



Scheduling Problems and Algorithms in Traffic and Transport

MAPSP 2011
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Zuse-Institute Berlin

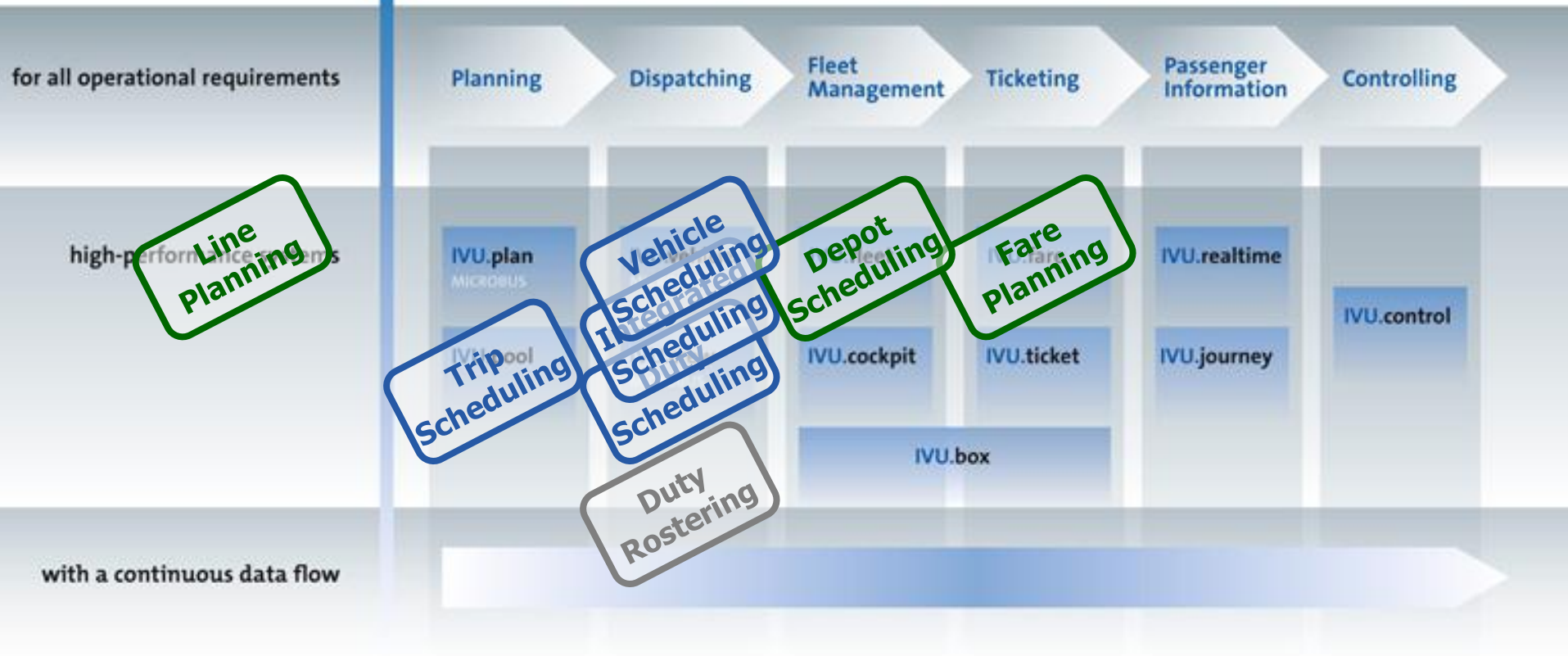
Joint work with Ivan Dovica, Martin Grötschel, Olga Heismann, Andreas Löbel,
Markus Reuther, Elmar Swarat, Thomas Schlechte, Steffen Weider

DFG Research Center MATHEON
Mathematics for Key Technologies



IVU suite

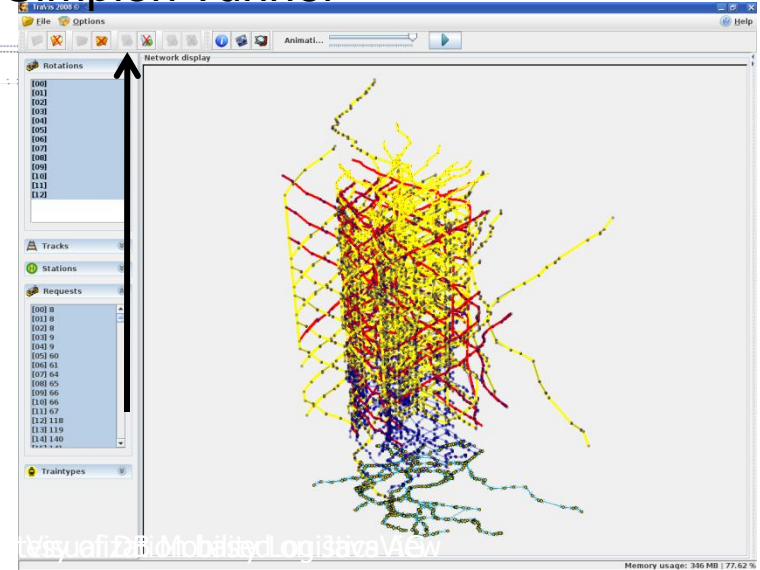
The IVU.suite for Public Transport



We want to avoid this!



Simplon Tunnel



Basic Rolling Stock Rostering Problem = Multicommodity Flow Problem

▷ Can be solved efficiently for networks with 10^9 arcs

Constraints complicating rolling stock roosting

▷ Discretization: Space/Time ("Multiscale Problems")

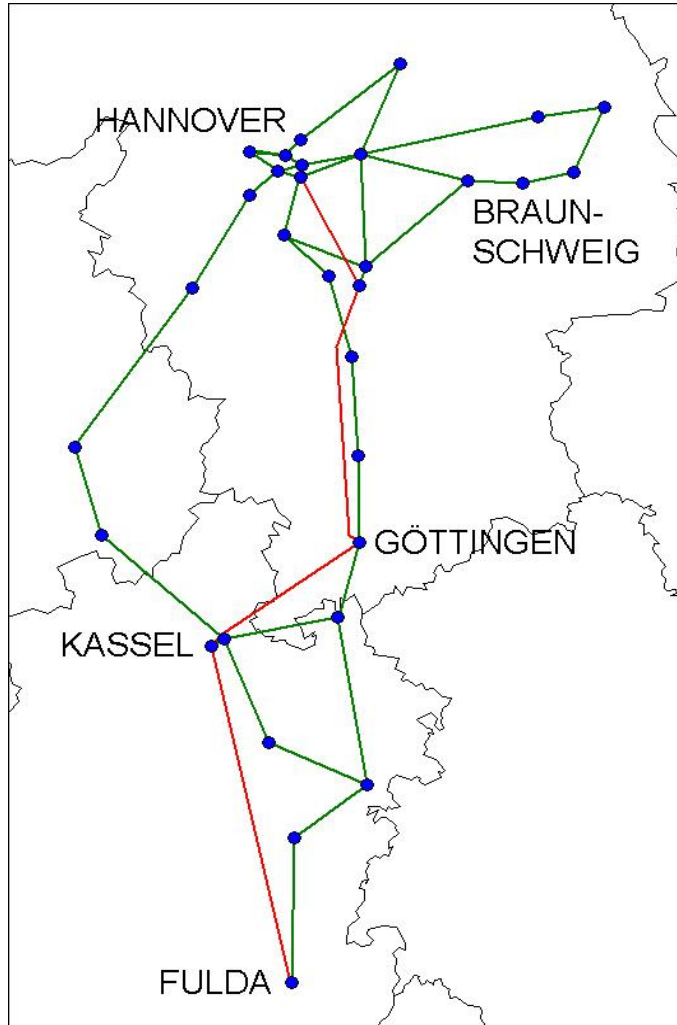
▷ Robustness: Delay Propagation

▷ Path Constraints: Maintenance, Parking

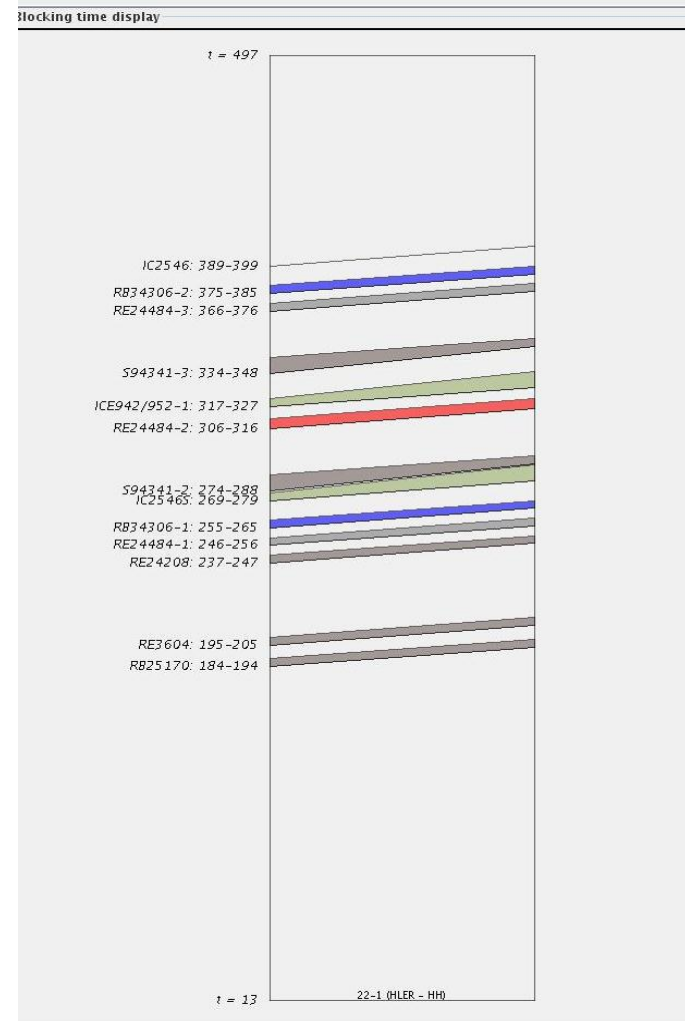
▷ Configuration Constraints: Track Usage, Train Composition, Uniformity

Integrated Routing and Scheduling

Routing



Scheduling



TraVis 2008 ©

File Options Edit Help

Animation

Train paths

Solution

Tracks

- [057] 21-2
- [058] 22-1
- [059] 22-2
- [060] 23-1
- [061] 23-2
- [062] 24-2
- [063] 24-1
- [064] 25-2
- [065] 25-1
- [066] 26-2
- [067] 26-1
- [068] 27-1
- [069] 27-2
- [070] 79-1
- [071] 79-2

Stations

- [00] HLER
- [01] HHI
- [02] HNOS
- [03] HWU
- [04] HWHN
- [05] HG
- [06] FK
- [07] FKW
- [08] HEBG
- [09] HWAR
- [10] HA
- [11] HHM
- [12] HWEZ
- [13] HLI
- [14] HH

Requests

Traintypes

Network display

Blocking time display

t = 497

IC2546: 389-399
 RB34306-2: 375-385
 RE24484-3: 366-376

S94341-3: 334-348

ICE942/952-1: 317-327
 RE24484-2: 306-316

S94341-2: 274-288
 IC25465: 269-279

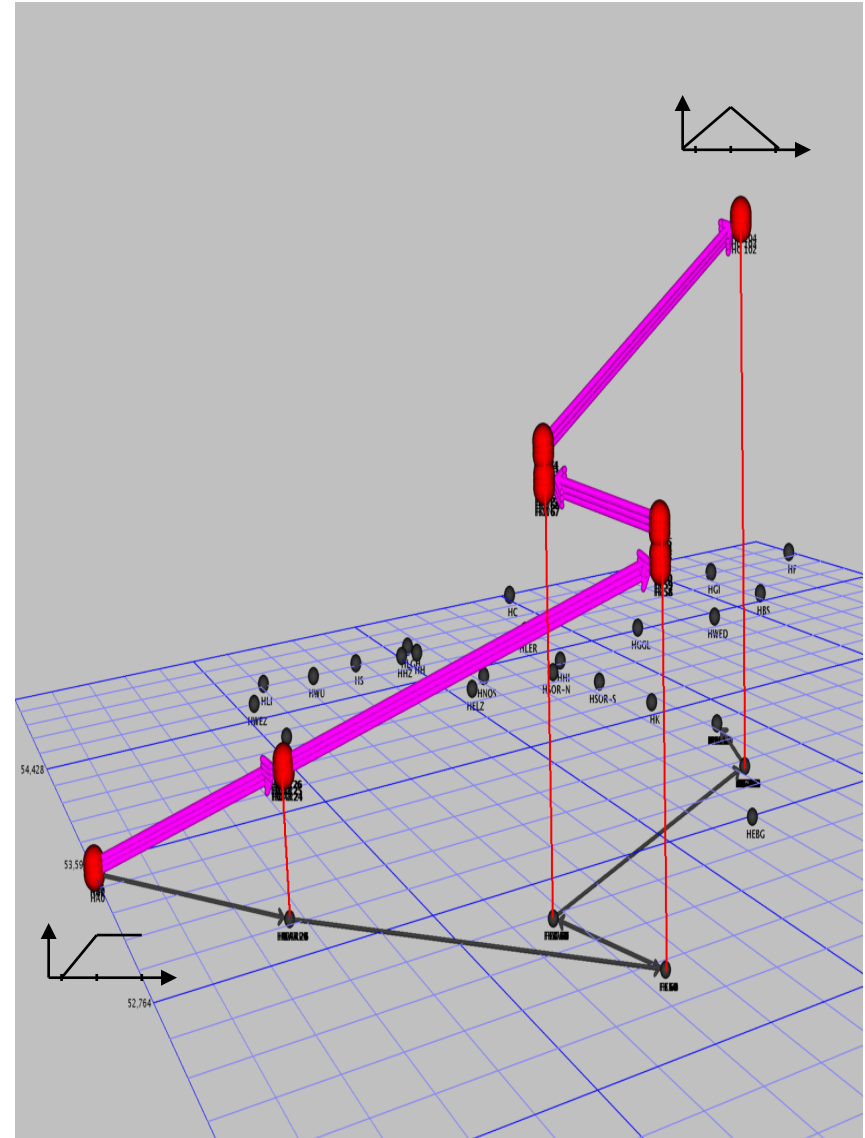
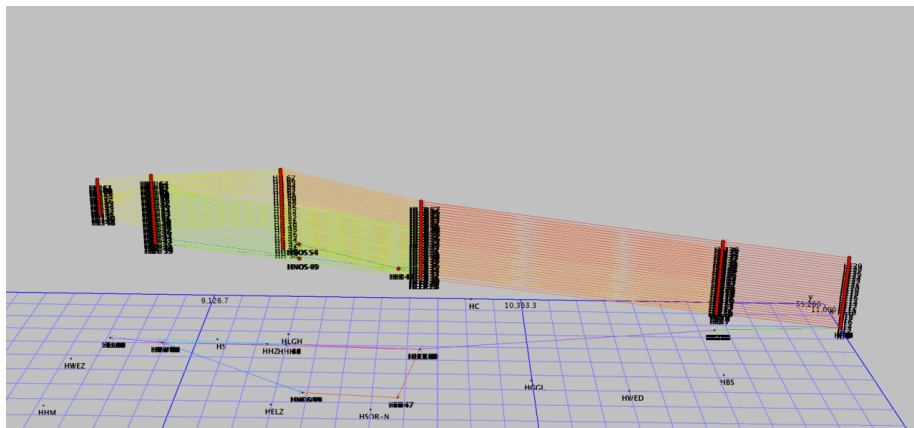
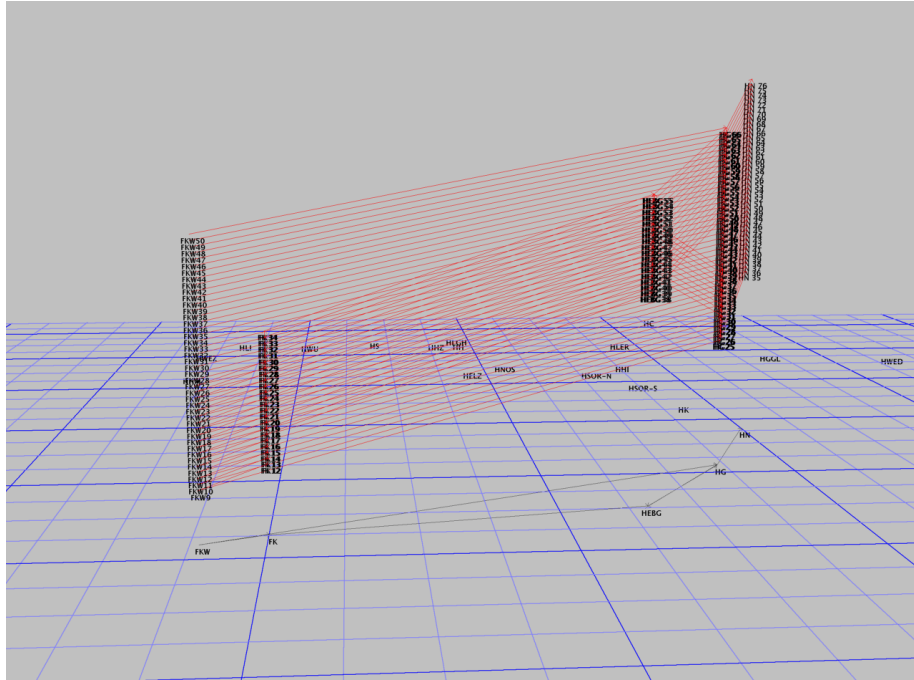
RB34306-1: 255-265
 RE24484-1: 246-256
 RE24208: 237-247

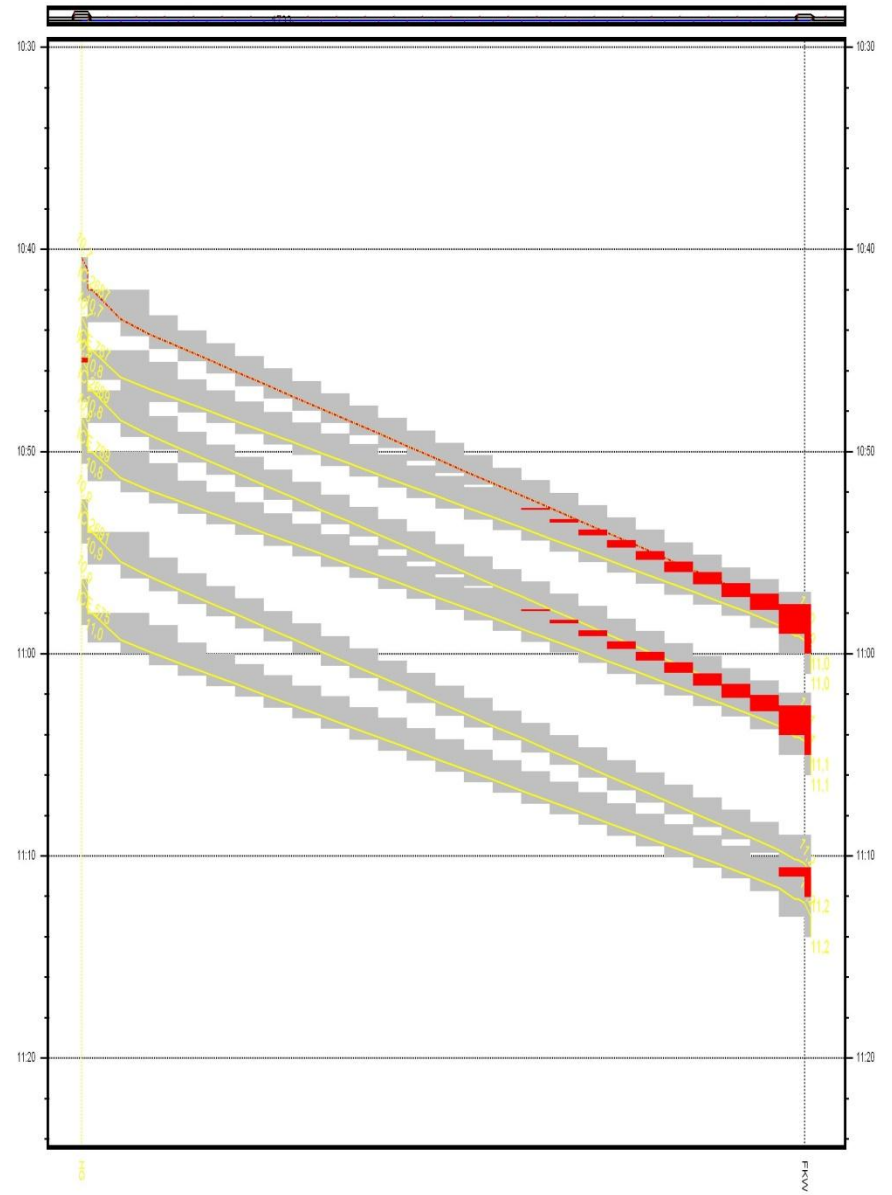
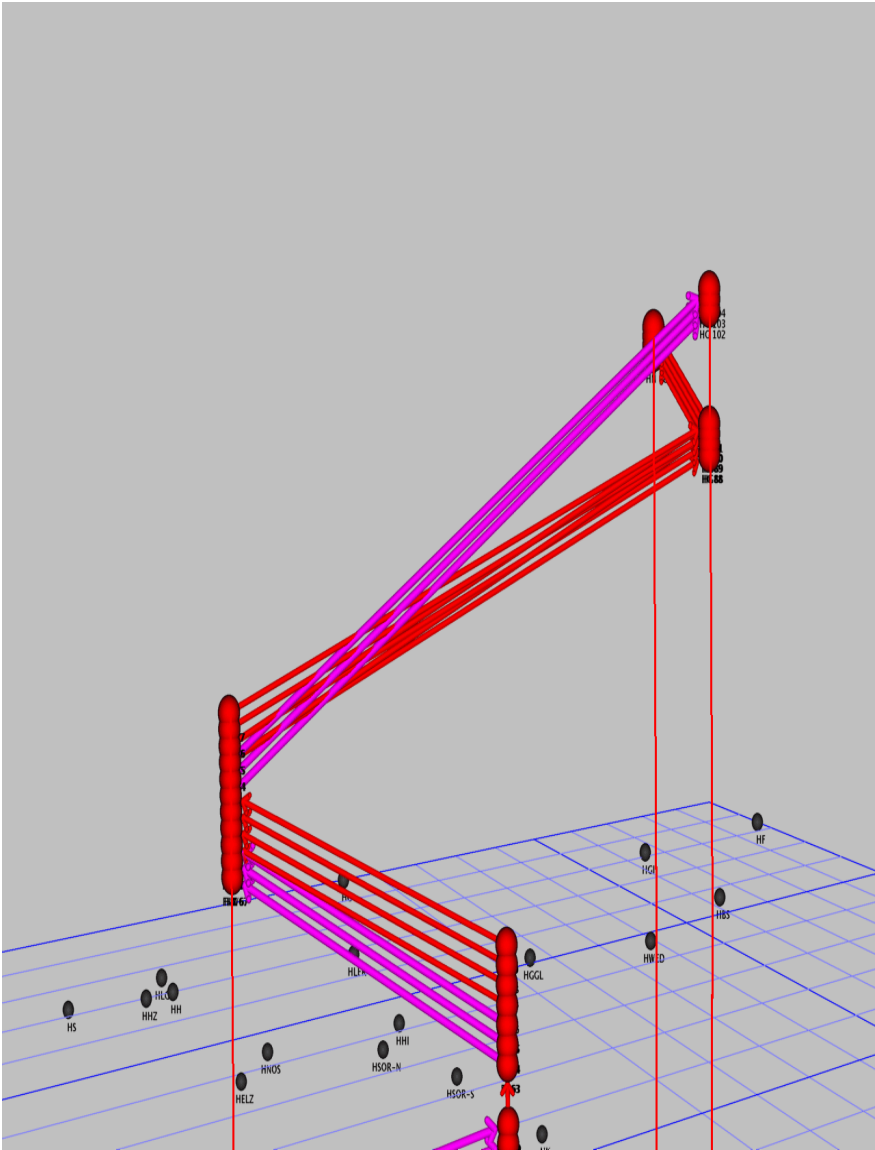
RE3604: 195-205
 RB25170: 184-194

