs* between two successive wait-nodes of one station,
  - *running arcs* connecting nodes of successive stations
  - *infeasible arcs* from each intermediate station's node to  $\tau^j$ .

# Train graphs: nodes

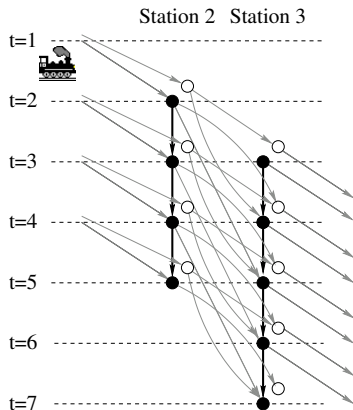


● stop nodes  
train *stops* at the station

○ run nodes  
train *passes* through the station

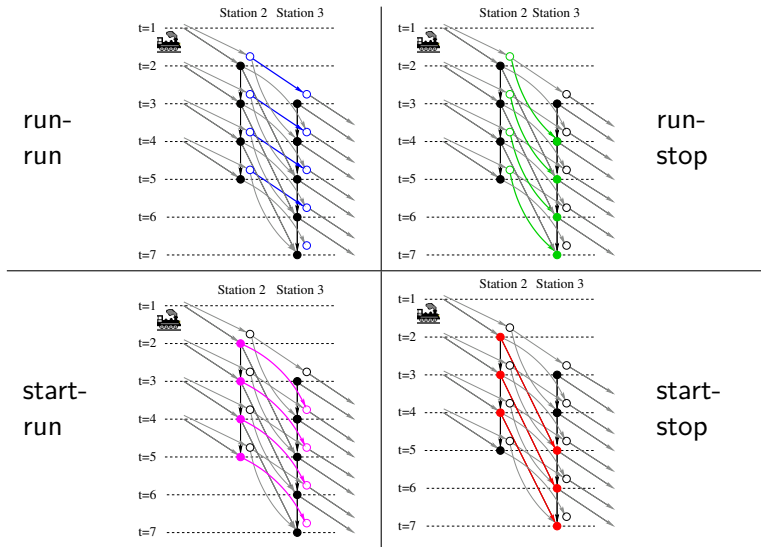
nodes

# Train graphs: waiting arcs

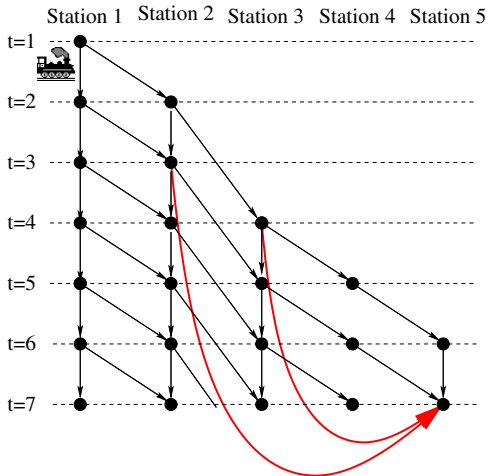


waiting arcs

# Train graphs: running arcs



# Train graphs: infeasible arcs



infeasible arcs

# Variables

Let  $\mathcal{A} := \bigcup_{j \in \mathcal{T}} A^j$  be the set of *all* arcs.  
Introduce binary variables for each arc:

$$x_a \in \{0, 1\}, a \in \mathcal{A},$$

with the interpretation for  $a \in A^j$ :

$$x_a = 1 \Leftrightarrow \text{train } j \text{ uses arc } a.$$



## Capacity constraints

Only a bounded number of trains may enter an infrastructure node  $v \in V$  at the same time  $t$  because of absolute capacities and directional capacities.