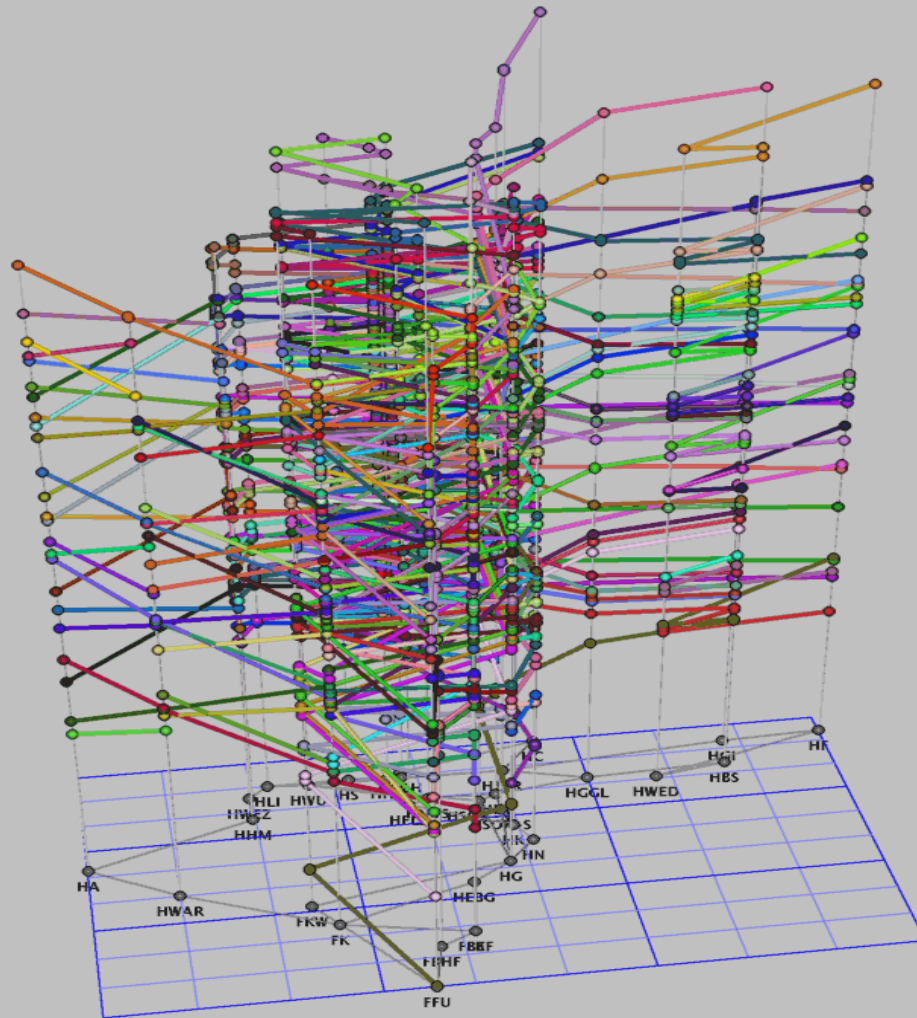
t = 13

22-1 (HLER - HH)

Train Routes are Flexible in Space and Time

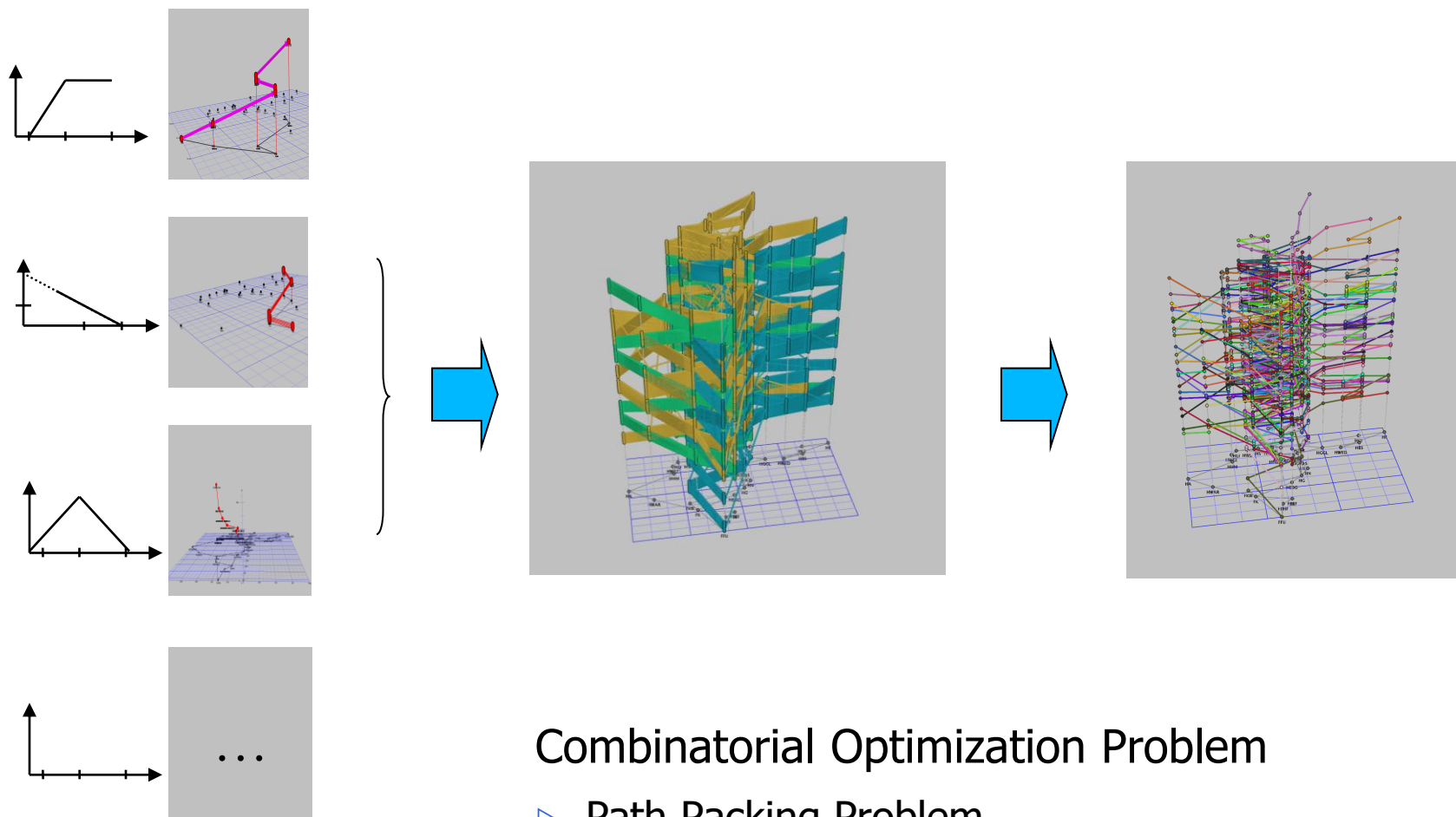






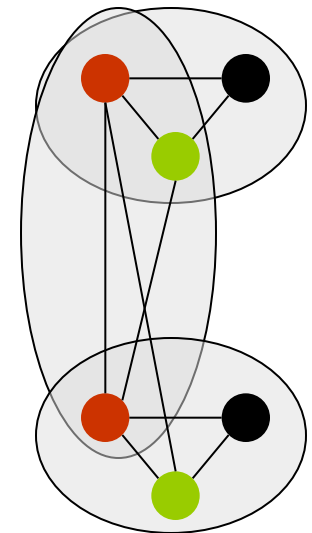
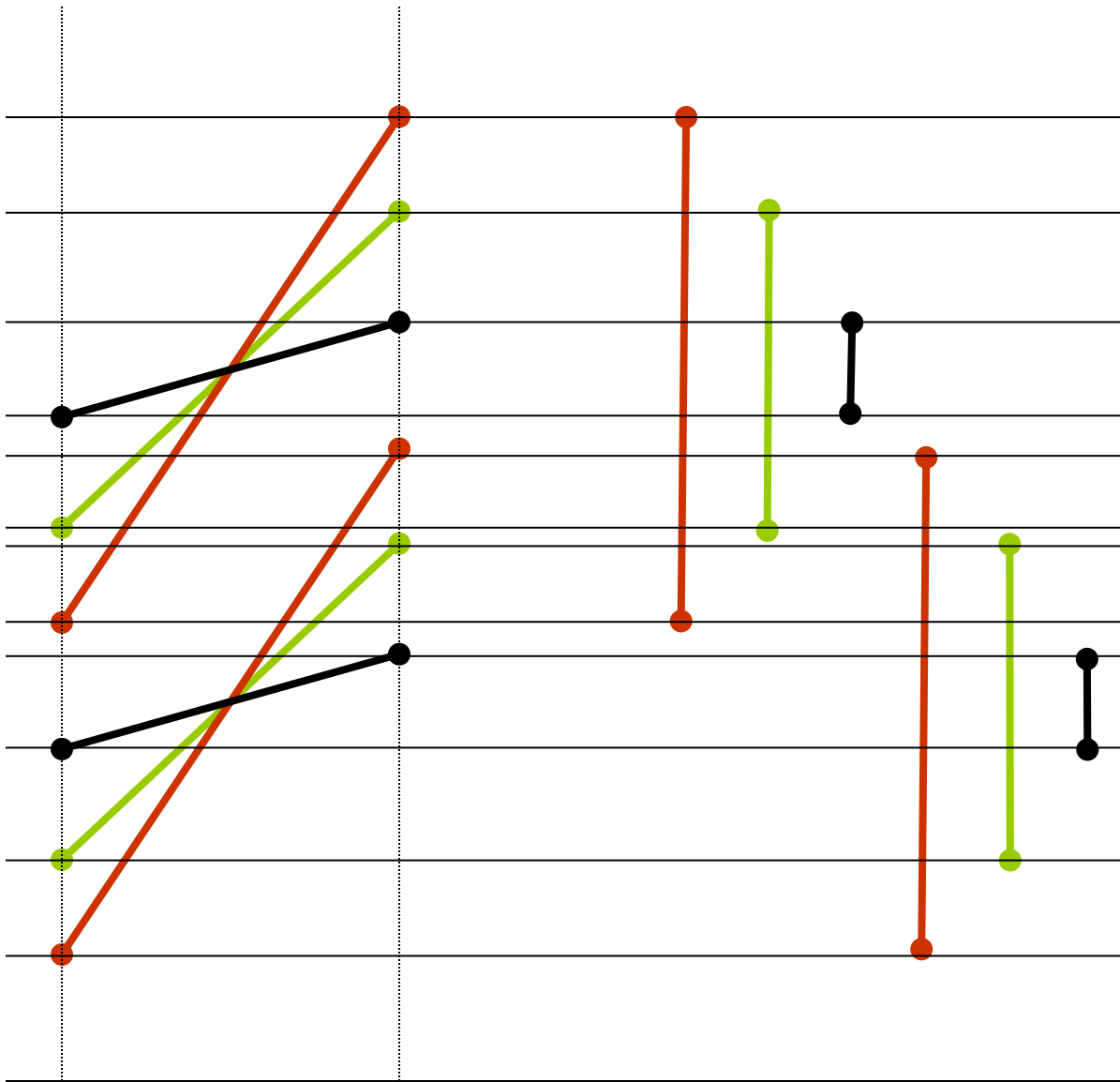


Track Allocation/Train Timetabling Problem





- ▷ Charnes and Miller (1956), Szpigel (1973), Jovanovic and Harker (1991),
- ▷ Cai and Goh (1994), Schrijver and Steenbeck (1994), Carey and Lockwood (1995)
- ▷ Nachtigall and Voget (1996), Odijk (1996) Higgings, Kozan and Ferreira (1997)
- ▷ **Brannlund, Lindberg, Nou, Nilsson (1998)**, Lindner (2000), Oliveira and Smith (2000)
- ▷ **Caprara, Fischetti and Toth (2002)**, Peeters (2003)
- ▷ Kroon and Peeters (2003), Mistry and Kwan (2004)
- ▷ Barber, Salido, Ingolotti, Abril, Lova, Tormas (2004)
- ▷ Semet and Schoenauer (2005),
- ▷ **Caprara, Monaci, Toth and Guida (2005)**
- ▷ Kroon, Dekker and Vromans (2005),
- ▷ Vansteenwegen and Van Oudheusden (2006), Liebchen (2006)
- ▷ **Cacchiani, Caprara, T. (2006), Cachhiani (2007)**
- ▷ Caprara, Kroon, Monaci, Peeters, Toth (2006)
- ▷ **Borndorfer, Schlechte (2005, 2007)**, Caimi G., Fuchsberger M., Laumanns M., Schüpbach K. (2007)
- ▷ **Fischer, Helmberg, Janßen, Krostitz (2008)**
- ▷ Lusby, Larsen, Ehrgott, Ryan (2009)
- ▷ Caimi (2009), Klages (2010)
- ▷ ...

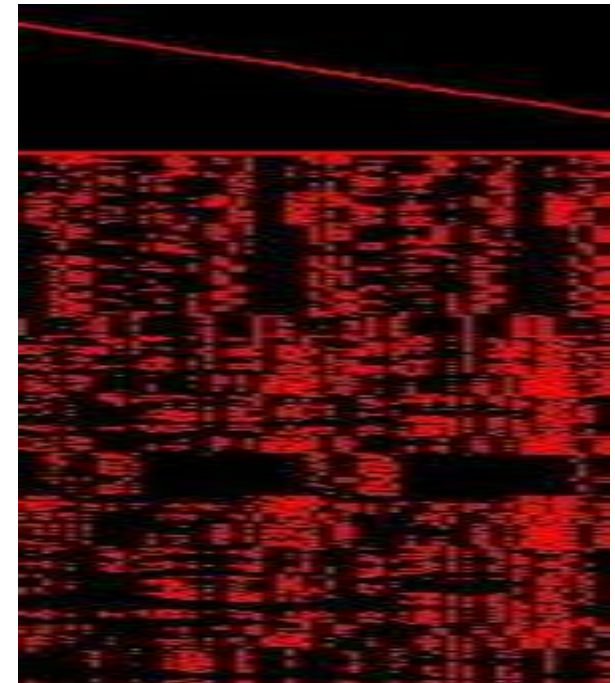
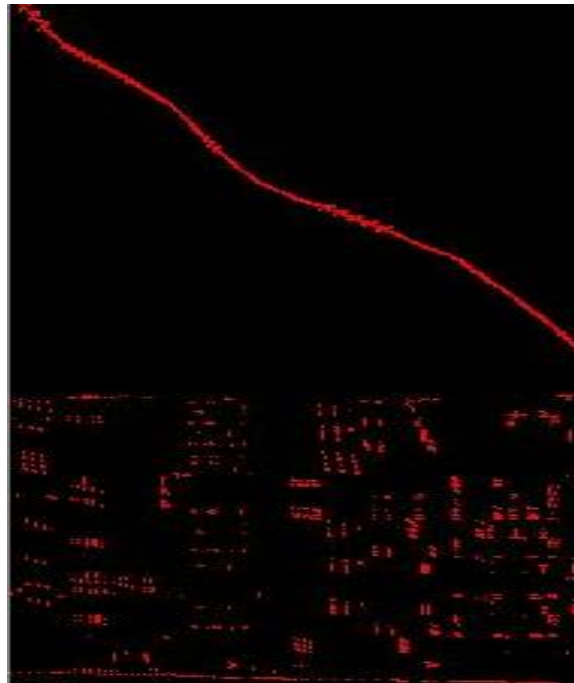
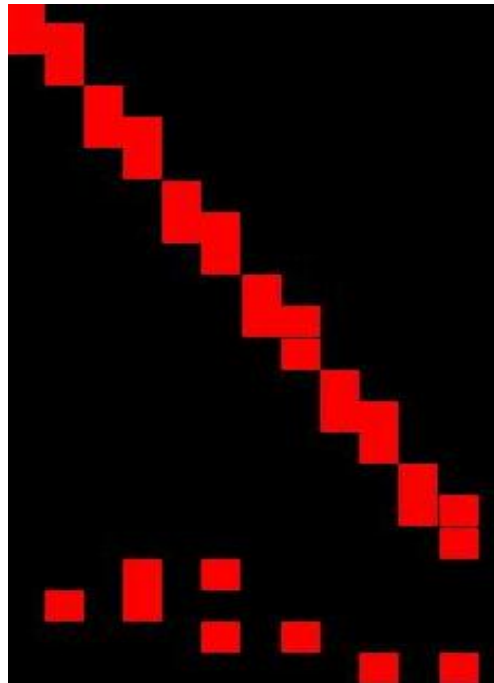


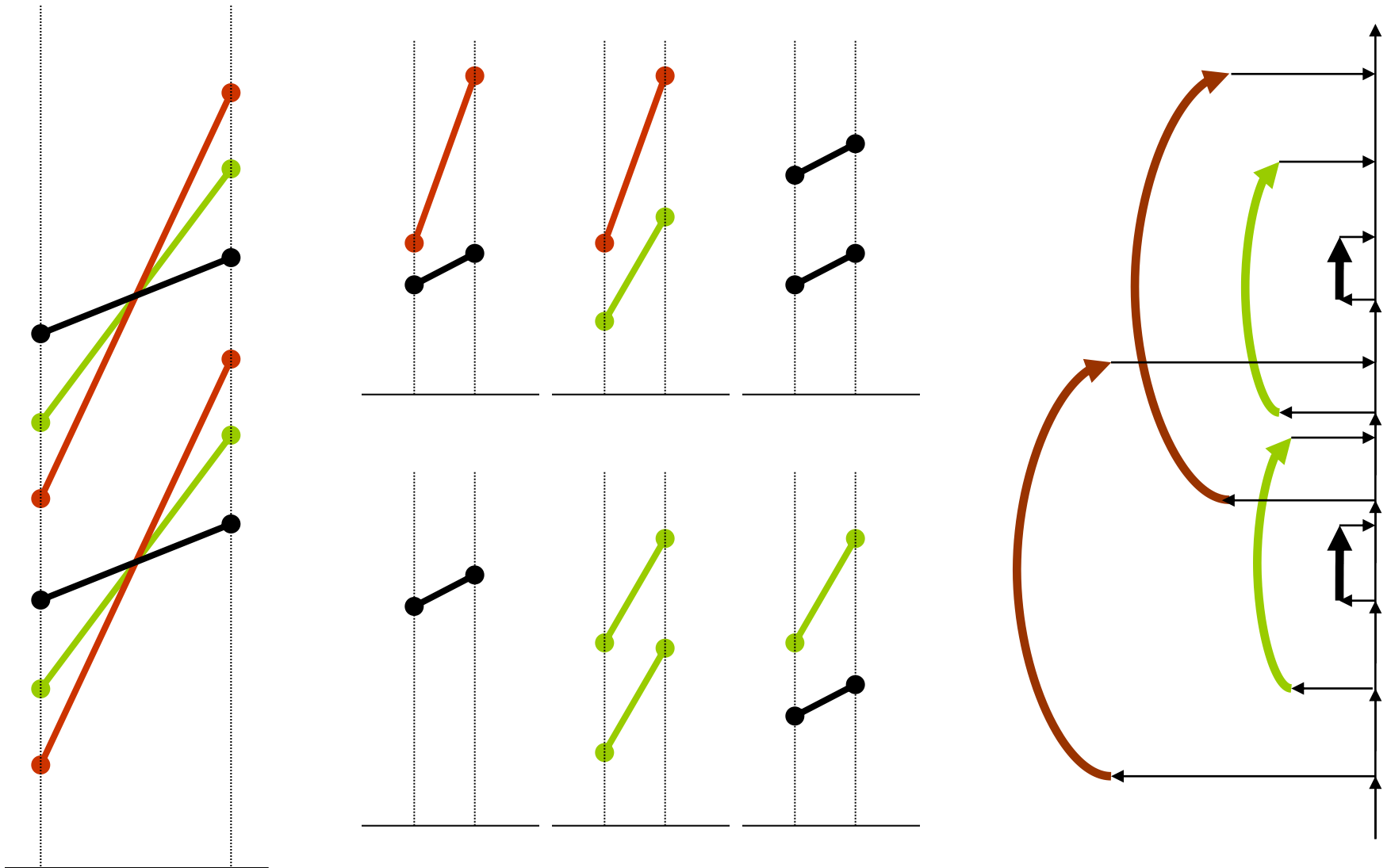
(APP) $\max \sum_{i \in I} \sum_{a \in A} c_a^i x_a^i$

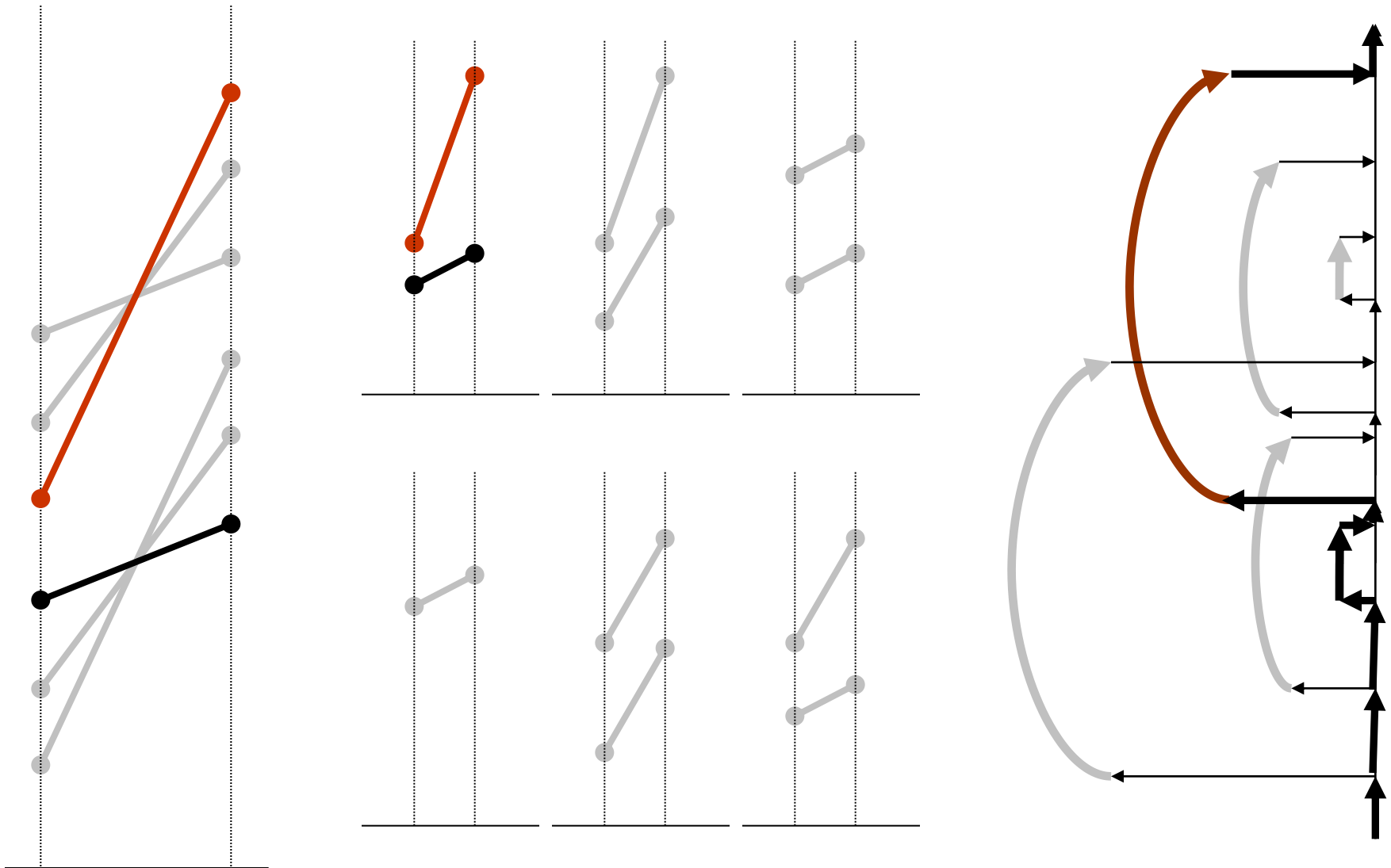
(i) $\sum_{a \in \delta_i^+(v)} x_a^i - \sum_{a \in \delta_i^-(v)} x_a^i = \beta_i(v) \quad \forall v \in V, i \in I$ Flow

(ii) $\sum_{(a,i) \in k} x_a^i \leq 1 \quad \forall k \in K$ Conflicts

(iii) $x_a^i \in \{0,1\} \quad \forall a \in A, i \in I$ Integ.







(APP) $\max \sum_{i \in I} \sum_{a \in A} c_a^i x_a^i$

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(PCP) $\max \sum_{i \in I} \sum_{p \in P_i} \sum_{a \in p} c_a^i x_p$

(i) $\sum_{p \in P_i} x_p \leq 1 \quad \forall i \in I$ Trains

(ii) $\sum_{q \in Q_j} y_q \leq 1 \quad \forall j \in J$ Configs

(iii) $\sum_{a \in p \in P} x_p - \sum_{a \in q \in Q} y_q \leq 0 \quad \forall a \in A$ Coupling

(iv) $x_p \in \{0,1\} \quad \forall p \in P$ Integ.

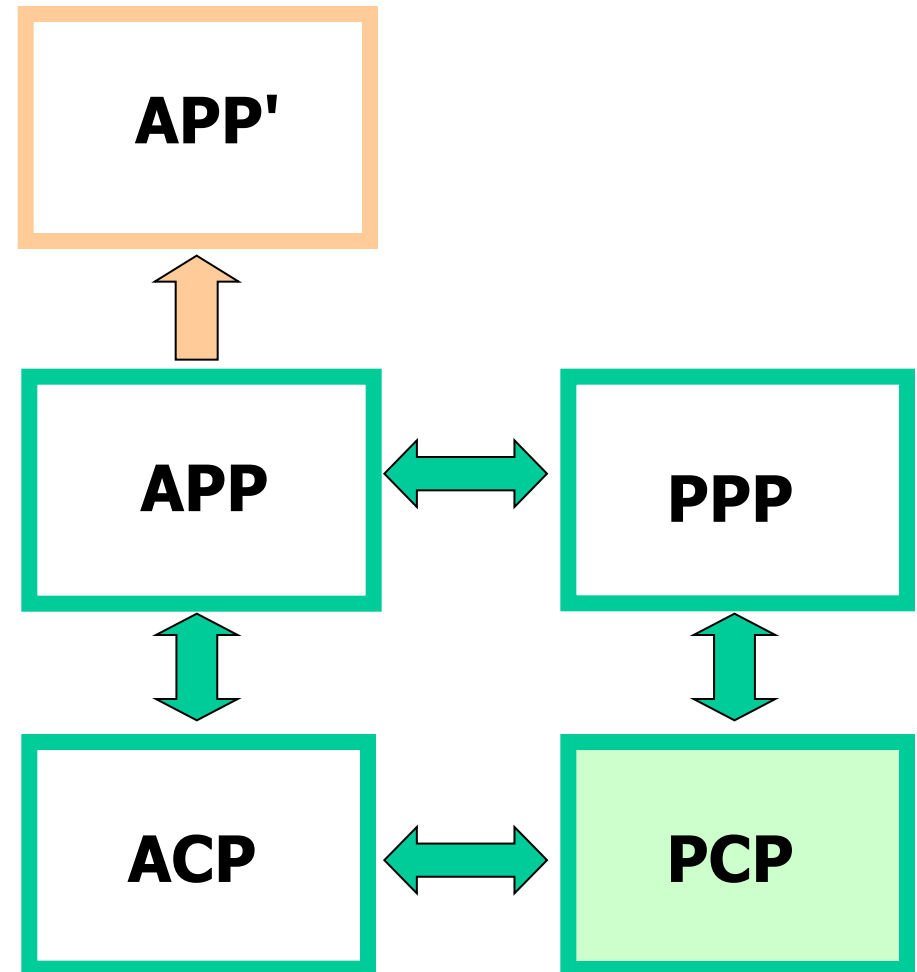
(v) $y_q \in \{0,1\} \quad \forall q \in Q$ Integ.

Theorem (B., Schlechte [2007]):

$$\begin{aligned}
 v_{LP}(PCP) &= v_{LP}(ACP) \\
 &= v_{LP}(APP) = v_{LP}(PPP) \\
 &\leq v_{LP}(APP').
 \end{aligned}$$

All LP-relaxations can be solved in polynomial time.

$$\begin{aligned}
 v_{IP}(PCP) &= v_{IP}(ACP) \\
 &= v_{IP}(APP) = v_{IP}(PPP) \\
 &= v_{IP}(APP').
 \end{aligned}$$



(APP) $\max \sum_{i \in I} \sum_{a \in A} c_a^i x_a^i$

(i) $\sum_{a \in \delta_i^+(v)} x_a^i - \sum_{a \in \delta_i^-(v)} x_a^i = \beta_i(v) \quad \forall v \in V, i \in I$ Flow

(ii) $\sum_{(a,i) \in k} x_a^i \leq 1 \quad \forall k \in K$ Conflicts

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(iv) $x_p \in \{0,1\} \quad \forall p \in P$ Integ.

(v) $y_q \in \{0,1\} \quad \forall q \in Q$ Integ.

$$(DUA) \min \sum_{i \in I} \gamma_i + \sum_{j \in J} \pi_j$$

$$(i) \quad \gamma_i + \sum_{a \in p} \lambda_a \geq \sum_{a \in p} c_a^i \quad \forall p \in P_i, i \in I \quad \text{Paths}$$

$$(ii) \quad \pi_j - \sum_{a \in q} \lambda_a \geq 0 \quad \forall q \in Q_j, j \in J \quad \text{Configs}$$

$$(iii) \quad \gamma, \pi, \lambda \geq 0$$

$$(PLP) \max \sum_{i \in I} \sum_{p \in P_i} \sum_{a \in p} c_a^i x_p$$

$$(i) \quad \sum_{p \in P_i} x_p \leq 1 \quad \forall i \in I \quad \text{Trains}$$

$$(ii) \quad \sum_{q \in Q_j} y_q \leq 1 \quad \forall j \in J \quad \text{Configs}$$

$$(iii) \quad \sum_{a \in p \in P} x_p - \sum_{a \in q \in Q} y_q \leq 0 \quad \forall a \in A \quad \text{Coupling}$$

$$(iv) \quad x_p \geq 0 \quad \forall p \in P \quad \text{Integ.}$$

$$(v) \quad y_q \geq 0 \quad \forall q \in Q \quad \text{Integ.}$$

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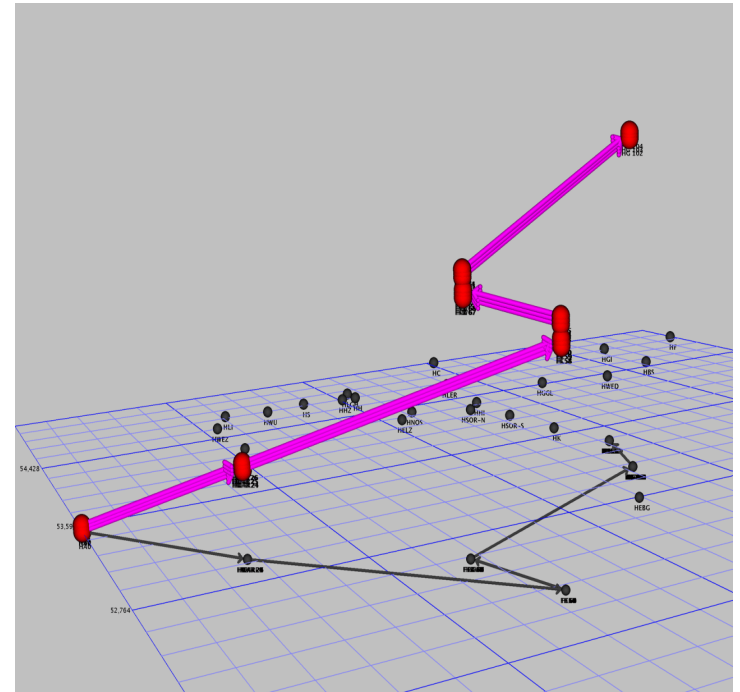
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$$(iii) \quad \gamma, \pi \geq 0$$

Proposition:

Route pricing = acyclic shortest path problem with arc weights

$$\bar{c}_a = -c_a + \lambda_a.$$



$$(DUA) \min \sum_{i \in I} \gamma_i + \sum_{j \in J} \pi_j$$

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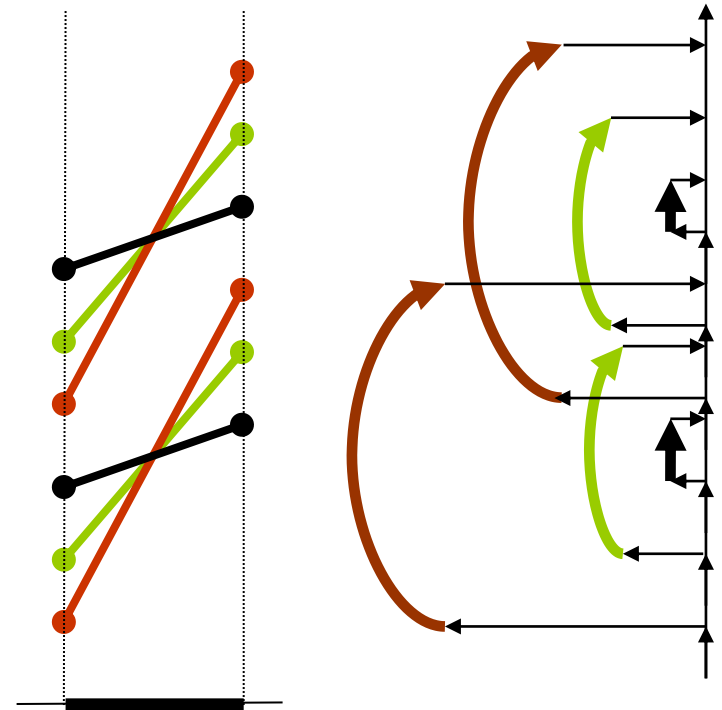
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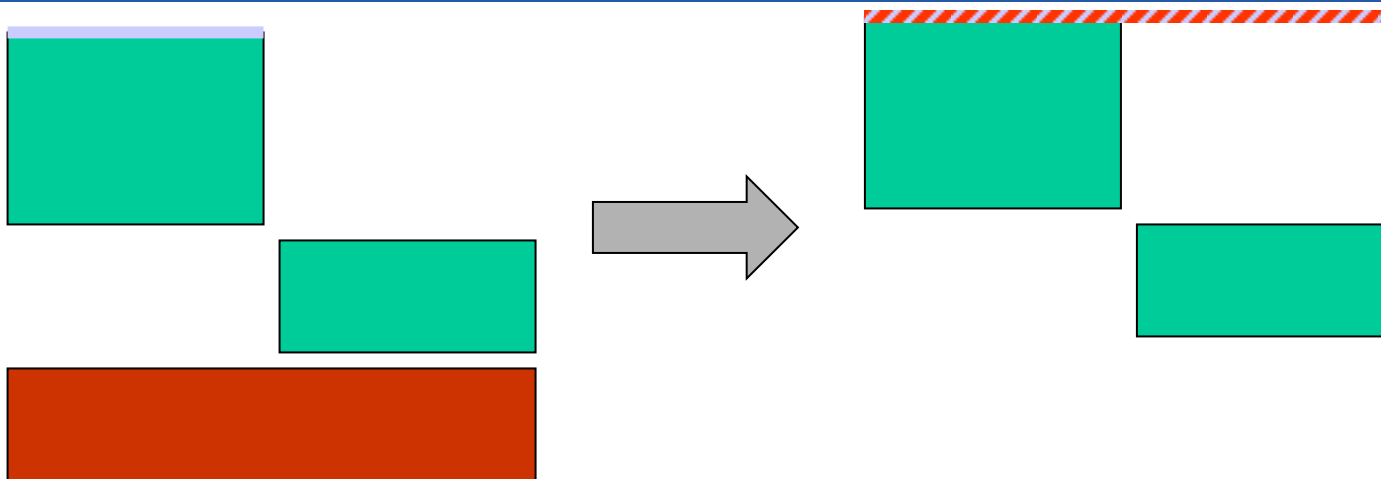
$$(iii) \quad \gamma, \pi \geq 0$$

Proposition:

Config pricing = acyclic shortest path problem with arc weights

$$\bar{c}_a = -\lambda_a.$$





$$(PLP) \max \sum_{i \in I} \sum_{p \in P_i} \sum_{a \in p} c_a^i x_p$$

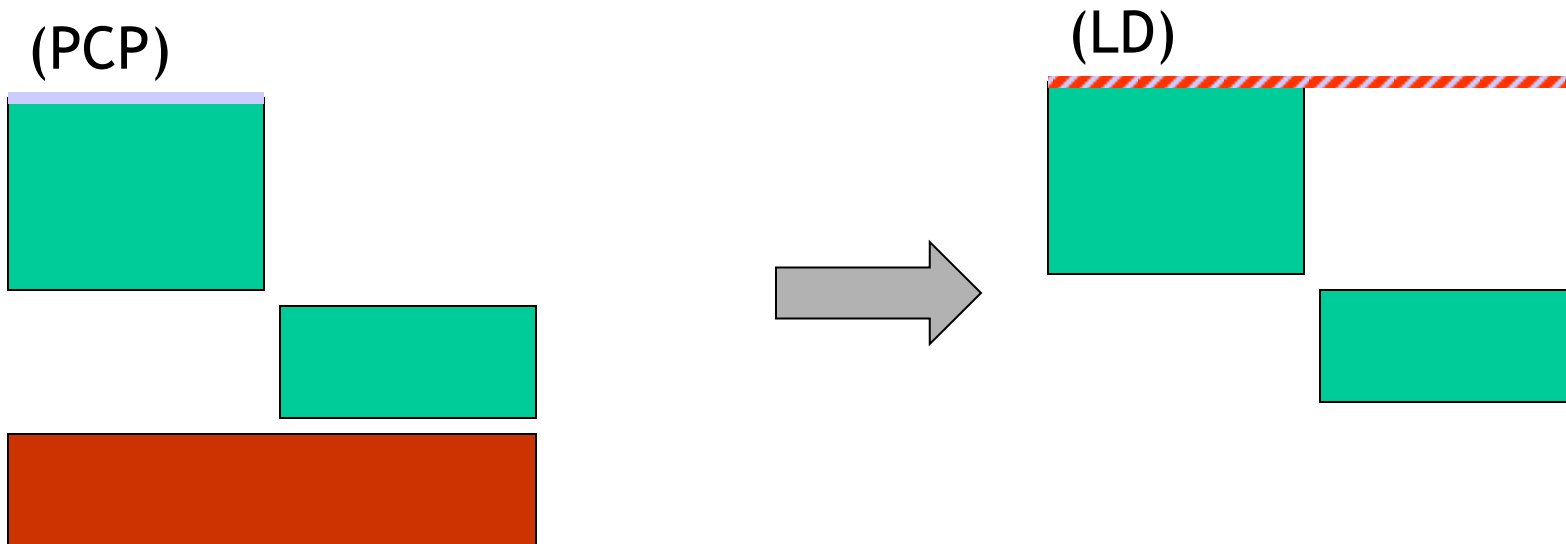
$$(i) \quad \sum_{p \in P_i} x_p \leq 1 \quad \forall i \in I \quad \text{Trains}$$

$$(ii) \quad \sum_{q \in Q_j} y_q \leq 1 \quad \forall j \in J \quad \text{Configs}$$

$$(iii) \quad \sum_{a \in p \in P} x_p - \sum_{a \in q \in Q} y_q \leq 0 \quad \forall a \in A \quad \text{Coupling}$$

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$$\text{(LD)} \quad \min_{\lambda \geq 0} \left[\max_{\substack{Ax=1, \\ x \in [0,1]^{|P|}}} (u^\top - \lambda^\top C)x + \max_{\substack{By=1, \\ y \in [0,1]^{|Q|}}} (\lambda^\top D)y \right]$$

- ▷ Problem
- ▷ Algorithm
 - ▶ Subgradient
 - ▶ Cutting Plane Model
 - ▶ Update
- ▷ Quadratic Subproblem

$$f(\lambda) := \min_{x \in X} c^T x + \lambda^T (b - Ax)$$

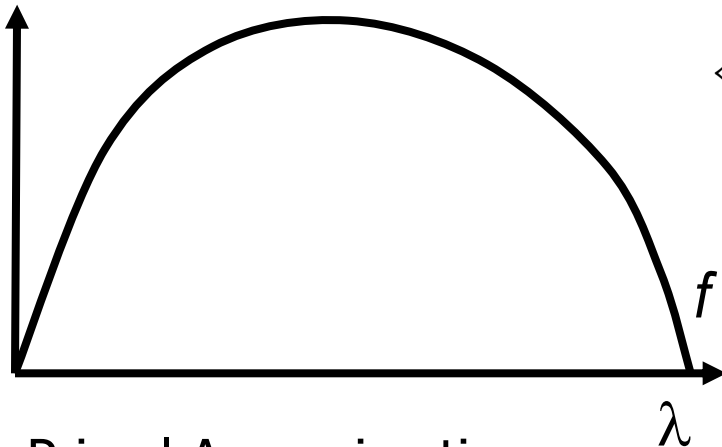
$$\bar{f}_\mu(\lambda) = c^T x_\mu + \lambda^T (b - Ax_\mu)$$

$$\hat{f}_k(\lambda) := \min_{\mu \in J_k} \bar{f}_\mu(\lambda)$$

$$\lambda_{k+1} = \operatorname{argmax}_\lambda \hat{f}_k(\lambda) - \frac{u_k}{2} \|\lambda - \hat{\lambda}_k\|^2$$

$$\max_\lambda \hat{f}_k(\lambda) - \frac{u_k}{2} \|\lambda - \hat{\lambda}_k\|^2 \Leftrightarrow \max v - \frac{u_k}{2} \|\lambda - \hat{\lambda}_k\|^2$$

s.t. $v \leq \bar{f}_\mu(\lambda)$, for all $\mu \in J_k$



$$\Leftrightarrow \max \sum_{\mu \in J_k} \alpha_\mu \bar{f}_\mu(\hat{\lambda}) - \frac{1}{2u_k} \left\| \sum_{\mu \in J_k} \alpha_\mu (b - Ax_\mu) \right\|^2$$

$$\text{s.t. } \sum_{\mu \in J_k} \alpha_\mu = 1$$

$$0 \leq \alpha_\mu \leq 1, \quad \text{for all } \mu \in J_k$$

- ▷ Primal Approximation
- ▷ Inexact Bundle Method

$$\|b - A\tilde{x}_k\| \rightarrow 0 \quad (k \rightarrow \infty)$$

$$\tilde{x}_{k+1} = \sum_{\mu \in J_k} \alpha_\mu x_\mu$$

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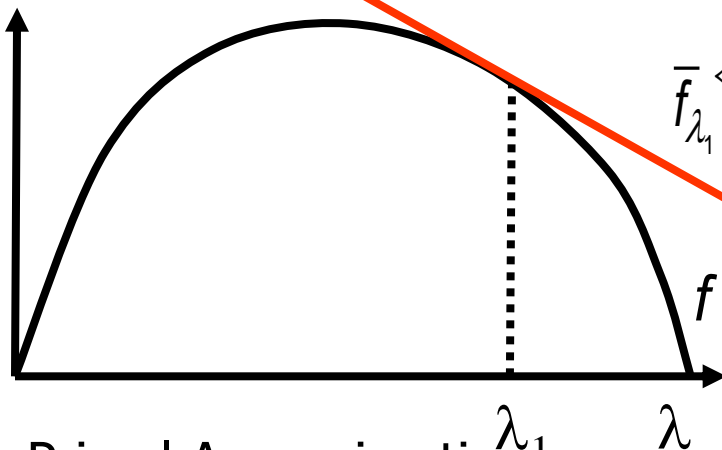
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$$\bar{f}_{\lambda_1} \Leftrightarrow \max \sum_{\mu \in J_k} \alpha_\mu \bar{f}_\mu(\hat{\lambda}) - \frac{1}{2u_k} \left\| \sum_{\mu \in J_k} \alpha_\mu (b - Ax_\mu) \right\|^2$$

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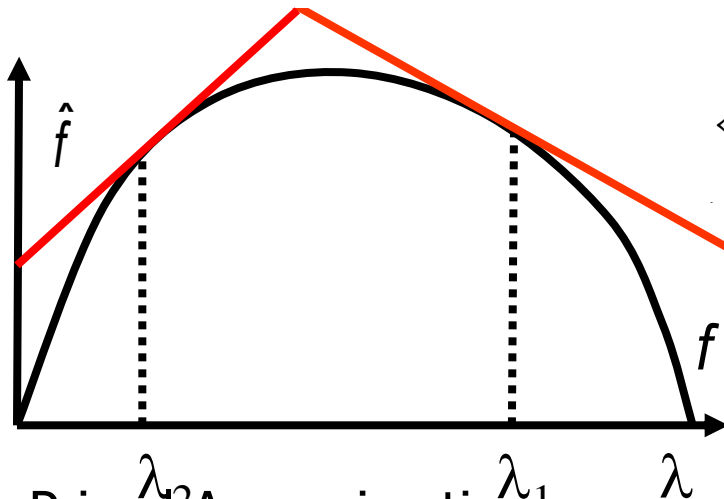
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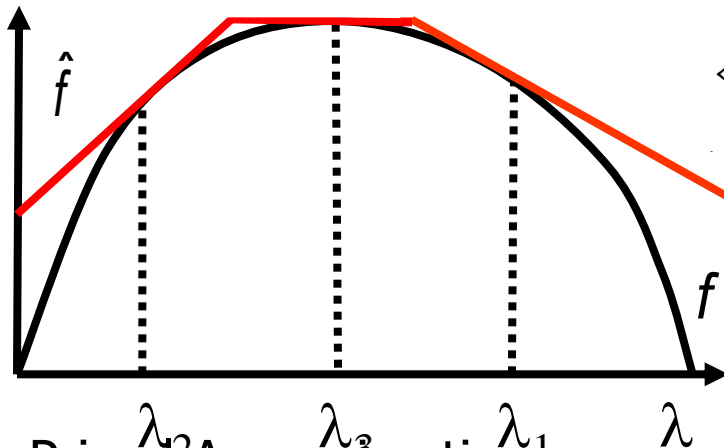
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- ▷ Primal Approximation
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$$\Leftrightarrow \max \sum_{\mu \in J_k} \alpha_\mu \bar{f}_\mu(\hat{\lambda}) - \frac{1}{2u_k} \left\| \sum_{\mu \in J_k} \alpha_\mu (b - Ax_\mu) \right\|^2$$

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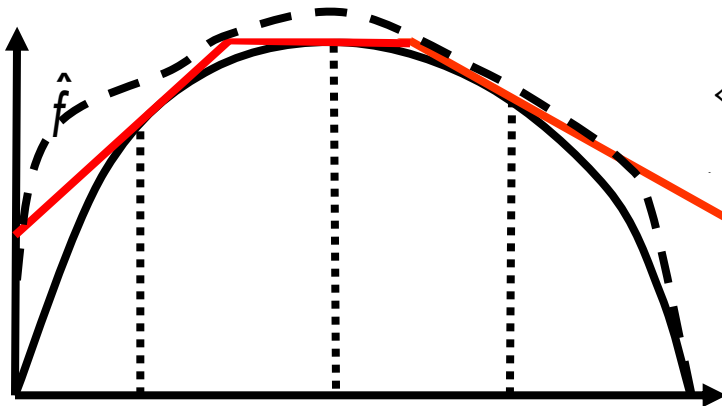
$$f(\lambda) := \min_{x \in X} c^T x + \lambda^T (b - Ax)$$

$$\bar{f}_\mu(\lambda) = c^T x_\mu + \lambda^T (b - Ax_\mu)$$

$$\hat{f}_k(\lambda) := \min_{\mu \in J_k} \bar{f}_\mu(\lambda)$$

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$$\begin{aligned} \max_\lambda \hat{f}_k(\lambda) - \frac{u_k}{2} \|\lambda - \hat{\lambda}_k\|^2 &\Leftrightarrow \max v - \frac{u_k}{2} \|\lambda - \hat{\lambda}_k\|^2 \\ \text{s.t. } &v \leq \bar{f}_\mu(\lambda), \text{ for all } \mu \in J_k \end{aligned}$$



$$\Leftrightarrow \max \sum_{\mu \in J_k} \alpha_\mu \bar{f}_\mu(\hat{\lambda}) - \frac{1}{2u_k} \left\| \sum_{\mu \in J_k} \alpha_\mu (b - Ax_\mu) \right\|^2$$

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$$\|b - A\tilde{x}_k\| \rightarrow 0 \quad (k \rightarrow \infty)$$

$$\tilde{x}_{k+1} = \sum_{\mu \in J_k} \alpha_\mu x_\mu$$

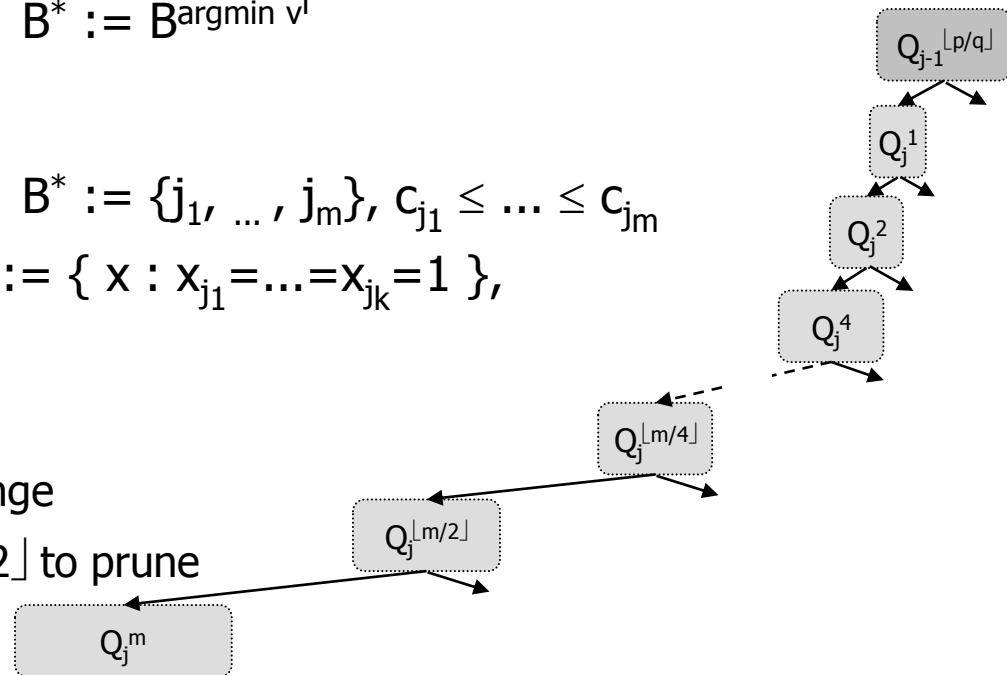
Perturbation Branching

- ▷ Sequence of perturbed IP objectives $c_j^{i+1} := c_j^i - \alpha(x_j^i)^2, \forall j, i=1,2,\dots$
- ▷ Fixing candidates in iteration i $B^i := \{ j : x_j^i \geq 1 - \varepsilon \}$
- ▷ Potential function in iteration i $v^i := c^T x^i - w|B^i|$
- ▷ Go on while not integer and potential decreases, else
 - ▶ Perturb for k_{\max} additional iterations, if still not successful
 - Fix a single variable and reset objective every k_s iterations
- ▷ Set of fixed variables (many) $B^* := B^{\arg \min v^i}$