Lead to constraints of the form

$$\sum_{a \in \delta^-(v,t)} x_a \leq c_v \quad \text{absolute capacities}$$

and

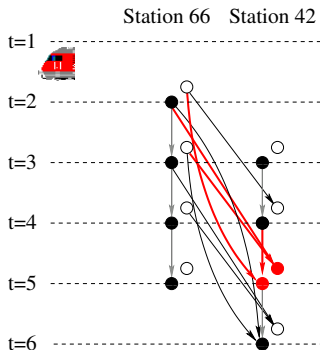
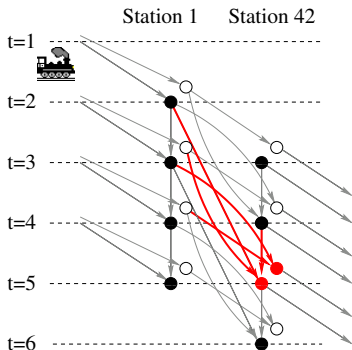
$$\sum_{a \in \delta^-(uv,t)} x_a \leq c_{uv}, \quad \text{directional capacities}$$

where

$$\delta^-(v, t) = \left\{ ((b', i', t')^j, (b, i, t)^j) \in \mathcal{A} : u_i^j = v \right\},$$
$$\delta^-(uv, t) = \left\{ ((b', i', t')^j, (b, i, t)^j) \in \mathcal{A} : u_{i-1}^j u_i^j = uv \right\}.$$

# Capacity constraints

**Example:** station 42 has capacity 1



$$\sum_{a \in \{\text{red arcs}\}} x_a \leq 1.$$

## Headway constraints

Between two trains on the same physical track minimal headway times are required for safety reasons (e.g. Lukac).

Two arcs

$$((b_1, i_1, t_1)^j, (b_2, i_2, t_2)^j) \in A^j \quad \text{and} \quad ((b'_1, i'_1, t'_1)^{j'}, (b'_2, i'_2, t'_2)^{j'}) \in A^{j'}$$

with  $t_1 \leq t'_1$  conflict if either

- $u_{i_1}^j u_{i_2}^j = u_{i'_1}^{j'} u_{i'_2}^{j'} = uv \in A$  and  
 $t_1 + t_{uv}^H(m(j), (b_1, b_2), m(j'), (b'_1, b'_2)) > t'_1$ , or
- $u_{i_1}^j u_{i_2}^j = u_{i'_2}^{j'} u_{i'_1}^{j'} = uv \in A_S$  and  
 $t_1 + t_{uv}^{HS}(m(j), (b_1, b_2), m(j'), (b'_1, b'_2)) > t'_1$ .

Lead to constraints of the type

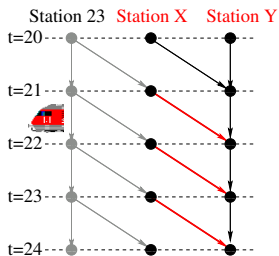
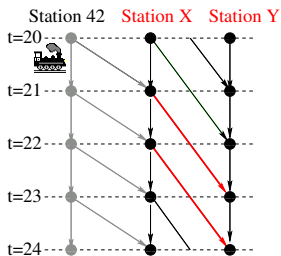
$$\sum_{a \in C} x_a \leq 1,$$

where  $C$  is a clique in the conflict graph.

# Headway constraints

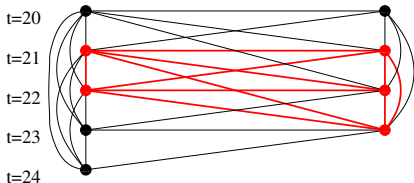
## Example:

- train 1 first, train 2 second: 3 minutes
- train 2 first, train 1 second: 2 minutes



Conflict graph

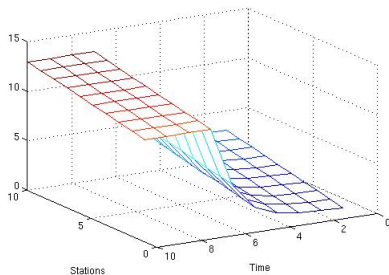
Constraint



$$\sum_{a \in \{\text{red arcs}\}} x_a \leq 1$$

# Objective function

- high costs on infeasible-arcs,
- no costs on running-arcs (running is good),
- increasing costs on waiting arcs (waiting is bad)



# ILP formulation

$$\text{maximize } \sum_{a \in \mathcal{A}} x_a w_a$$

subject to

$$\begin{array}{l} \text{flow conservation} \left\{ \begin{array}{l} \sum_{a \in \delta^+(\sigma^j)} x_a = 1, \quad j \in T, \\ \sum_{a \in \delta^+(v)} x_a = \sum_{a \in \delta^-(v)} x_a, \quad j \in T, v \in V^j \setminus \{\sigma^j, \tau^j\}, \end{array} \right. \\ \\ \text{capacity} \left\{ \begin{array}{l} \sum_{a \in \delta^-(v,t)} x_a \leq c_v, \quad v \in V, t \in S, \\ \sum_{a \in \delta^-(uv,t)} x_a \leq c_{uv}, \quad uv \in A, t \in S, \end{array} \right. \\ \\ \text{headway} \left\{ \sum_{a \in C} x_a \leq 1, \quad C \in \mathcal{C}, \right. \\ \\ \text{binary} \left\{ x_a \in \{0, 1\}, \quad a \in \mathcal{A}. \right. \end{array}$$

# Solution methods

Goal: rounding heuristics based on a relaxation of the ILP.