Binary Search Branching

- ▷ Set of fixed variables (many) $B^* := \{j_1, \dots, j_m\}, c_{j_1} \leq \dots \leq c_{j_m}$
- ▷ Sets Q_j^k at perturbation branch j $Q_j^k := \{ x : x_{j_1} = \dots = x_{j_k} = 1 \}, k=0, \dots, m$

- ▷ Branch on Q_j^m
 - ▶ Repeat perturbation branching to plunge
 - ▶ Backtrack to $Q_j^{\lfloor m/2 \rfloor}$ and set $m := \lfloor m/2 \rfloor$ to prune



$$(\text{PRICE } (x)) \quad \exists \bar{p} \in \mathcal{P}_i : \quad \gamma_i < \sum_{a \in \bar{p}} (p_a - \lambda_a)$$

$$\eta_i := \max_{p \in \mathcal{P}_i} \sum_{a \in p} (p_a - \lambda_a) - \gamma_i, \quad \forall i \in I \implies \eta_i + \gamma_i \geq \sum_{a \in p} (p_a - \lambda_a) \quad \forall i \in I, p \in \mathcal{P}_i$$

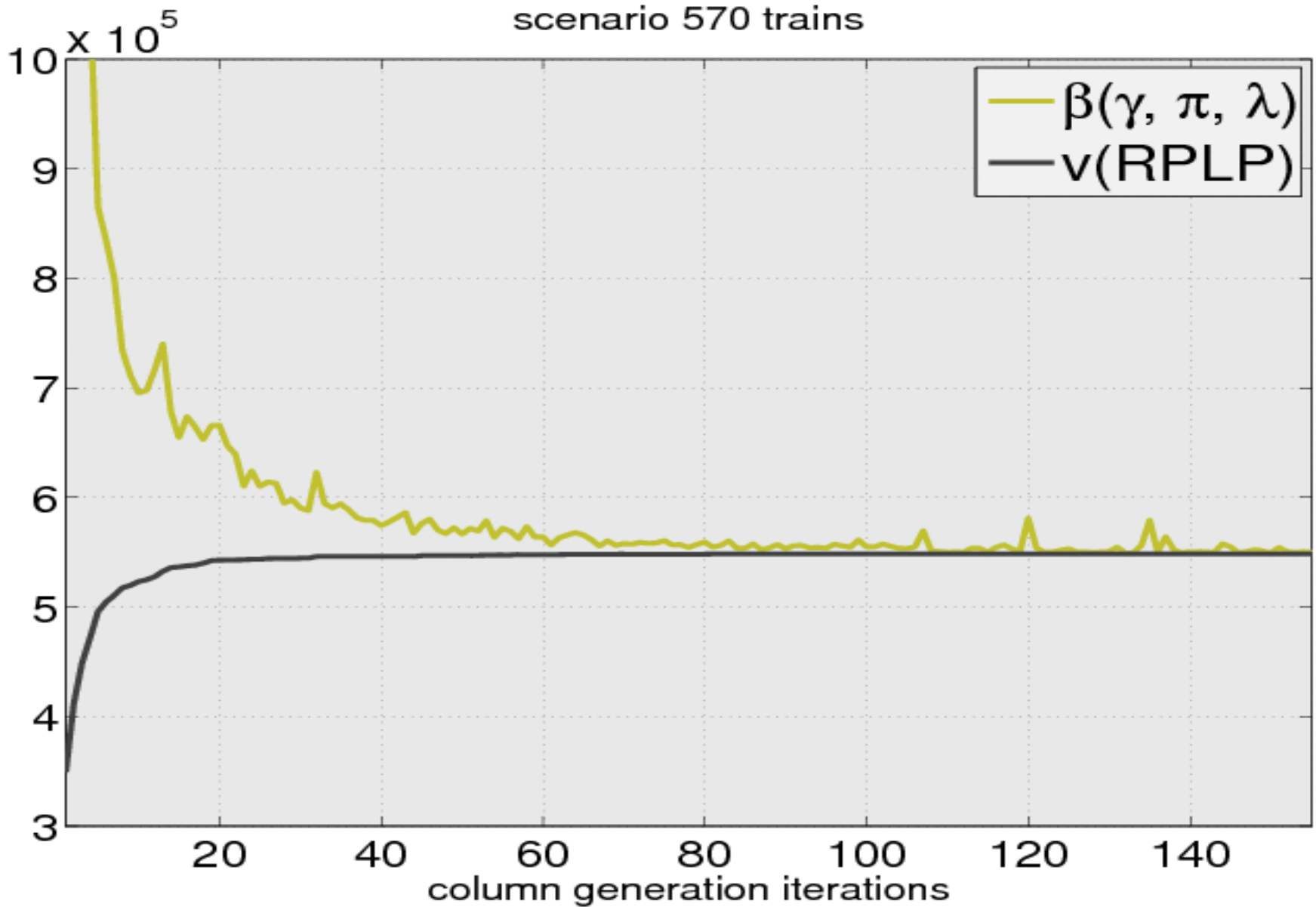
$$(\text{PRICE } (y)) \quad \exists \bar{q} \in \mathcal{Q}_j : \quad \pi_j < \sum_{a \in \bar{q}} \lambda_a$$

$$\theta_j := \max_{\bar{q} \in \mathcal{Q}_j} \sum_{a \in \bar{q}} \lambda_a - \pi_j, \quad \forall j \in J \implies \theta_j + \pi_j \geq \sum_{a \in q} \lambda_a \quad \forall j \in J, q \in \mathcal{Q}_j$$

$(\max\{\eta + \gamma, 0\}, \max\{\theta + \pi, 0\}, \lambda)$ is feasible for (DLP)

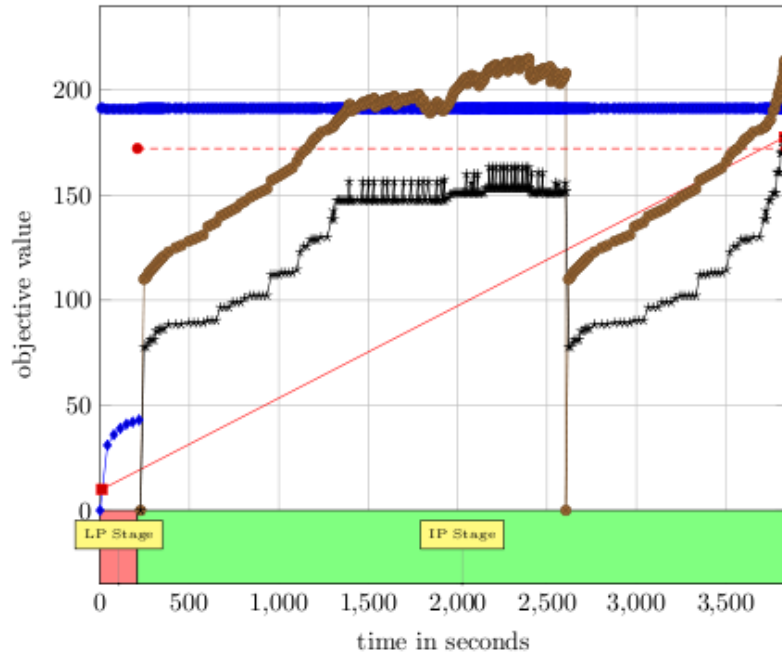
$$\beta(\gamma, \pi, \lambda) := \sum_{i \in I} \max\{\gamma_i + \eta_i, 0\} + \sum_{j \in J} \max\{\pi_j + \theta_j, 0\}$$

Lemma (BS [2007]): $v_{LP}(PCP) \leq \beta(\gamma, \pi, \lambda)$

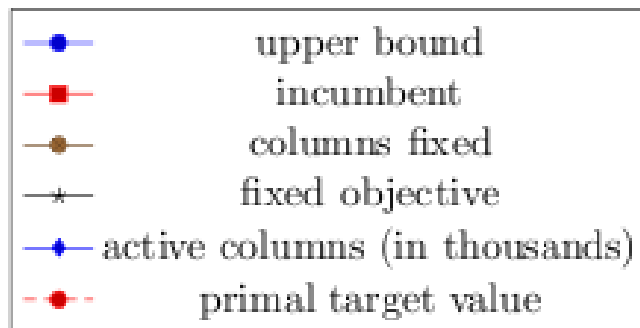
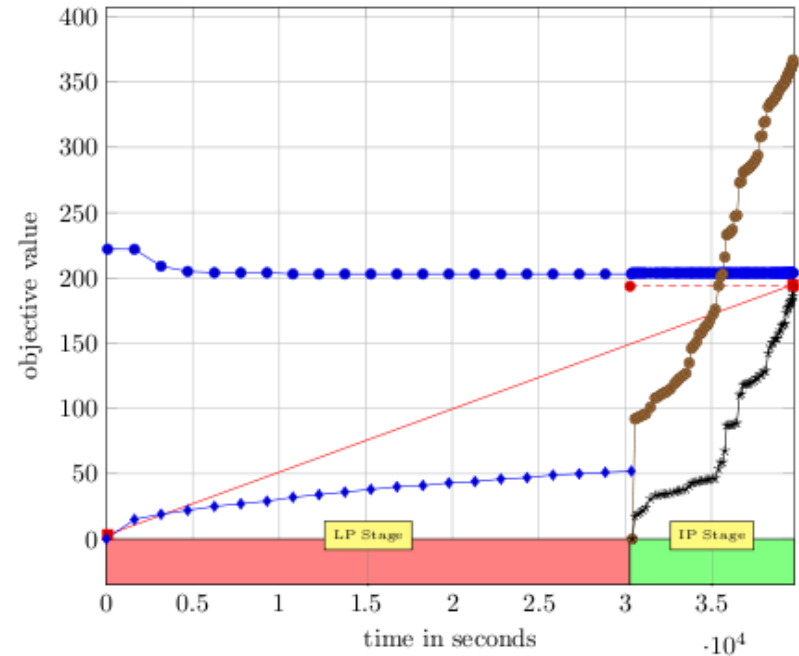


▷ HaKaFu, req32, 1140 requests, 30 mins time windows

TS-OPT run, model PCP, PCP-24H-NS-BUNDLE-BNB-100401-17:22:40



TS-OPT run, model PCP, PCP-24H-NS-BUNDLE-BNB-TW-30-100331-15:46:57



<i>Article</i>	<i>Stations</i>	<i>Tracks</i>	<i>Trains</i>	<i>Modell/Approach</i>
Szpigel [1973]	6	5	10	Packing/Enumeration
Brännlund et al. [1998]	17	16	26	Packing/ Lagrange, BAB
Caprara et al. [2002]	74 (17)	73 (16)	54 (221)	Packing/ Lagrange, BAB
B. & Schlechte [2007]	37	120	570	Config/PAB
Caprara et al. [2007]	102 (16)	103 (17)	16 (221)	Packing/PAB
Fischer et al. [2008]	656 (104)	1210 (193)	117 (251)	Packing/Bundle, IP Rounding
Lusby et al. [2008]	???	524	66 (31)	Packing/BAP
B. & Schlechte [2010]	37	120	>1.000	Config/Rapid Branching

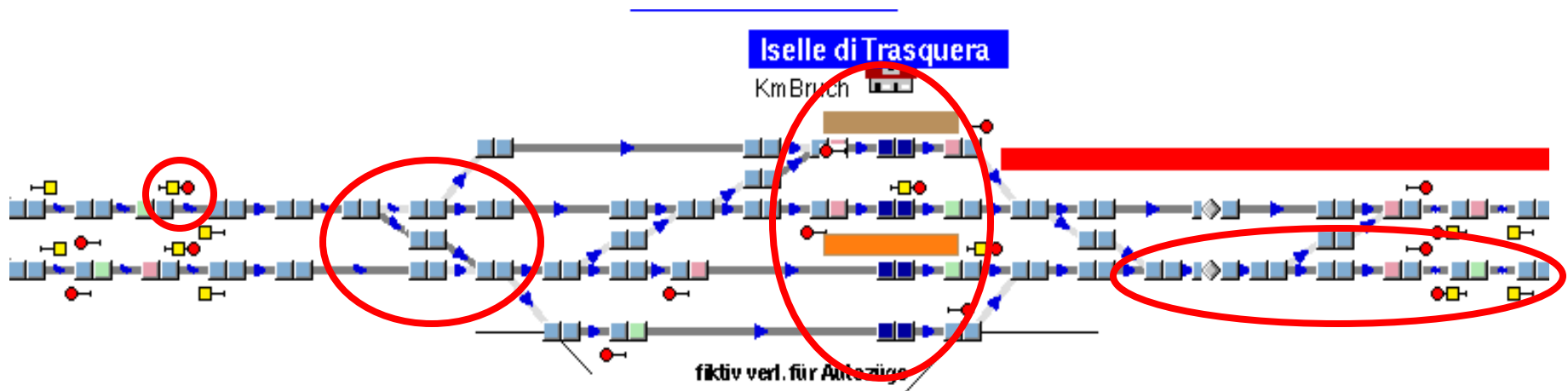
▷ BAB: Branch-and-Bound

▷ BAP: Branch-and-Price

▷ PAB: Price-and-Branch

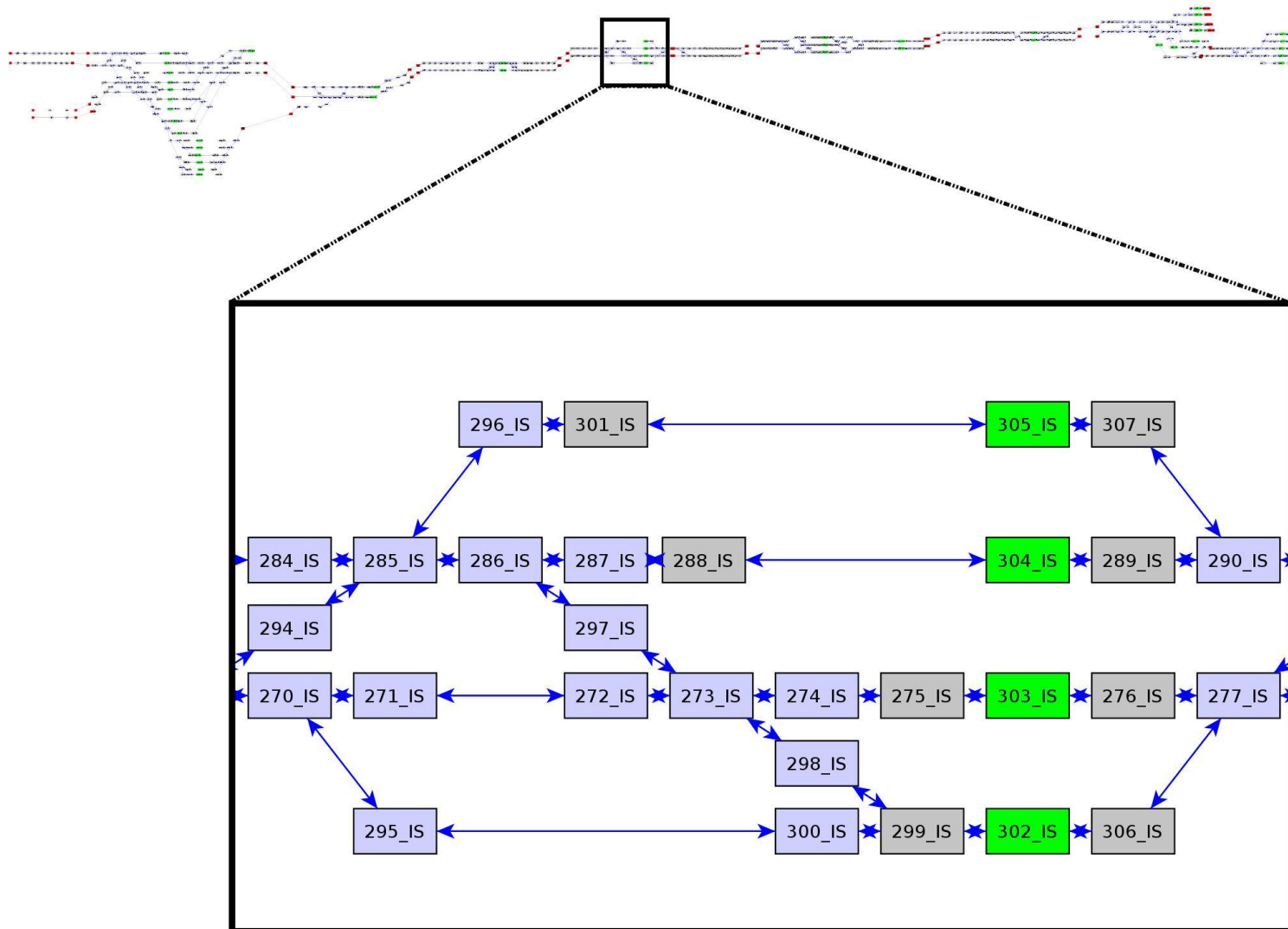
Discretization and Scheduling

- ▷ Detailed railway infrastructure data given by simulation programs (Open Track)

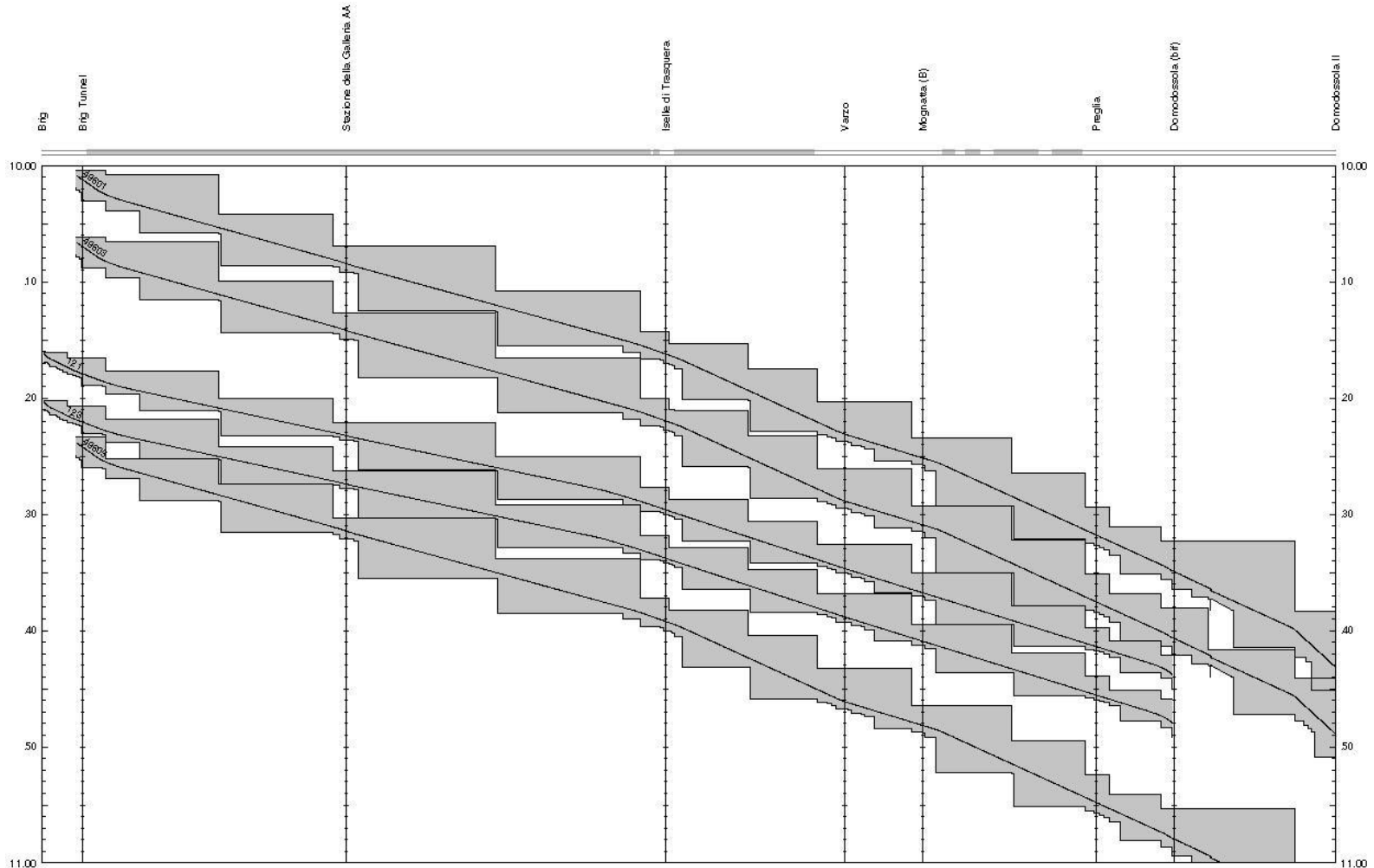


- ▷ Signals
- ▷ Switches
- ▷ Tracks (with max. speed, acceleration, gradient)
- ▷ Stations and Platforms

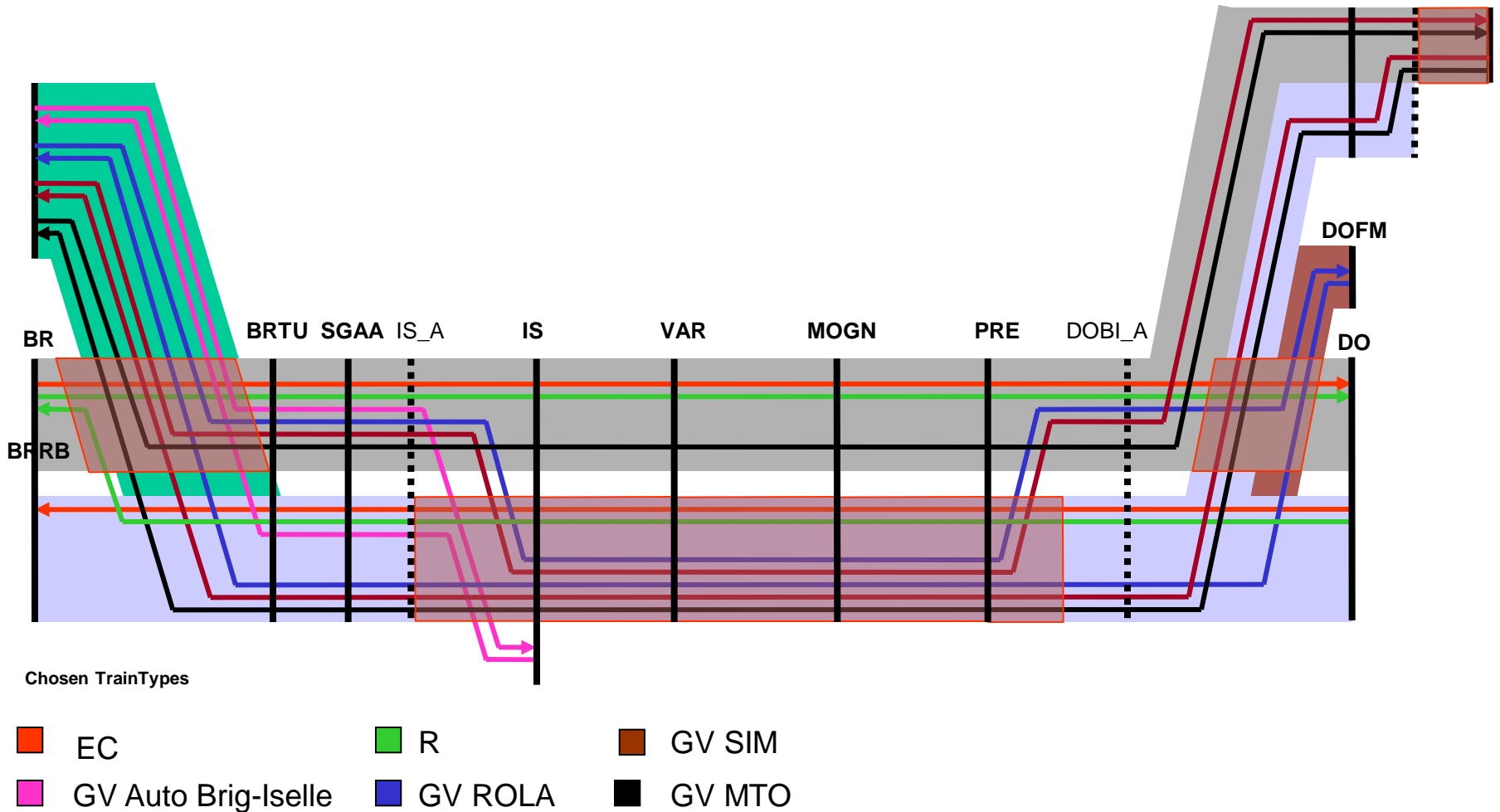
- ▶ Simplon micrograph: 1154 nodes and 1831 arcs, 223 signals etc.



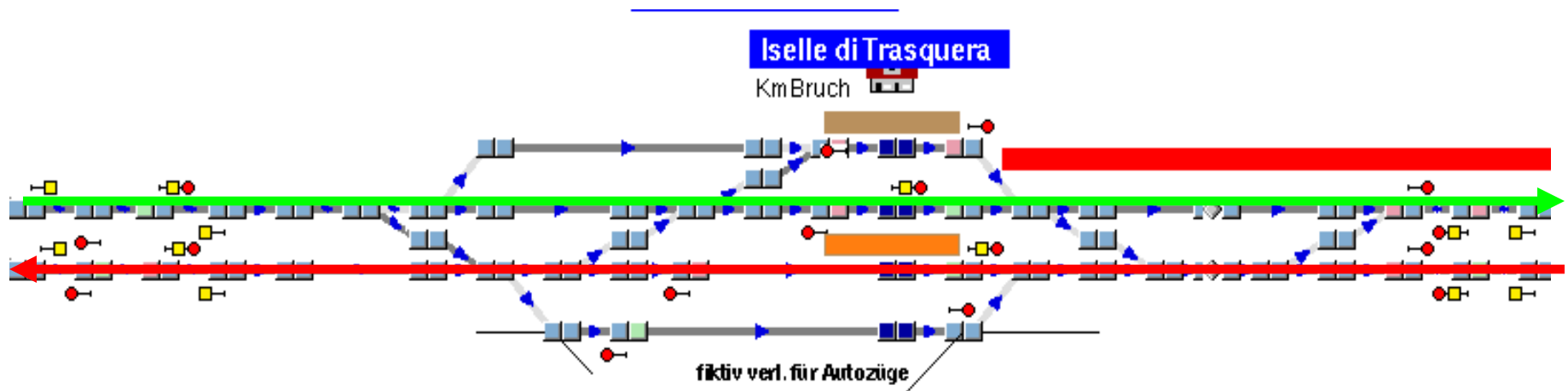
- ▷ Simulation tools provide exact running and blocking times
- ▷ Basis for calculation of minimal headway times



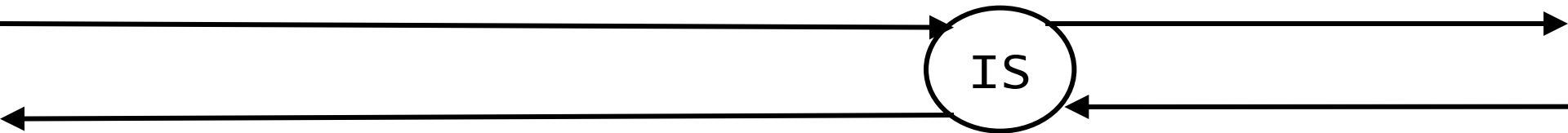
- ▶ Simulation of all possible routes with appropriate train types



- ▷ Generation of artificial nodes – „pseudo“ stations

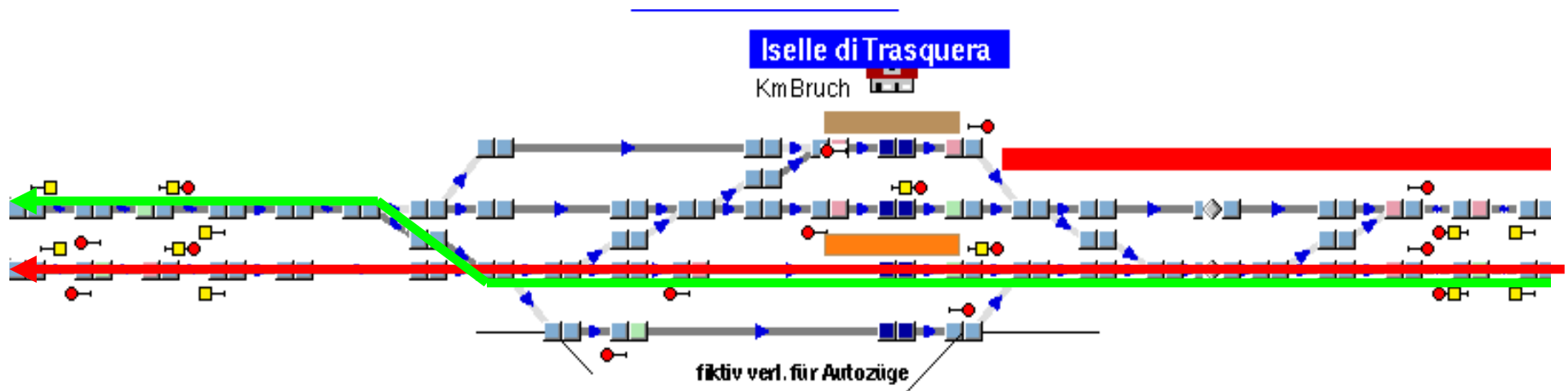


- ▷ No interactions between train routes

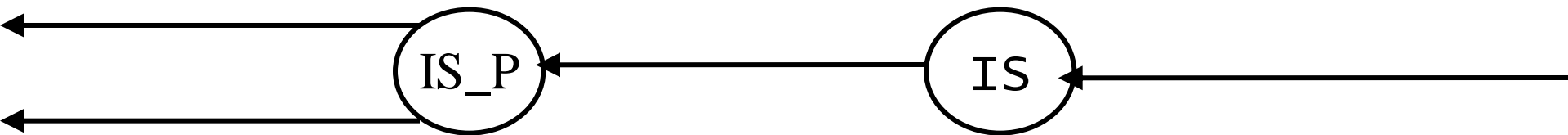


- ▷ Macro network definition is based on set of train routes

- ▷ Generation of artificial nodes – „pseudo“ stations

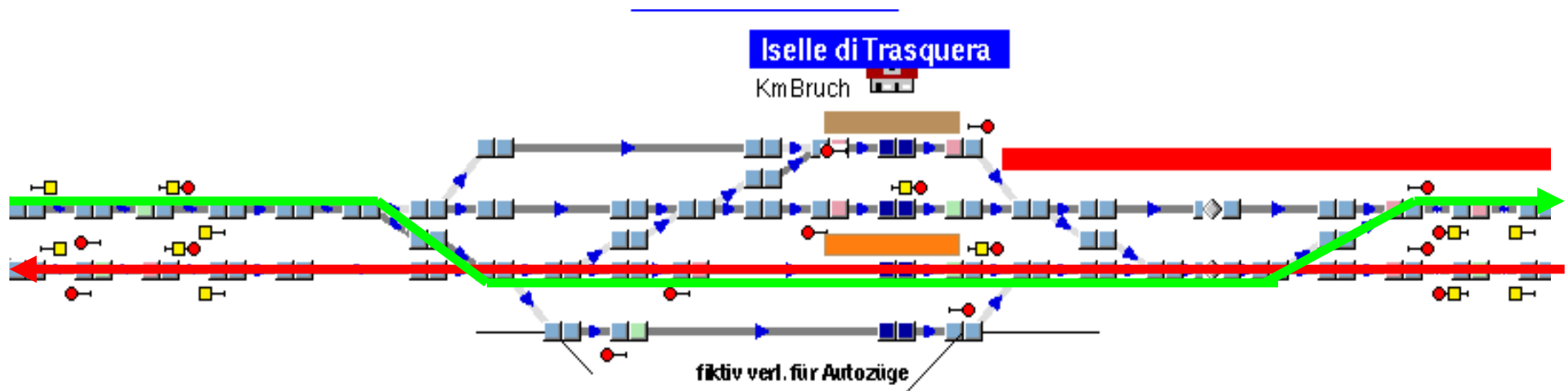


- ▷ Diverging of train routes

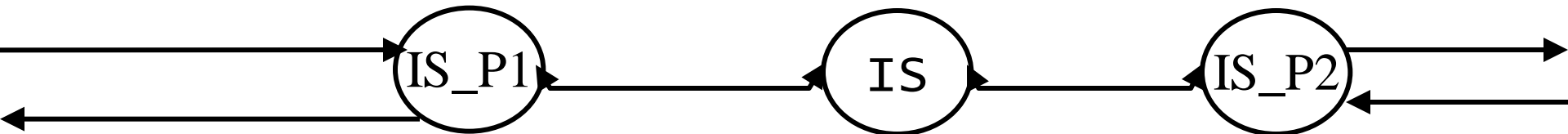


- ▷ The same holds for converging routes

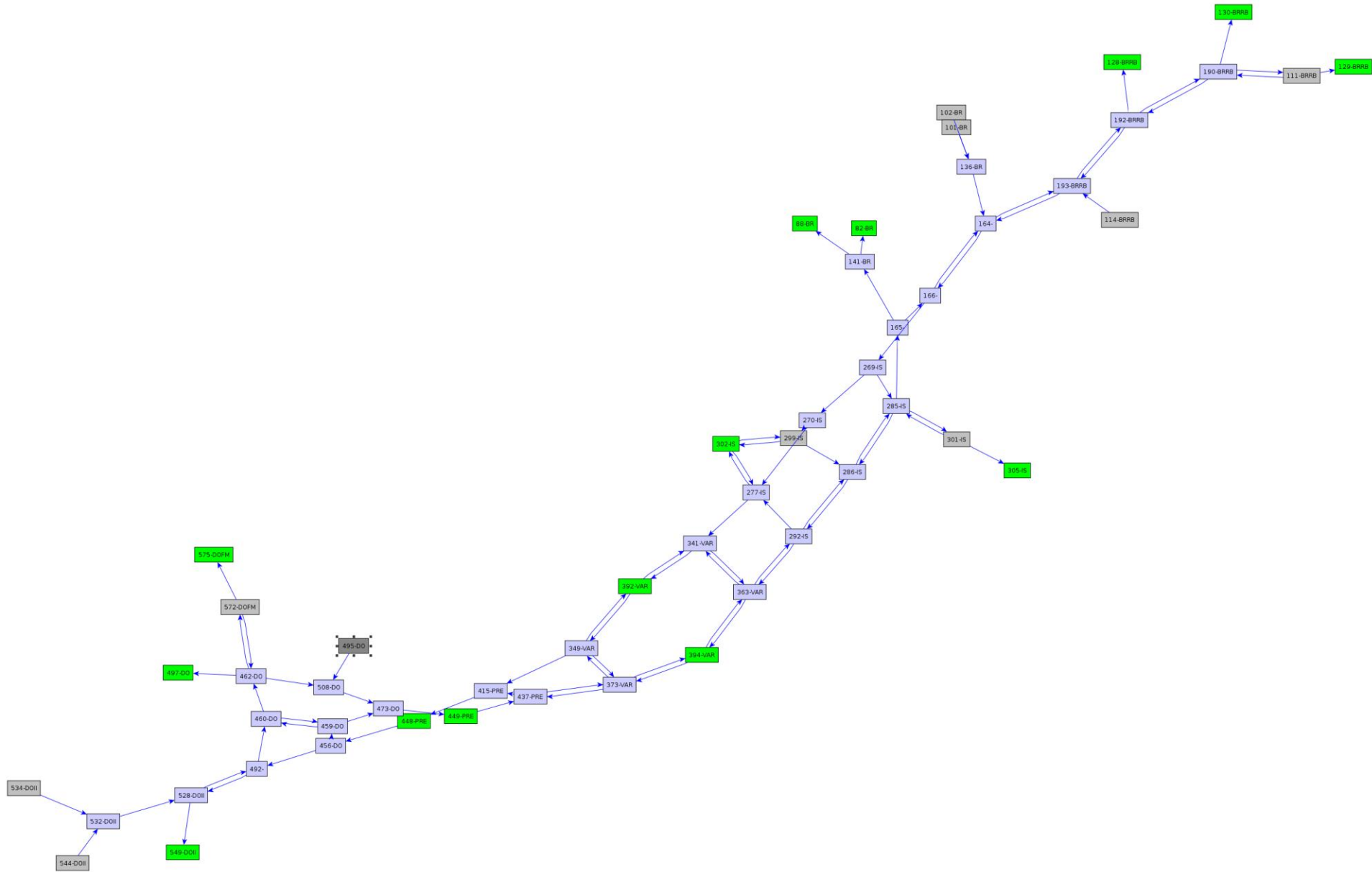
- ▷ Generation of artificial nodes – pseudo stations



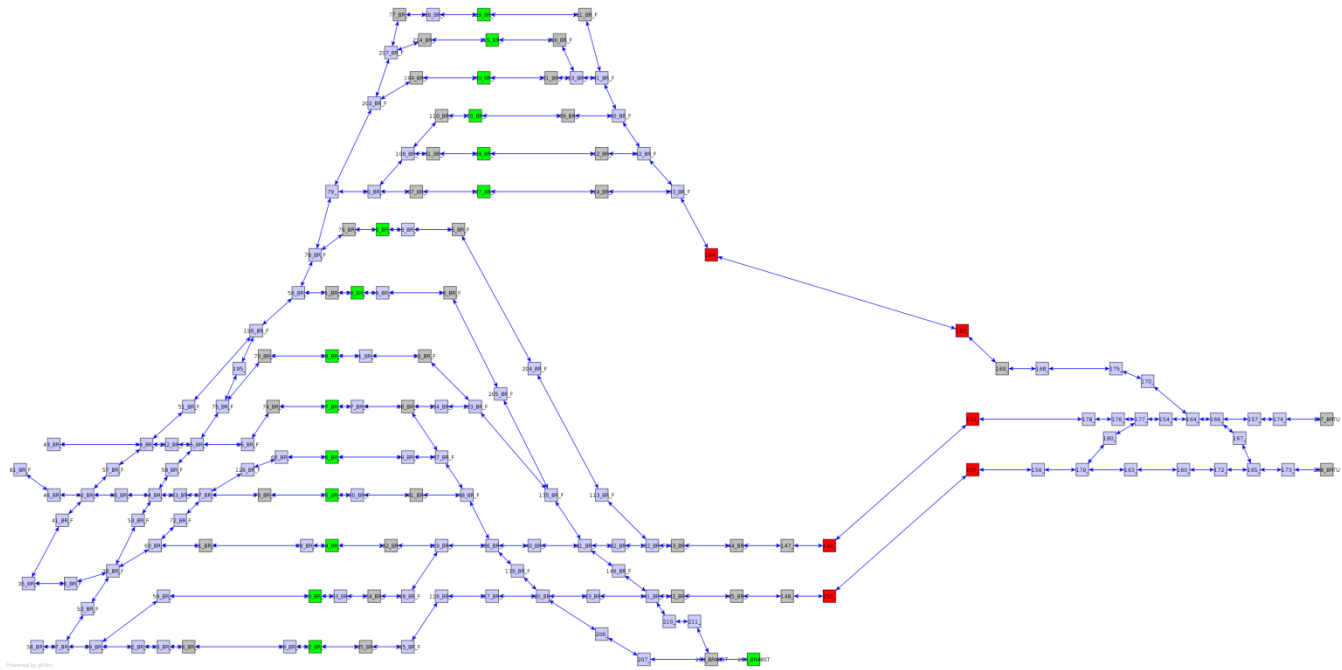
- ▷ crossing of train routes



- ▷ Two pseudo stations were generated



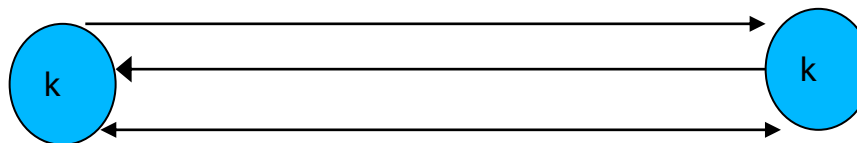
- ▷ Frequently many macroscopic station nodes are in the area of big stations
- ▷ Further aggregation is needed



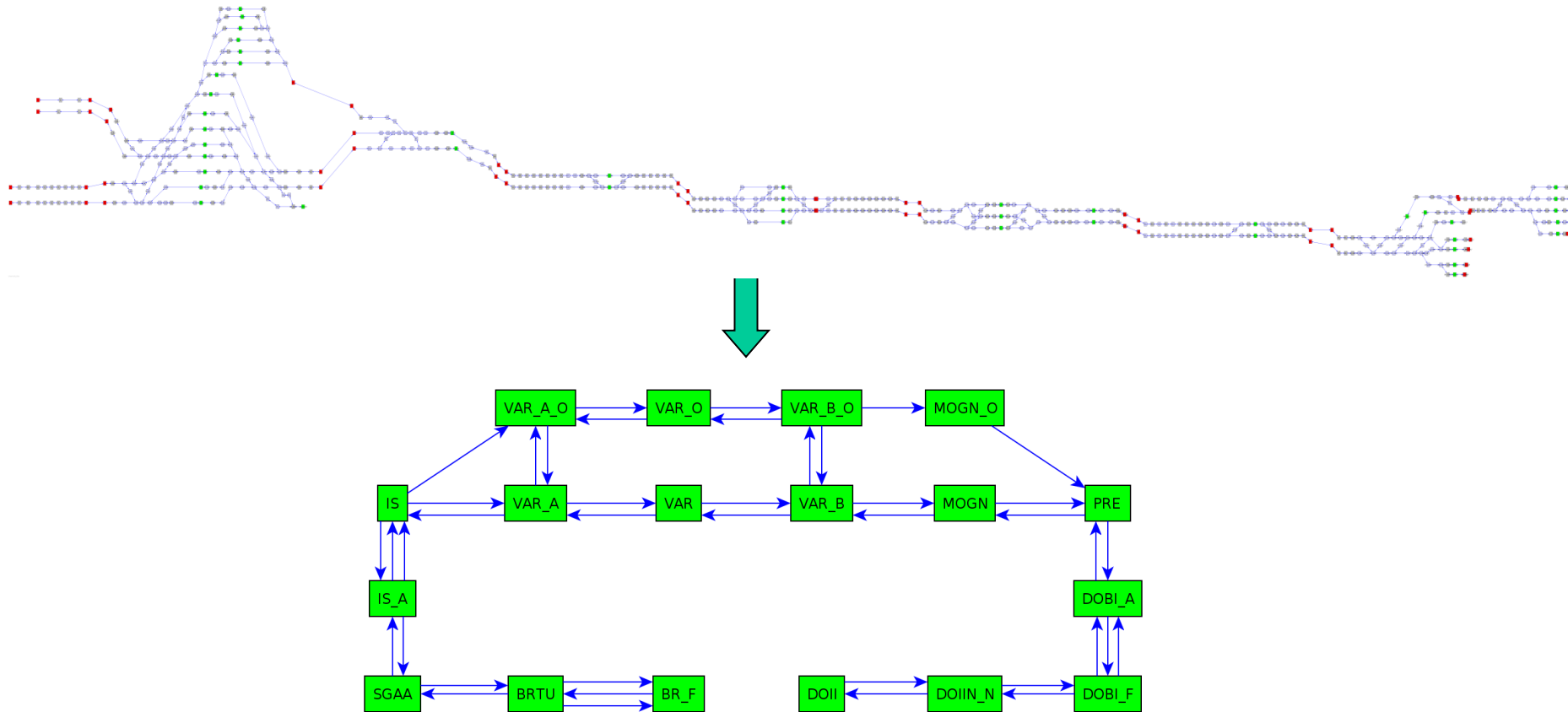
Powered by ATIS

k =

EC	2
R	4
GV Auto	2
GV Rola	2
GV SIM	4
GV MTO	6

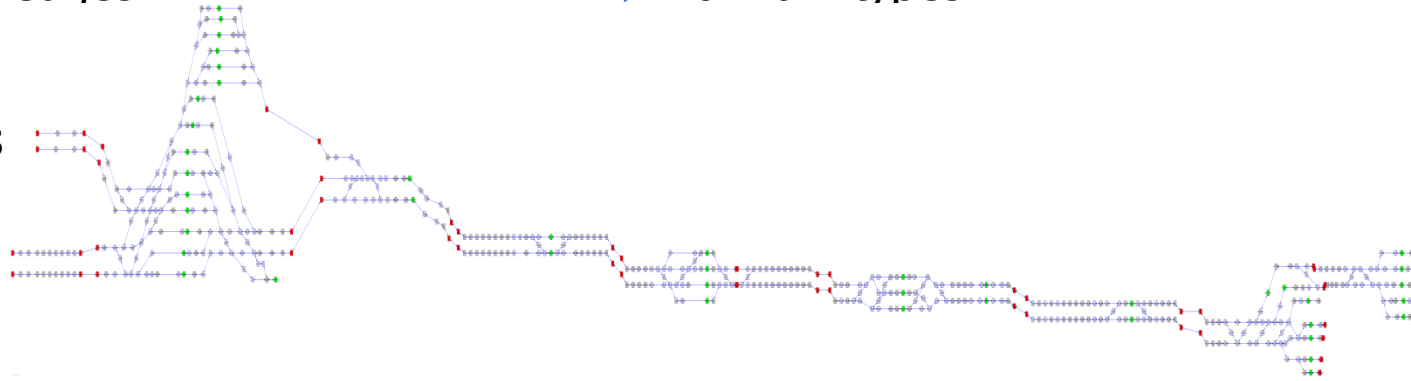


- ▷ Planned times in macro network are possible in micro network
- ▷ Valid headways lead to valid block occupations (no conflicts)
 - ⇒ feasible macro timetable can be transformed to feasible micro timetable



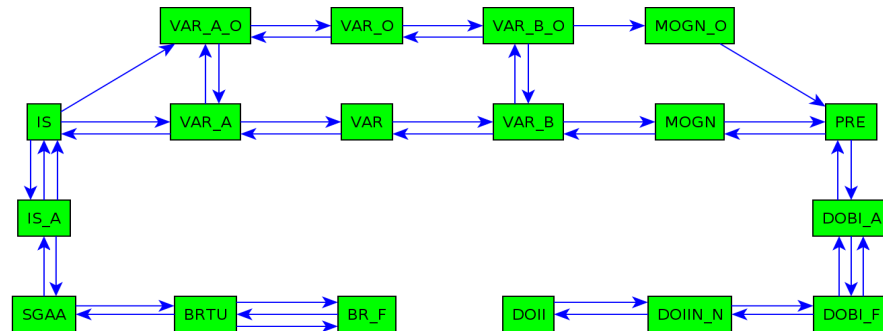
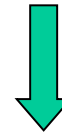
Micro

- ▷ 12 stations
- ▷ 1154 OpenTrack nodes
- ▷ 1831 OpenTrack edges
- ▷ 223 signals
- ▷ 8 track junctions
- ▷ 100 switches
- ▷ 6 train types
- ▷ 28 "routes"
- ▷ 230 "block segments"



Macro

- ▷ 18 macro nodes
- ▷ 40 tracks
- ▷ 6 Train types

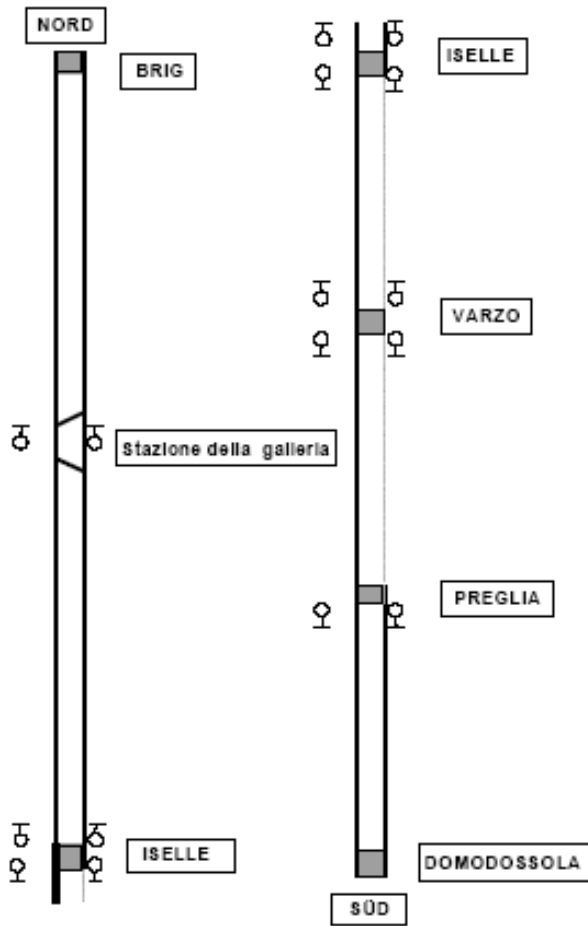


Cumulative Rounding Procedure

- ▷ Compute macroscopic running time with specific rounding procedure
- ▷ Consider again routes of trains (represented by standard trains)
- ▷ Example with $\Delta = 6$

Station	Dep/Pass	Rounded	Buffer
A	0	0	0
B	11	12 (2)	1
C	20	24 (4)	4
D	29	30 (5)	1

- ▷ **Theorem:** If micro-running time $d \geq \Delta$ for all tracks of the current train route, the cumulative rounding error (buffer) is always in $[0, \Delta)$.