Because of the large size of the instances, solving the LP relaxation by a state-of-the-art solver is too slow.

⇒ solve the Lagrangian dual obtained by relaxation of the coupling constraints.

# Lagrange dual and decomposition

Let

- $Dx \leq d$  be the coupling constraints,
- $D^j, j \in T$ , be the columns corresponding to the  $x_a, a \in A^j$ ,
- $\mathcal{X}^j = \{x \in \mathbb{R}^{A^j} : x \text{ is valid path in } G^j\}$ .

The LP reads

$$\max_{\substack{Dx \leq d \\ x \in \mathcal{X}}} w^T x$$

with the Lagrangian dual problem

$$\inf_{y \geq 0} \left( d^T y + \sum_{j \in T} \max_{x^j \in \mathcal{X}^j} \left[ (w^j - D^{jT} y)^T x^j \right] \right).$$



# Bundle method

The bundle method requires the evaluation of

$$\varphi(y) = d^T y + \sum_{j \in T} \max_{x^j \in \mathcal{X}^j} \left[ \left( w^j - D^j{}^T y \right)^T x^j \right]$$

for given  $y$ .

These are *independent shortest-path problems*.

Each optimal solution  $x(y)$  of the shortest path problems yields a *subgradient*

$$g(y) = d - Dx(y).$$

The bundle method (see, e.g., Lemaréchal)

- requires an oracle returning the *function value* and a *subgradient*,
- generates a sequence of *convex-combinations* of the paths returned by the oracle, the so called *primal aggregates*.

# Primal aggregates and separation

The primal aggregates

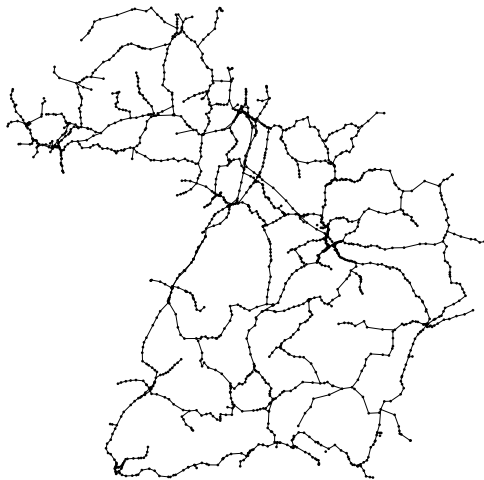
- converge to an optimal solution of the LP-relaxation of the TTP  $\Rightarrow$  can be used by rounding heuristics,
- may be used for *primal separation* of the conflict constraints, see Helmberg (2004).

Why primal separation?

- capacity constraints: relatively small number, easy to separate,
- headway constraints: possibly exponentially large number, separated by heuristics.

## Numerical results

Three test instances based on south-west network of DB (roughly Baden-Wuerttemberg):



## Numerical results

Three test instances based on south-west network of DB (roughly Baden-Wuerttemberg):

1. A small part of the network containing the five most frequently used arcs,
2. the main long-distance and freight traffic route along the river Rhine,
3. the whole subnet.

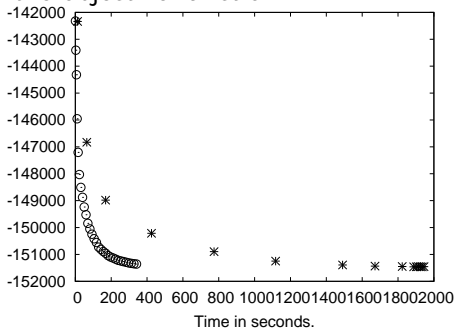
Instance	Nodes	Arcs	Passenger	Freight	Variables
1	104	193	242	9	317336
2	656	1210	50	67	2448842
3	2103	4681	2501	659	8990060