Source: Wikipedia

Slalom route

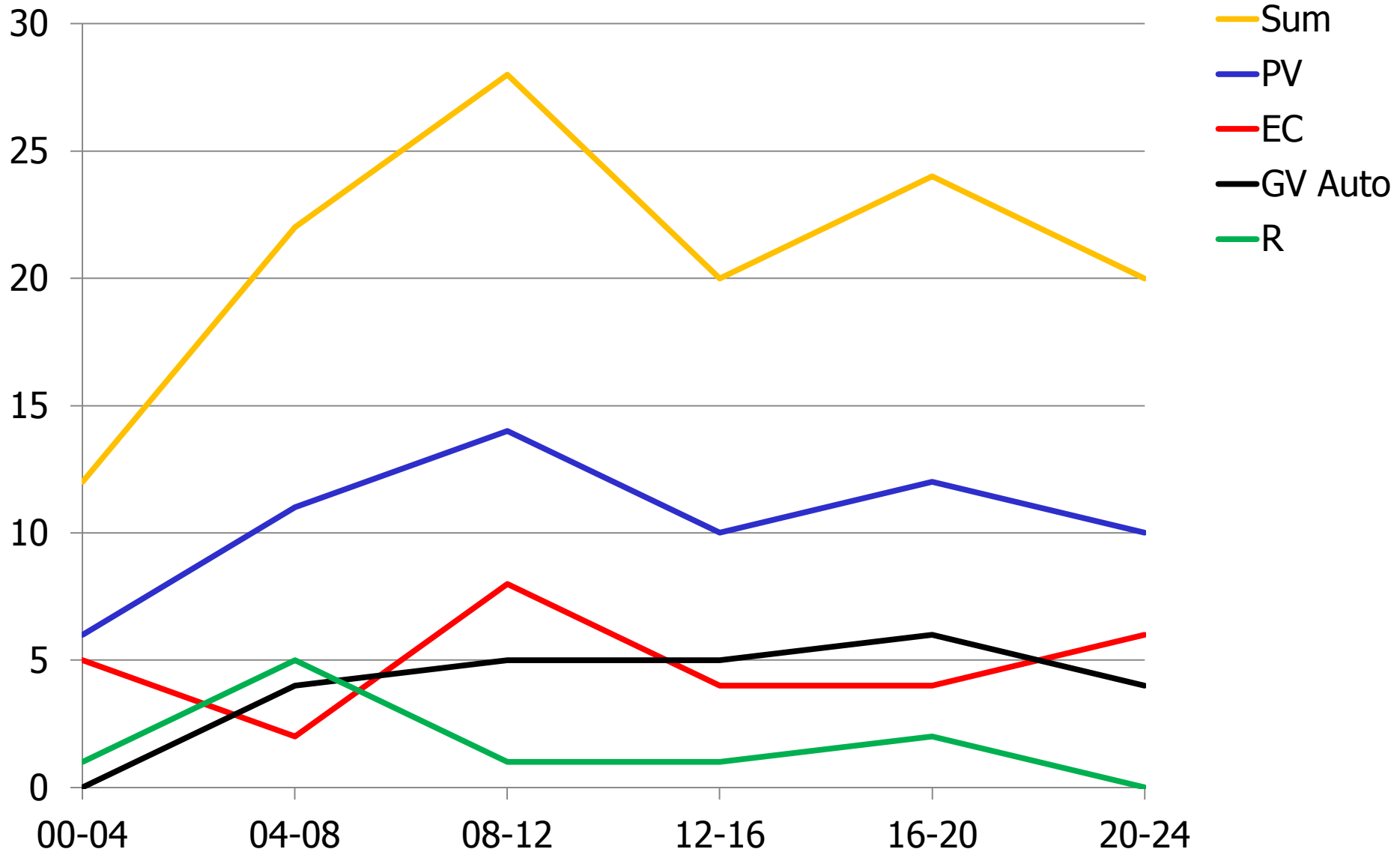
- ▶ ROLA trains traverse the tunnel on the “wrong” side

Crossing of trains

- ▶ complex crossings of AUTO trains in Iselle

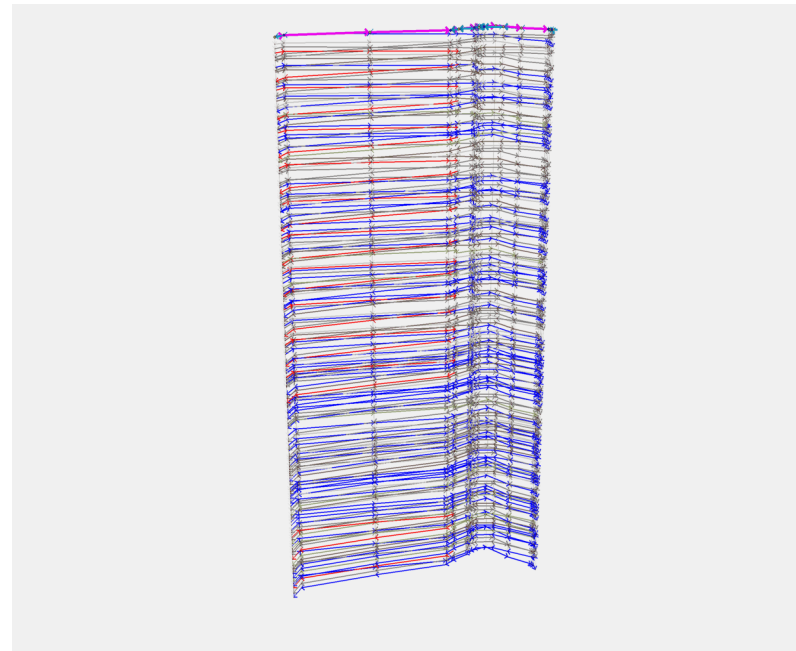
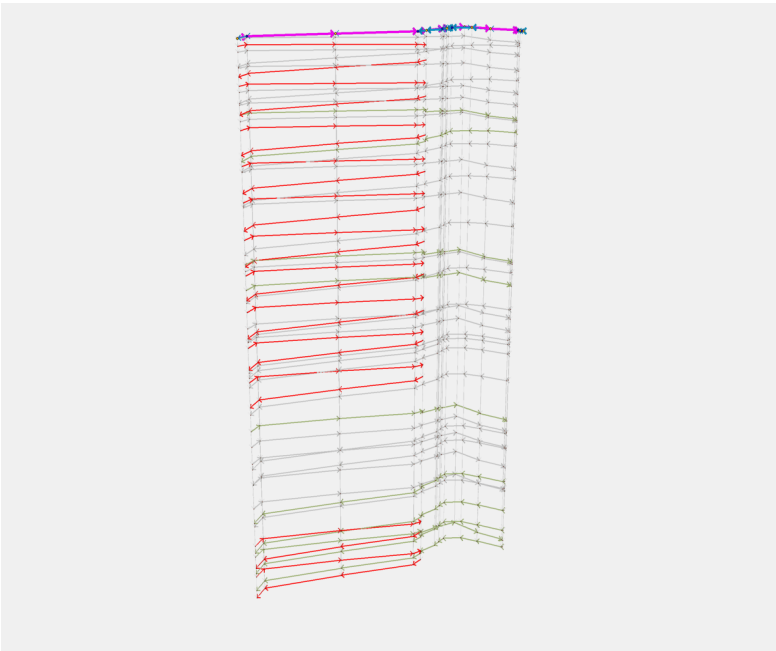
Conflicting routes

- ▶ complex routings in station area Domodossola and Brig



Estimation of the maximum theoretical corridor capacity

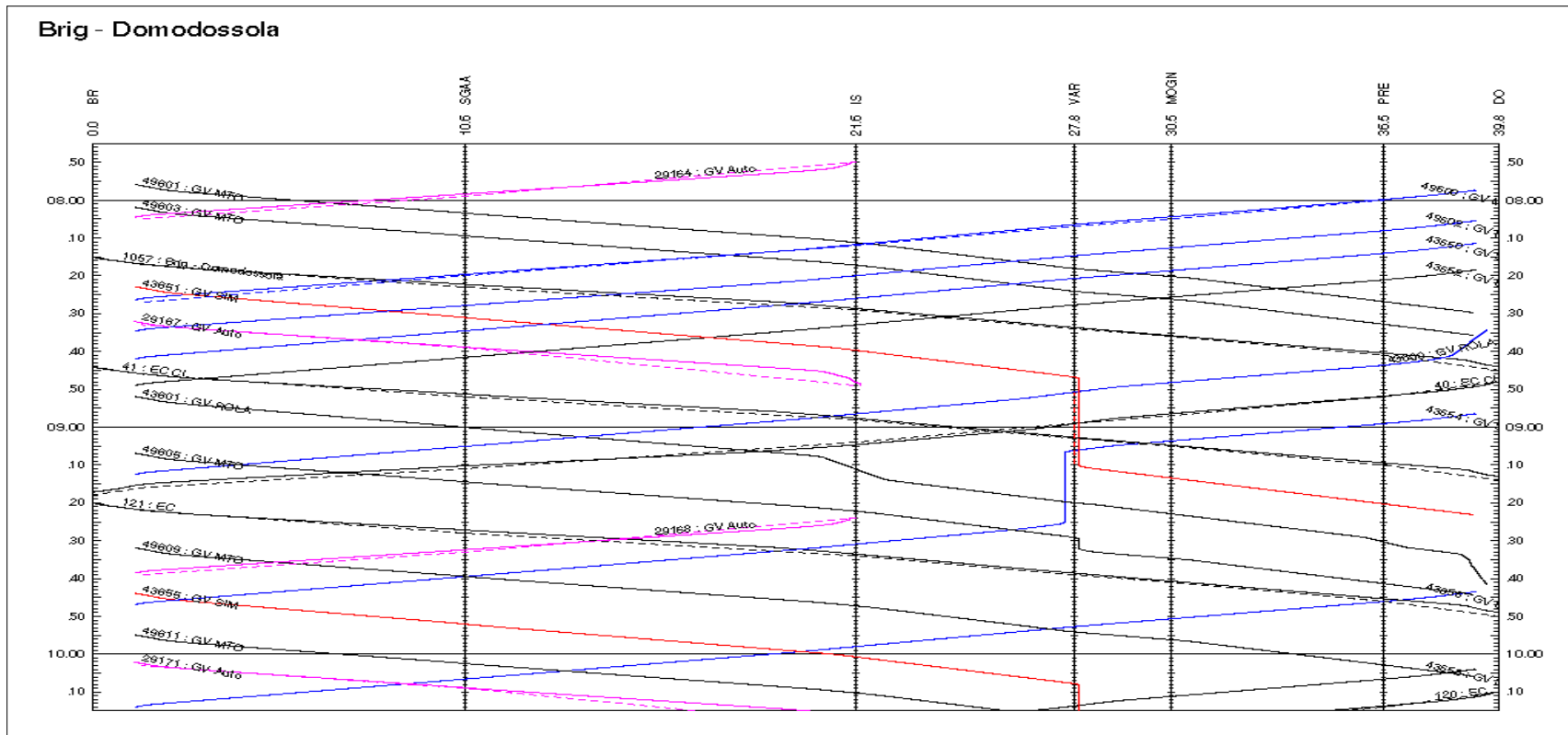
- ▷ Network accuracy of 6s
- ▷ Consider complete routing through stations
- ▷ Saturate by additional cargo trains

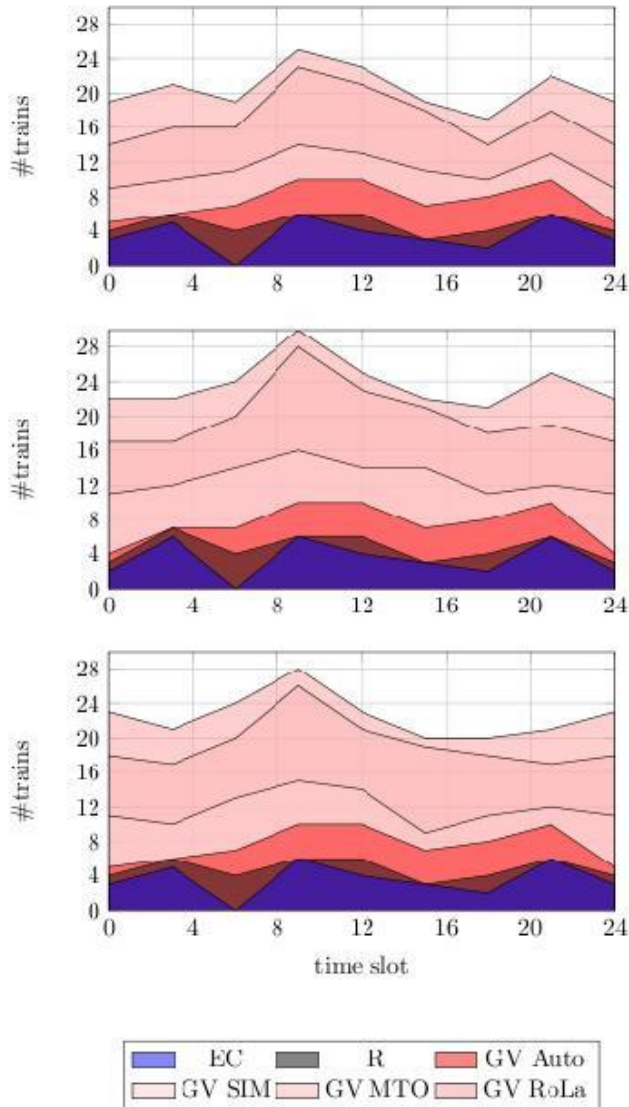


- ▷ Conflict free train schedules in simulation software (1s accuracy)

Aggregation-Test (Micro->Macro->Micro)

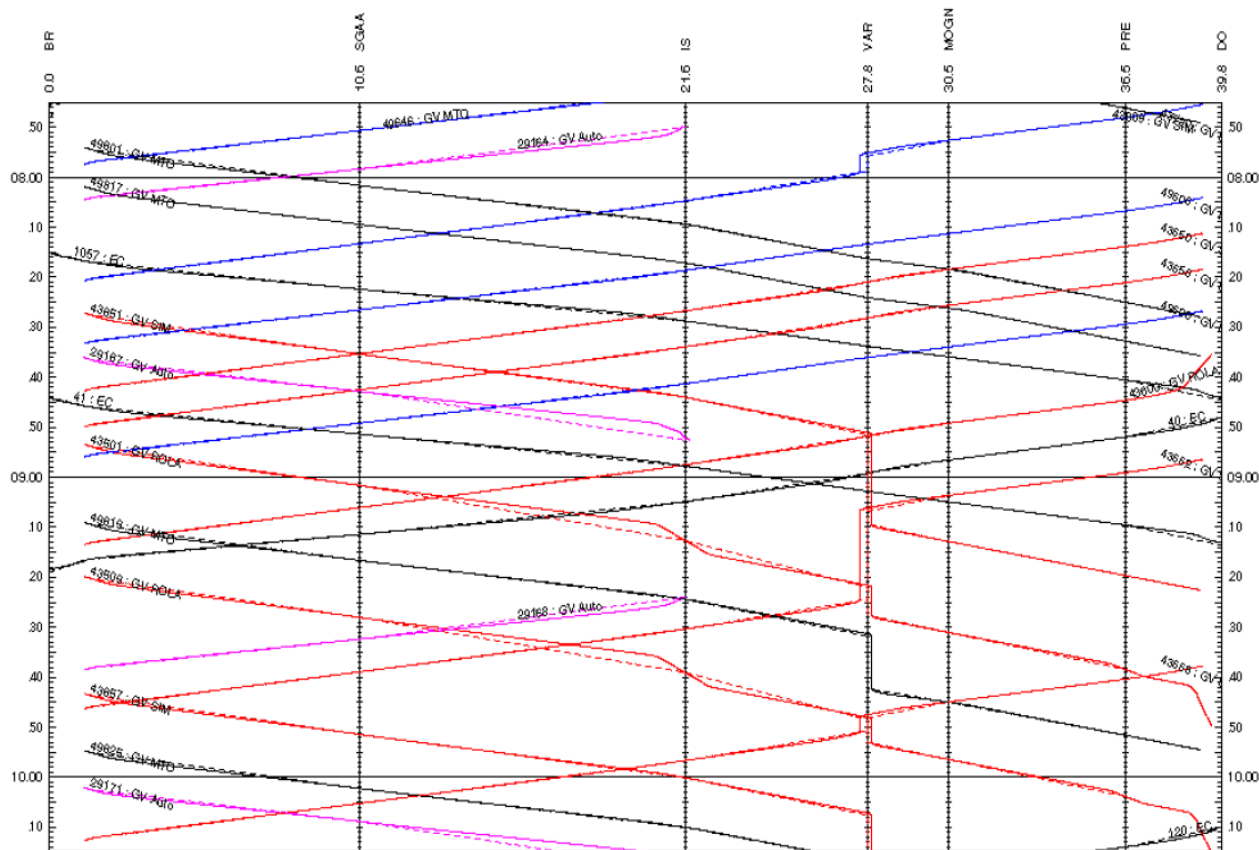
- ▷ Microscopic feasible 4h (8:00-12:00) reference plan in Open Track
- ▷ Reproducing this plan by an Optimization run
- ▷ Reimport to Open Track





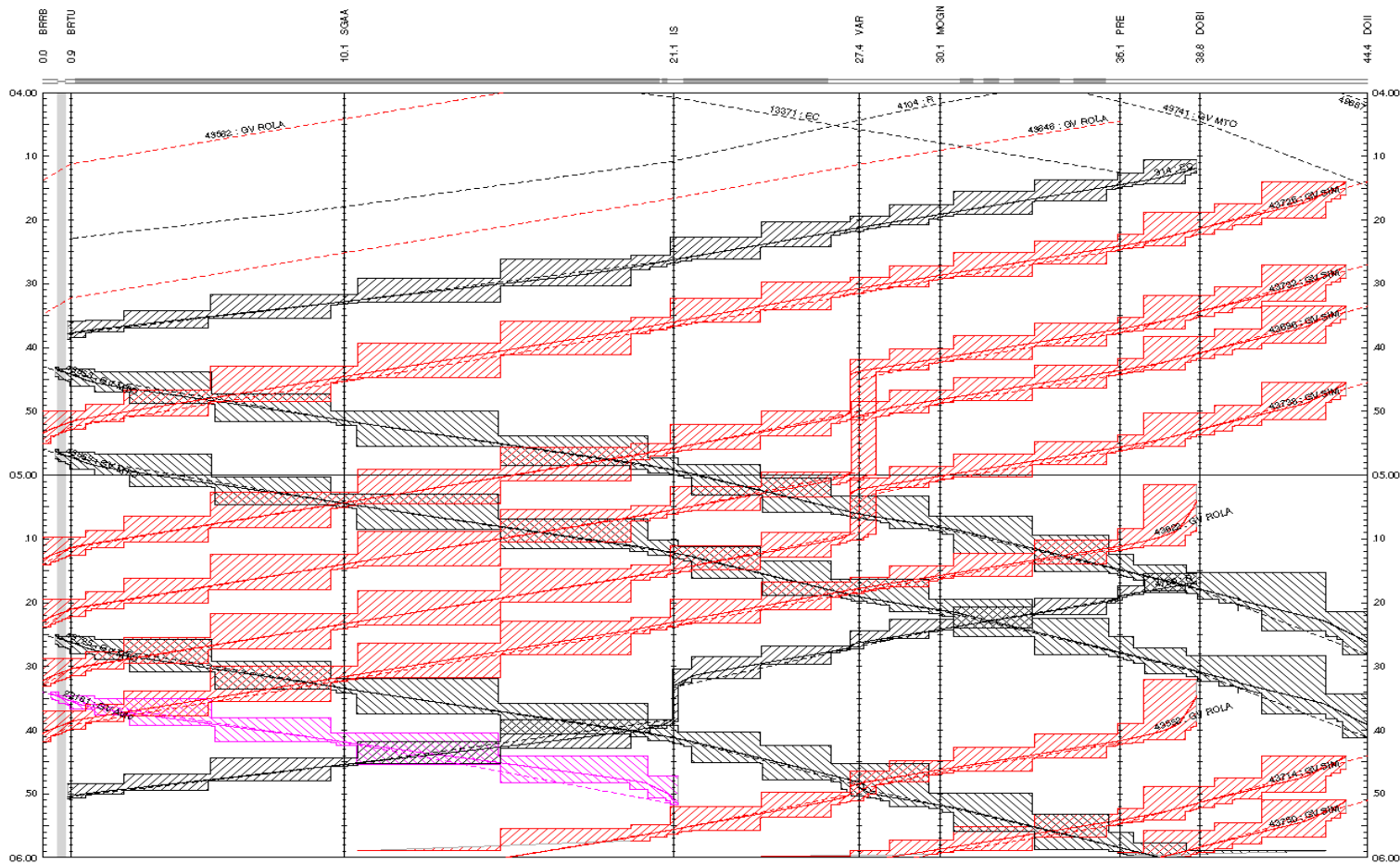
- ▷ 180 trains for network small (without station routing and buffer times)
- ▷ 196 trains for network big with precise routing through stations (without buffer times)
- ▷ 175 trains for network big with precise routing through stations and buffer times

- ▷ No delays, no early coming
- ▷ Feasible train routing and block occupation
- ▷ Timetable is valid in micro-simulation