## Solving the relaxation

Memory and time consumption by CPLEX and ConicBundle (on an Intel Xeon Dual Core, 3 GHz, 16 GB RAM):

Instance	CPLEX	ConicBundle	Size
1	33s	12s	160 MB
2	1945s	341s	1 GB
3	—	2512s	6 GB

Development of the objective function:



## First integer results

First round heuristics based on successive fixation of arcs yielded good results for instance 1 and 2, but not for 3:

Instance	Time	Infeasible trains	Late trains	Average delays
1	39s	0	0	0
2	697s	0	0	0
3	3182s	40	906	865s
3b	10h	9	778	603s

# Reducing the problem size

## Problem:

- instances are too large,
- separation of headway constraints too expensive.

## Solution ideas:

- create train-graphs dynamically,
- instead of separation of headway constraints, model feasible *configurations* by configuration-networks.







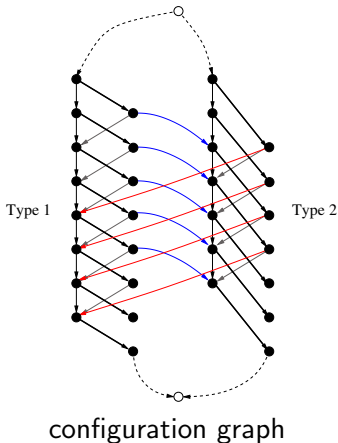
# Configuration networks

**Goal:** Replace headway constraints by configuration networks, that model *feasible* train runs.

# Configuration networks: structure

(Borndörfer et al, 2007)

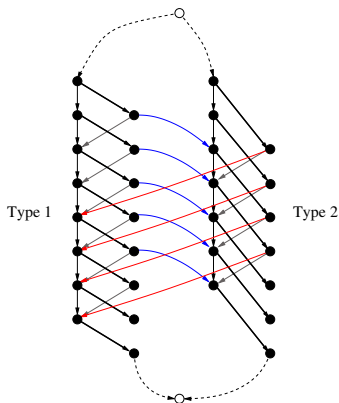
- one *configuration network* for each infrastructure arc,
- train-arcs are activated by the configuration-networks,



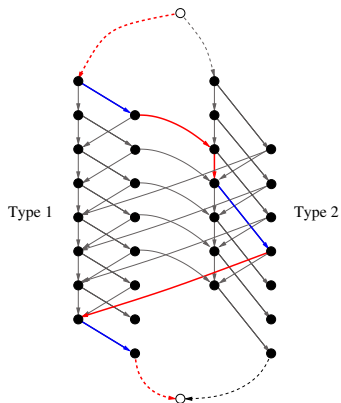
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configuration graph

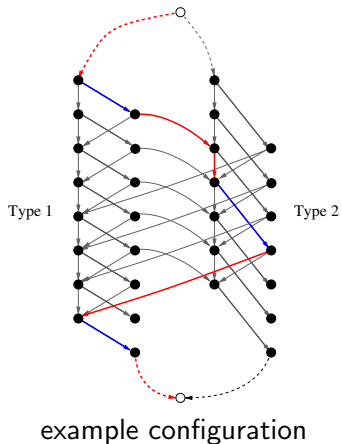
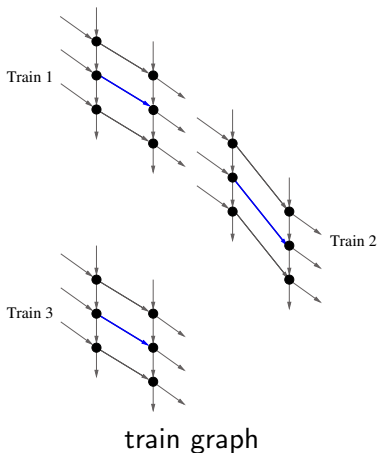


example configuration

# Configuration networks: structure

(Borndörfer et al, 2007)

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- train-arcs are activated by the configuration-networks,



# Configuration networks

## Pros:

- no separation of headway constraints necessary,
- instead simple coupling constraints between train-graphs and configuration networks.

## Cons:

- number of variables increases a lot,
- dynamic generation of configuration networks required.

## Next steps

- implementation of (dynamic) configuration networks,
- exploit dual sensitivity information for better rounding heuristics,
- robustness.

Thank you for your attention.