▷ Network big with buffer times

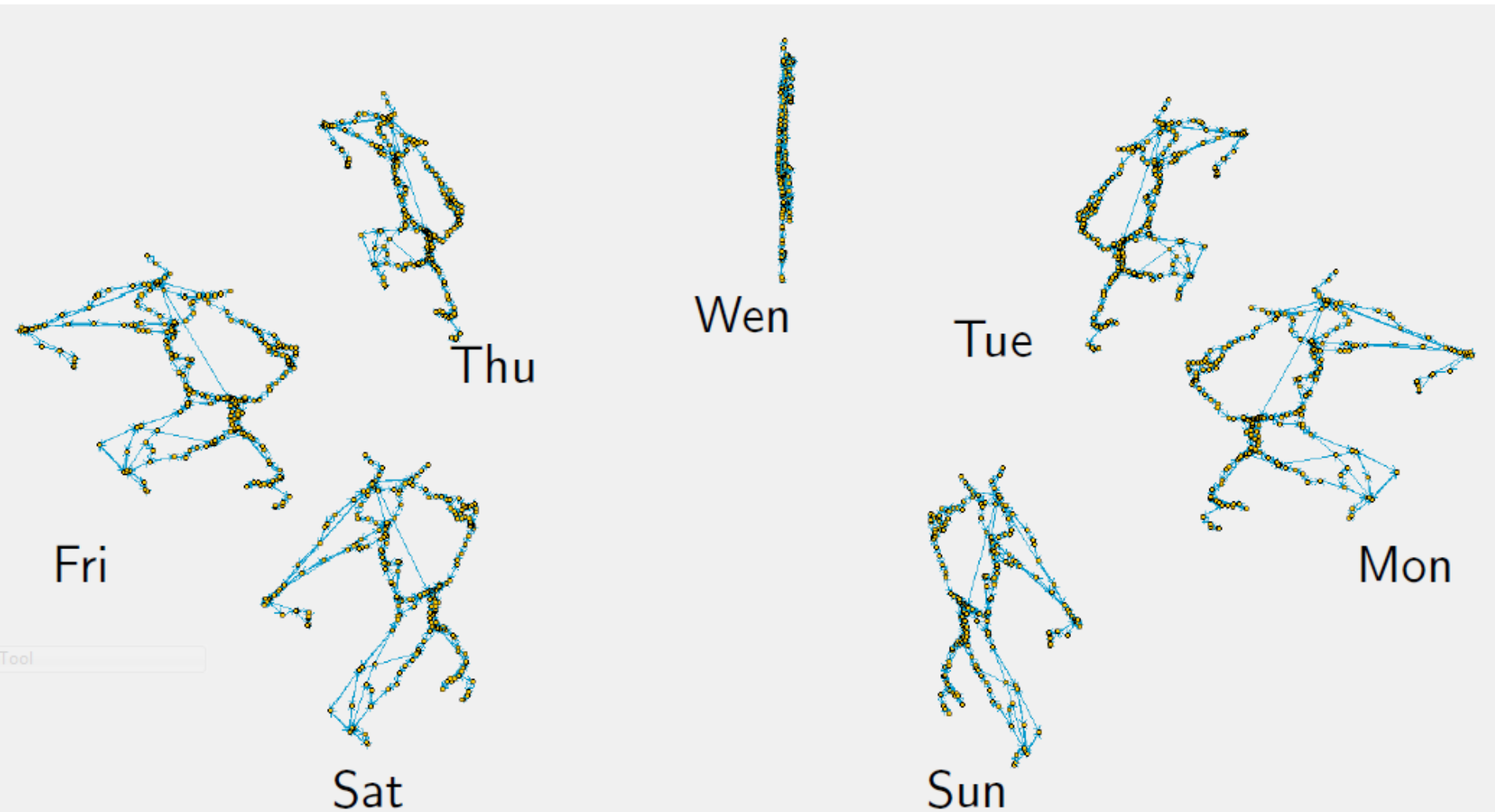
Brig RB - Domodossola II

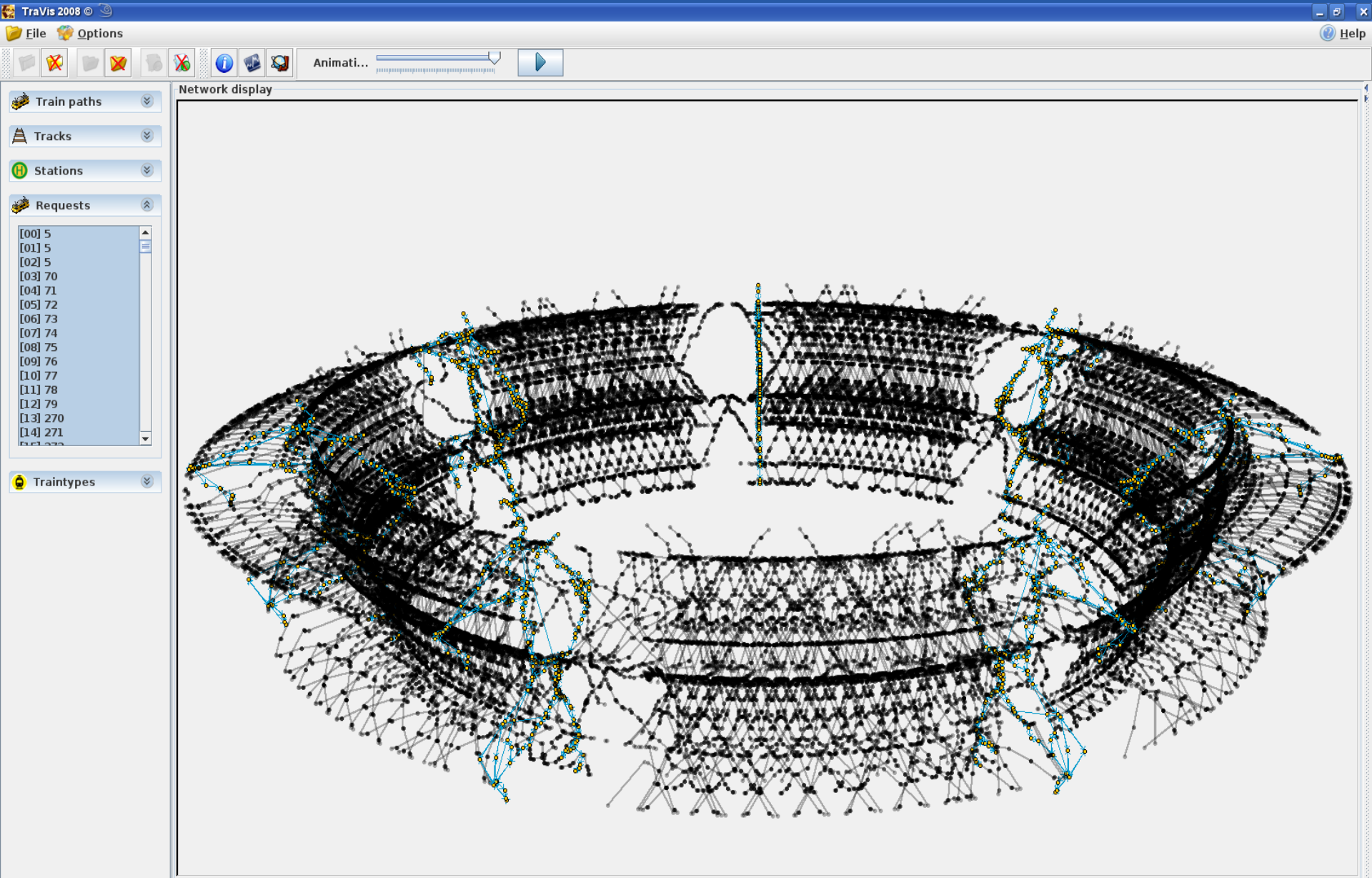


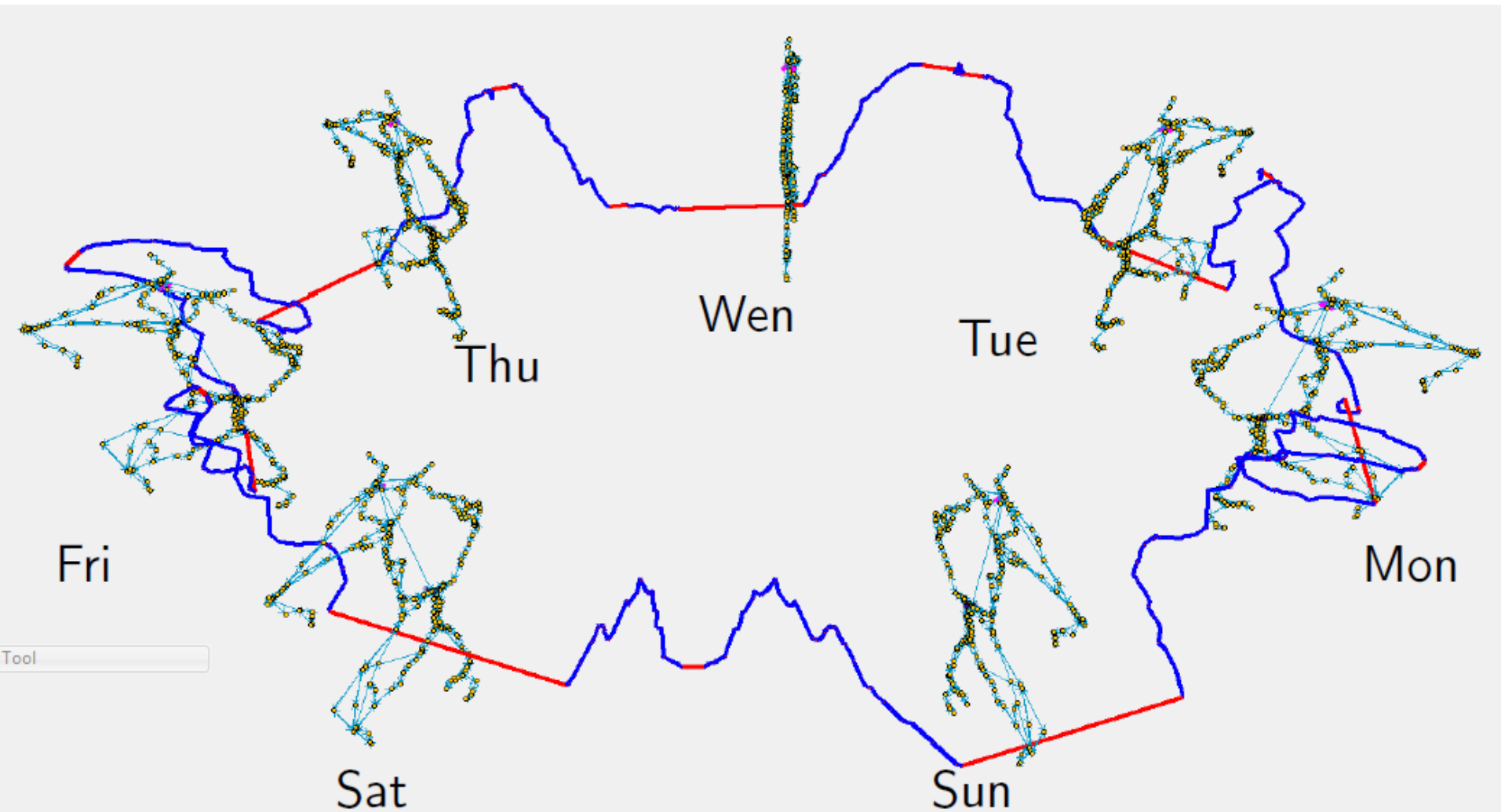
- ▷ Network big with buffer times

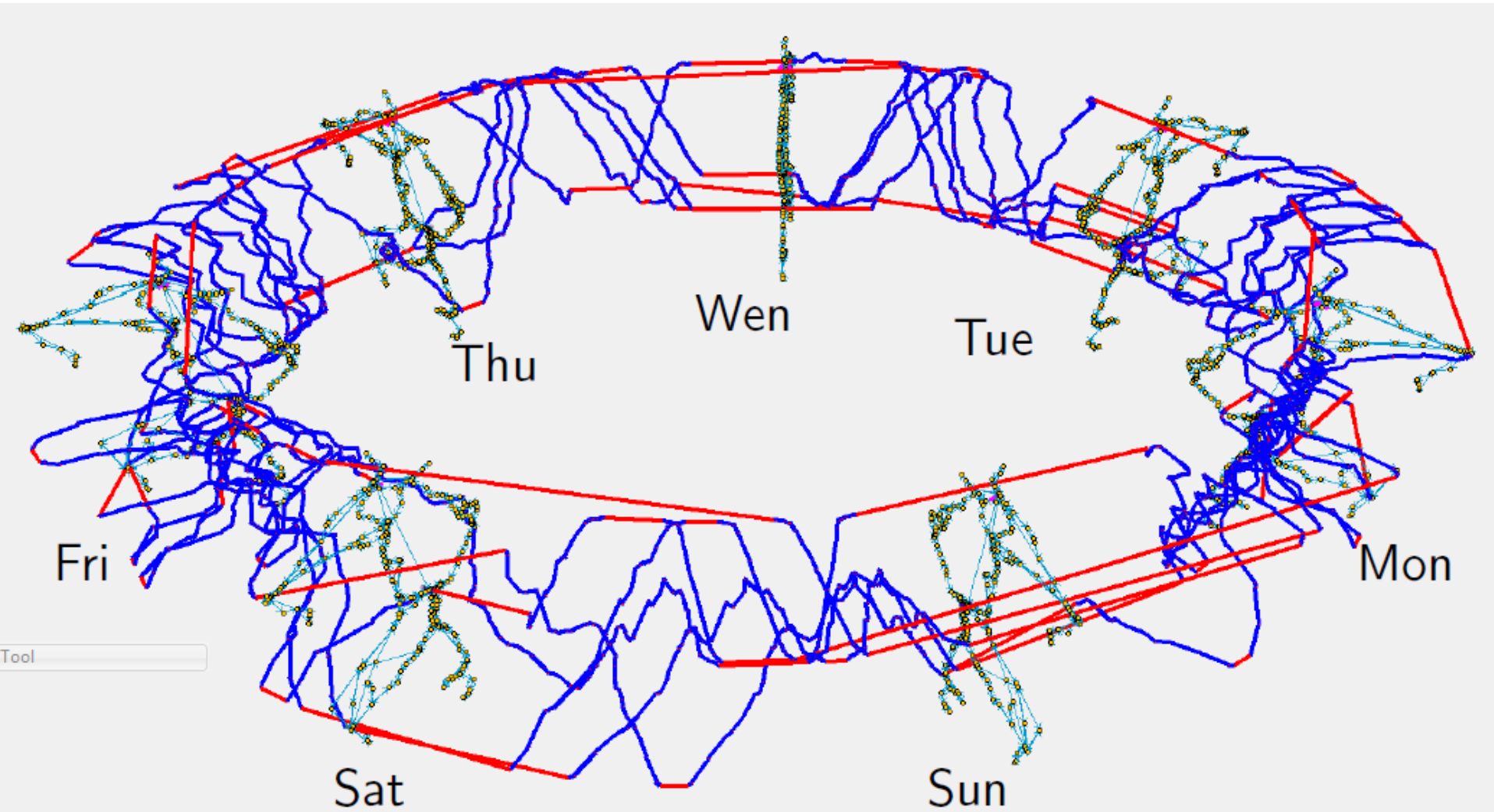
Time discretization dt/s	6	10	30	60
Number of trains	196	187	166	146
Cols in IP	504314	318303	114934	61966
Rows in IP	222096	142723	53311	29523
Solution time in secs	72774.55	12409.19	110.34	10.30

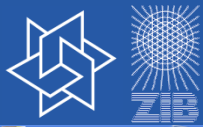
Hypergraph Scheduling











Rotation Schedule

(Blue: Timetable, Red: Deadheads)

Travis 2008 ©

File Options

Animati...

Help

Rotations

- [00]
- [01]
- [02]
- [03]
- [04]
- [05]
- [06]

Tracks

- [006] AA G#AA
- [000] AA#AAR
- [001] AA#AE F
- [002] AA#ALA
- [003] AA#ALAA
- [004] AA#HB
- [005] AA#HH
- [007] AAH#ABCH
- [008] AAH#ABG
- [009] AAMP#AH
- [010] AAMP#AHROP
- [011] AAR#AA
- [012] AAR#ADF
- [013] AAR#ALA
- [014] AAR#ALAA

Stations

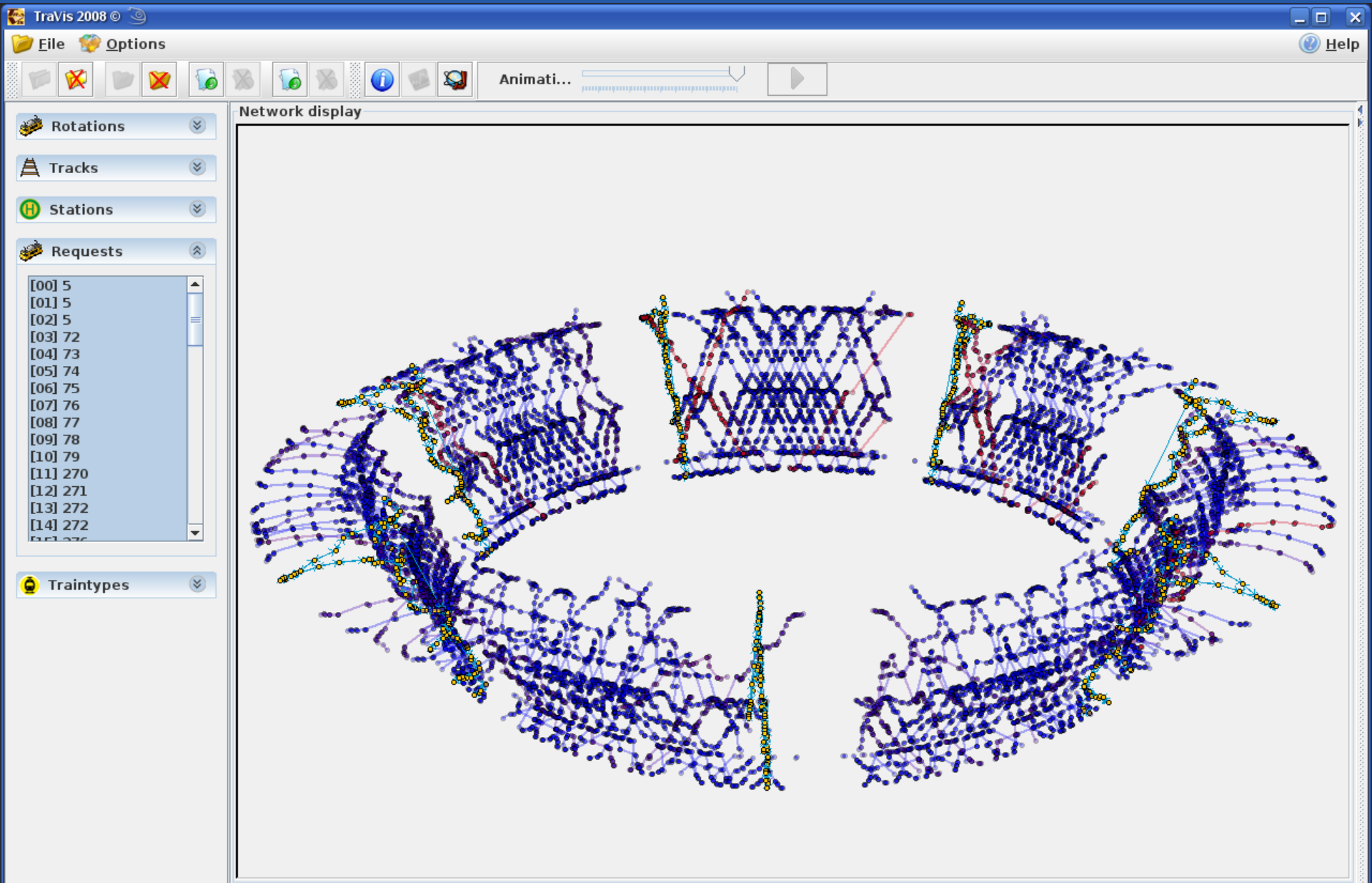
- [000] AA
- [001] AA G
- [002] AAH
- [003] AAMP
- [004] AAR
- [005] ABCH
- [006] ABG
- [007] ABLZ
- [008] ABVS
- [009] ADF
- [010] AE F
- [011] AEL
- [012] AERI

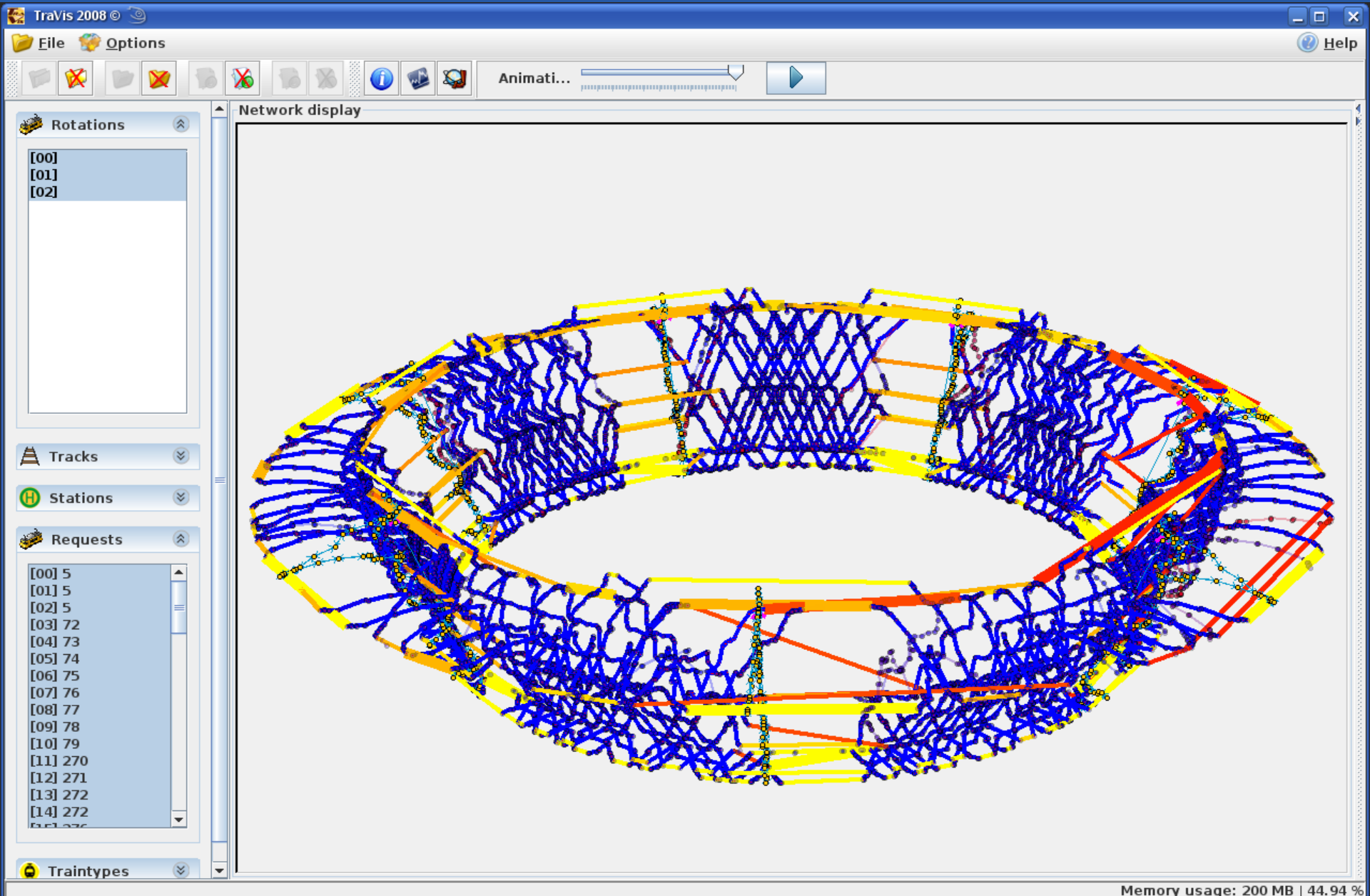
Network display

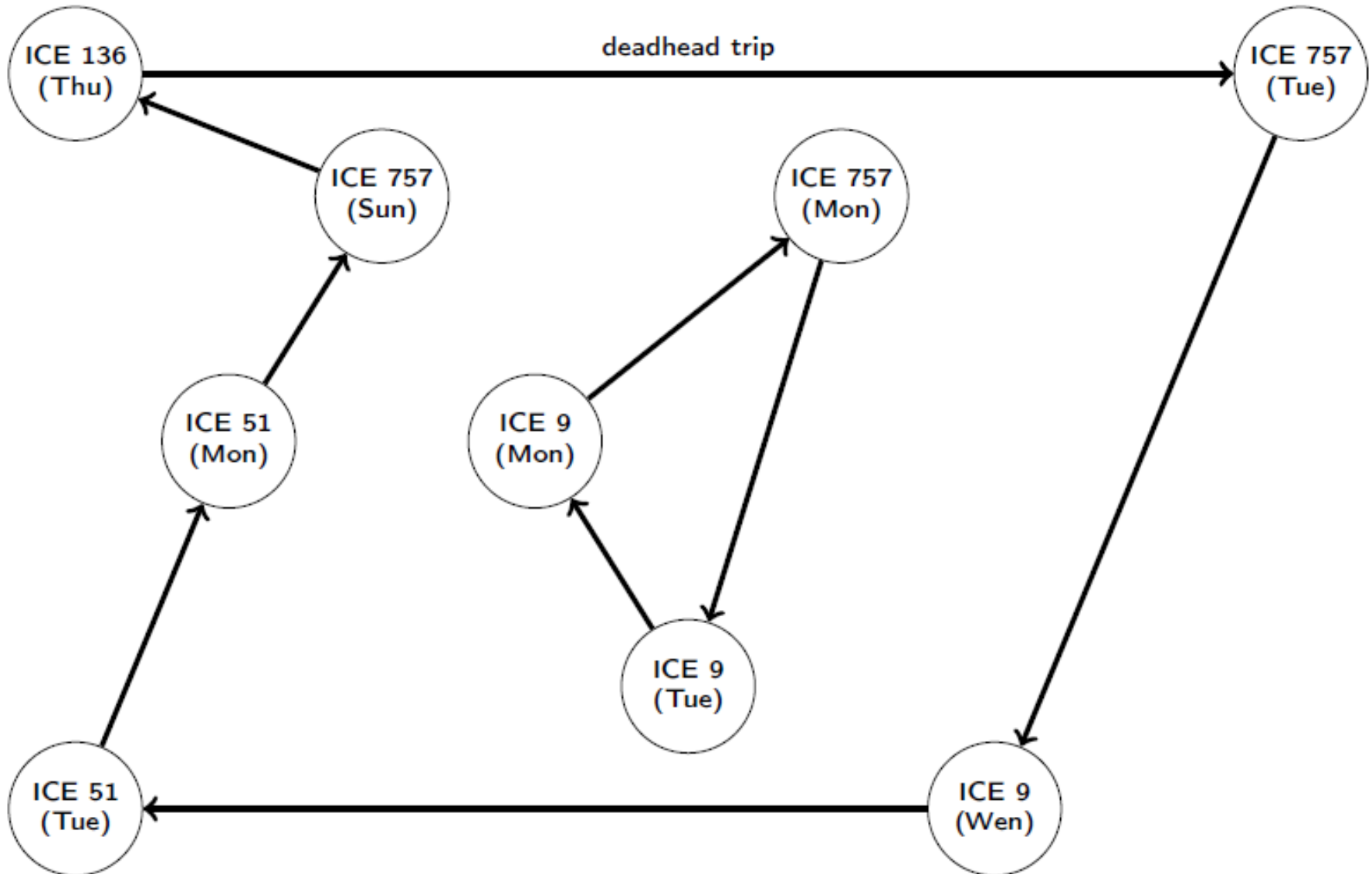
Memory usage: 349 MB | 78.38 %

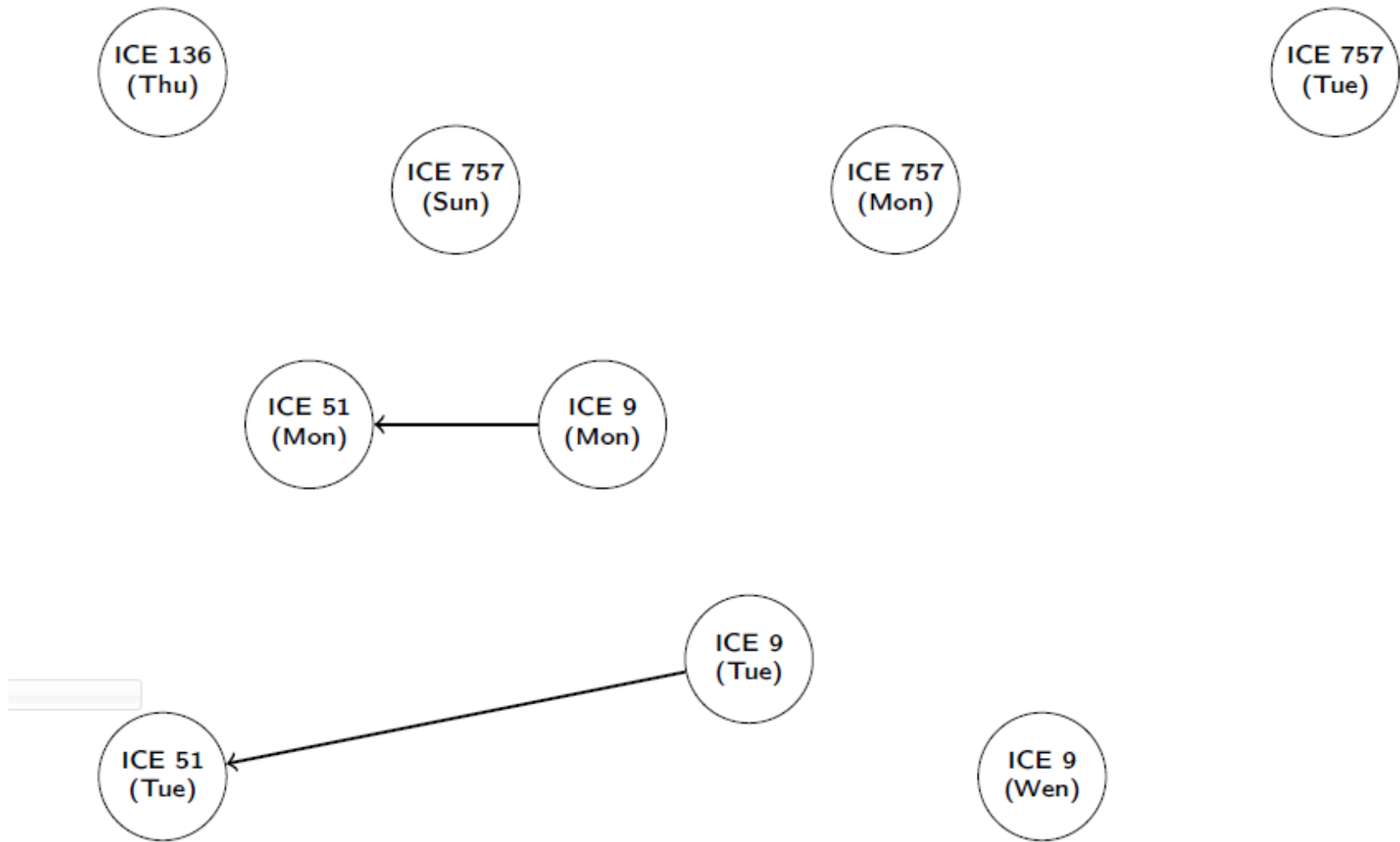
Wagenstandanzeiger Gleis 11

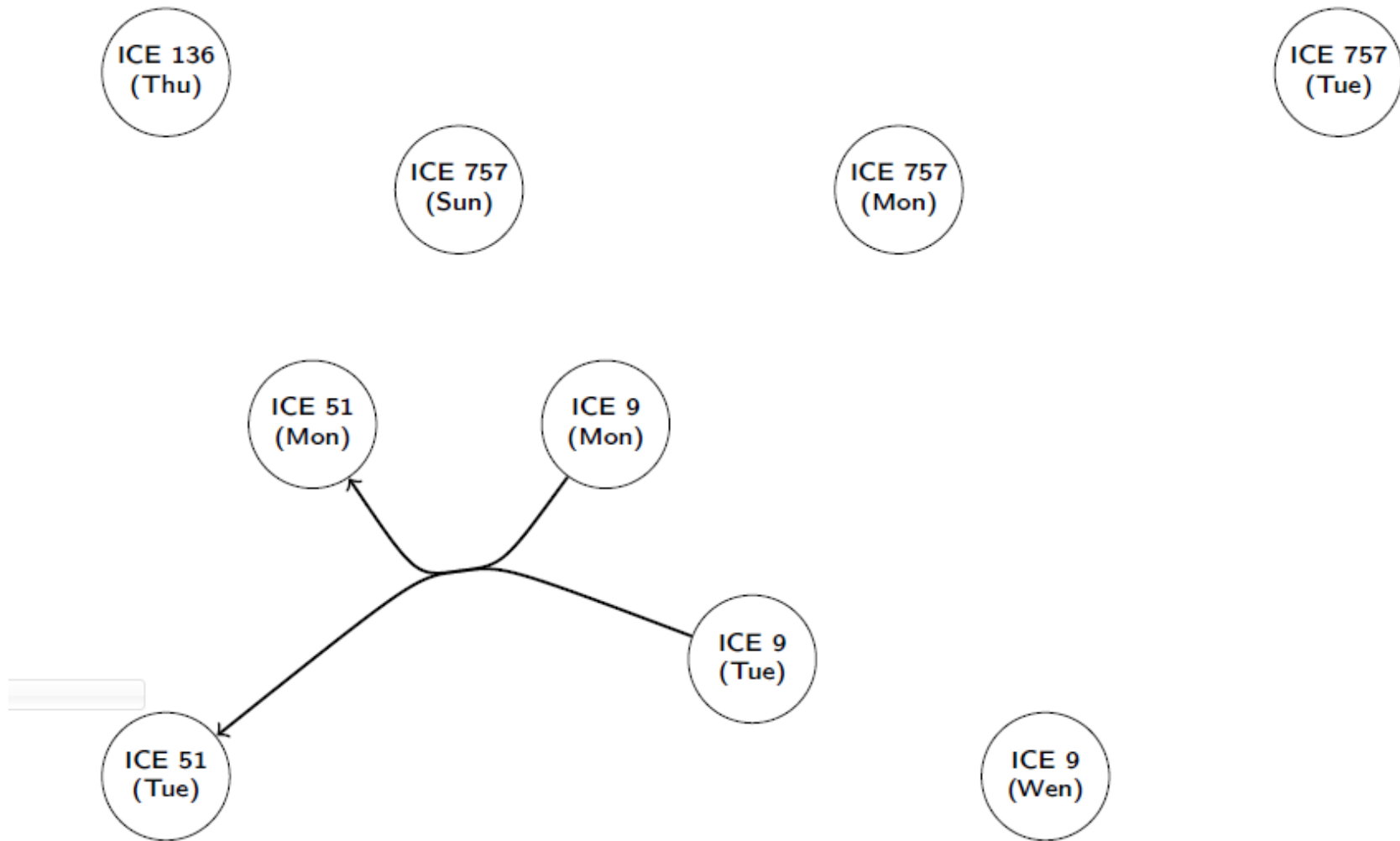
Zeit	Zug	Richtung	G	F	E	D	C	B	A
00.34	EN 348	Jan. Knapik Poznan Gl. Warszawa / Warschau	266	265	264	263	262	261	260
05.36	IC 2001	Braunschweig Magdeburg Leipzig / Halle Flugh. Leipzig	11	6	7	8	9	10	11
06.21	ICE 740 / 750	Zugleitung in Hamm D bis G Köln / Bonn Flughafen A bis C Köln	27	26	25	24	23	22	21
06.40	IC 148	Denzlingen Bad Bentheim Hengelo Amsterdam Flughafen	12	11	10	9	8	7	6
07.45	IC 2234	Dienstag bis Donnerstag	4	5	6	7	8	9	10
07.45	IC 2236	Montag und Freitag	4	5	6	7	8	9	10
08.45	IC 2134	Bremen Delmenhorst Oldenburg	11	6	7	8	9	10	11
09.40	IC 2044	Bielefeld Dortmund Essen Düsseldorf	11	6	7	8	9	10	11
10.45	IC 2132	Ostfriesland Bremen Oldenburg Emden Norddeich Mole	11	6	7	8	9	10	11
11.40	IC 2046	Bielefeld Götersloh Hamm Dortmund	11	6	7	8	9	10	11
12.45	IC 2130	Verden Bremen Delmenhorst Oldenburg	11	6	7	8	9	10	11
13.40	IC 2048	Bielefeld Dortmund Essen Düsseldorf	11	6	7	8	9	10	11
14.45	IC 2038	Verden Bremen Delmenhorst Oldenburg	11	6	7	8	9	10	11
15.31	ICE 848	Zugleitung in Hamm D bis G Köln / Bonn Flughafen A bis C Köln	27	26	25	24	23	22	21
16.45	IC 2038	Bremen Oldenburg Emden Norddeich Mole	11	6	7	8	9	10	11
17.40	IC 2142	Dortmund Essen Duisburg Köln	11	6	7	8	9	10	11
18.45	IC 2034	Verden Bremen Delmenhorst Oldenburg	11	6	7	8	9	10	11
19.40	IC 2144	So. Köln Bielefeld Götersloh Hamm Dortmund	11	6	7	8	9	10	11
20.45	IC 2032	Verden Bremen Delmenhorst Oldenburg	11	6	7	8	9	10	11

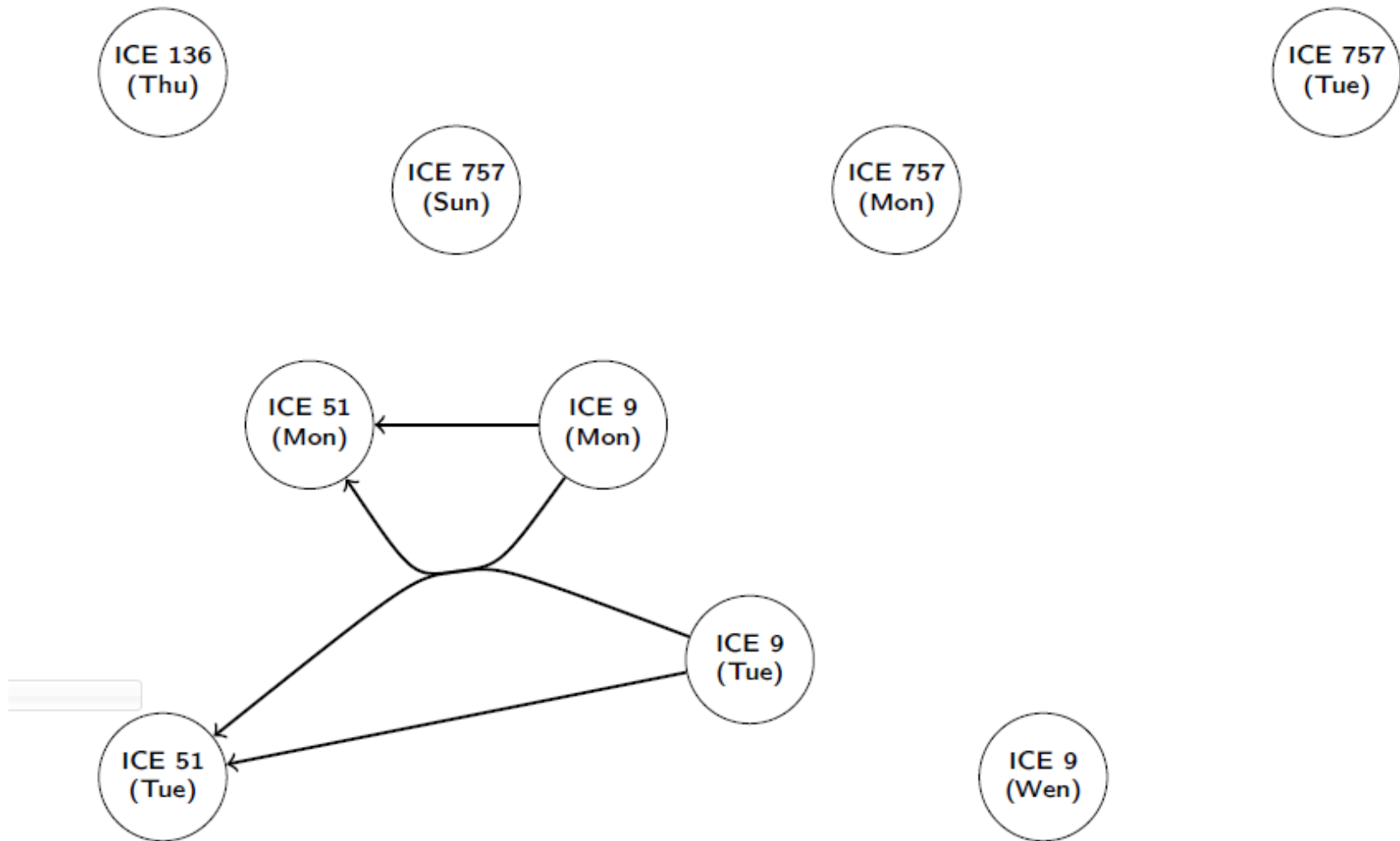


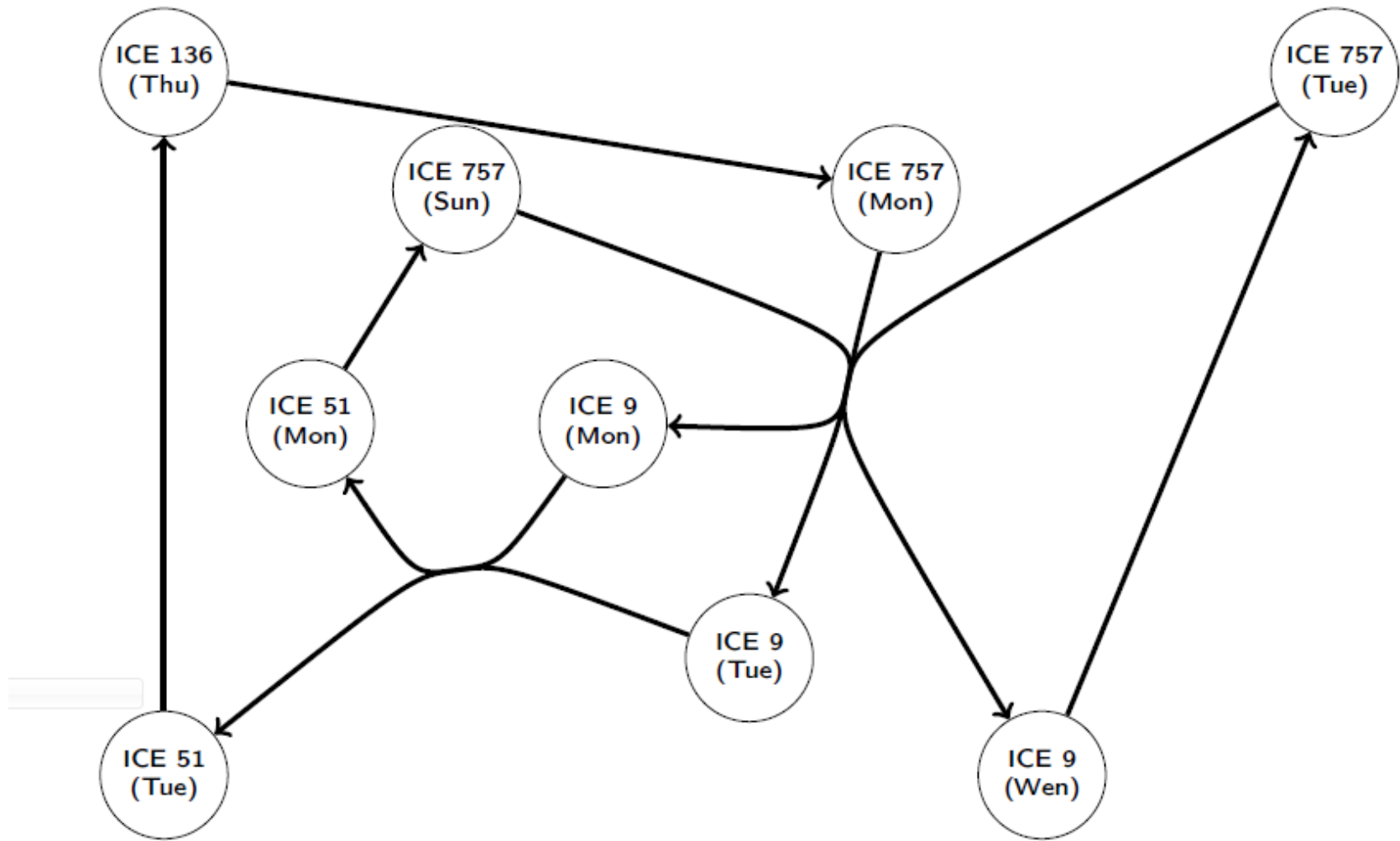












Definition: Let $D=(V,A)$ be a directed hypergraph w. arc costs c_a

- ▷ $H \subseteq A$ hyperassignment $:\Leftrightarrow \delta^+(v) \cap H = \delta^-(v) \cap H = 1$
- ▷ Hyperassignment Problem $:\Leftrightarrow \operatorname{argmin} c(H), H$ hyperassignment

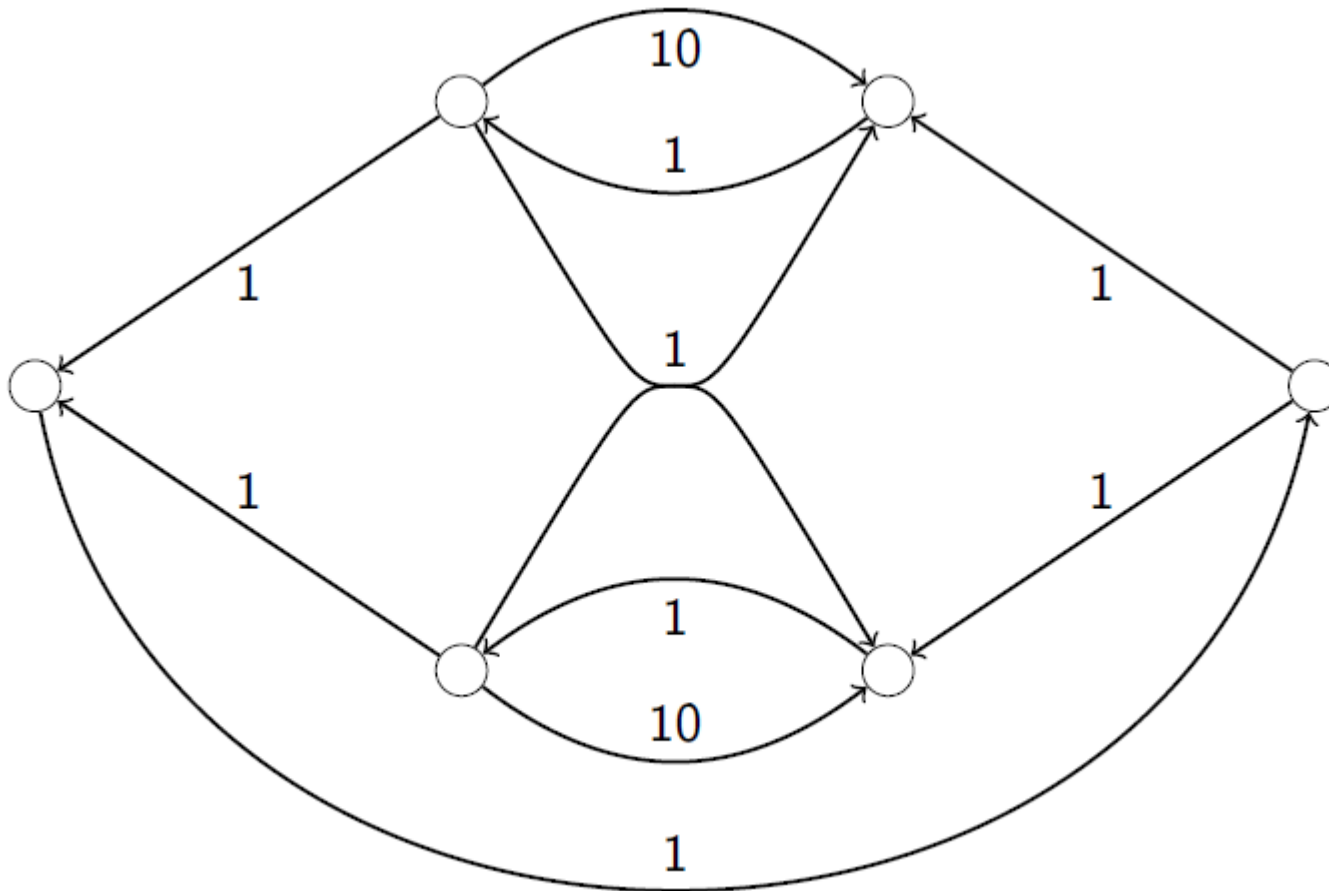
$$\begin{aligned} \min \quad & c^T x \\ & x(\delta^+(v)) = 1 \quad \forall v \in V \\ & x(\delta^-(v)) = 1 \quad \forall v \in V \\ & x \in \{0,1\}^A \end{aligned}$$

Literature

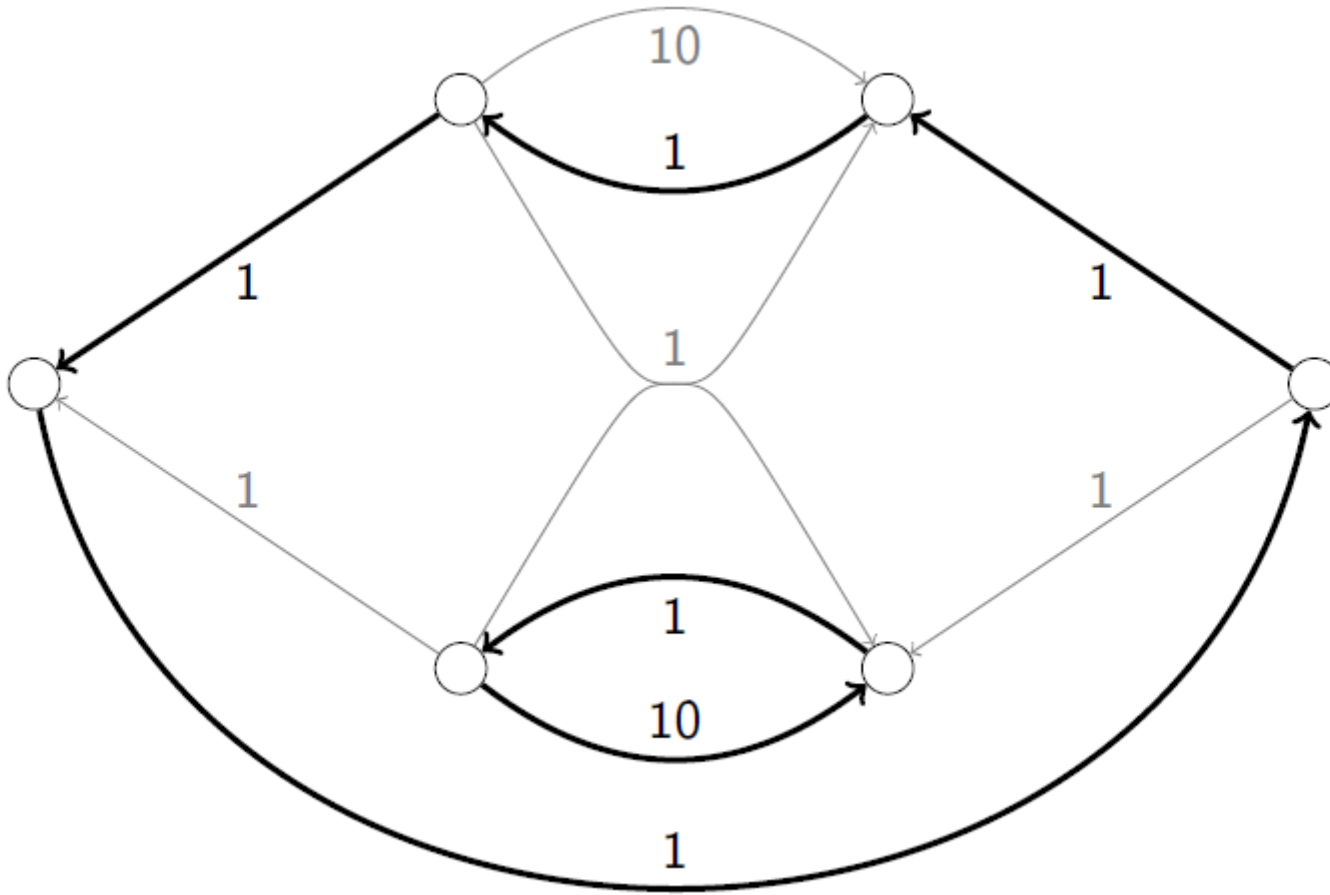
- ▷ Cambini, Gallo, Scutellà (1992): Minimum cost flows on hypergraphs; solves only the LP relaxation
- ▷ Jeroslow, Martin, Rarding, Wang (1992): Gainfree Leontief substitution flow problems; does not hold for the hyperassignment problem

Theorem: The HAP is NP-hard (even for simple cases).

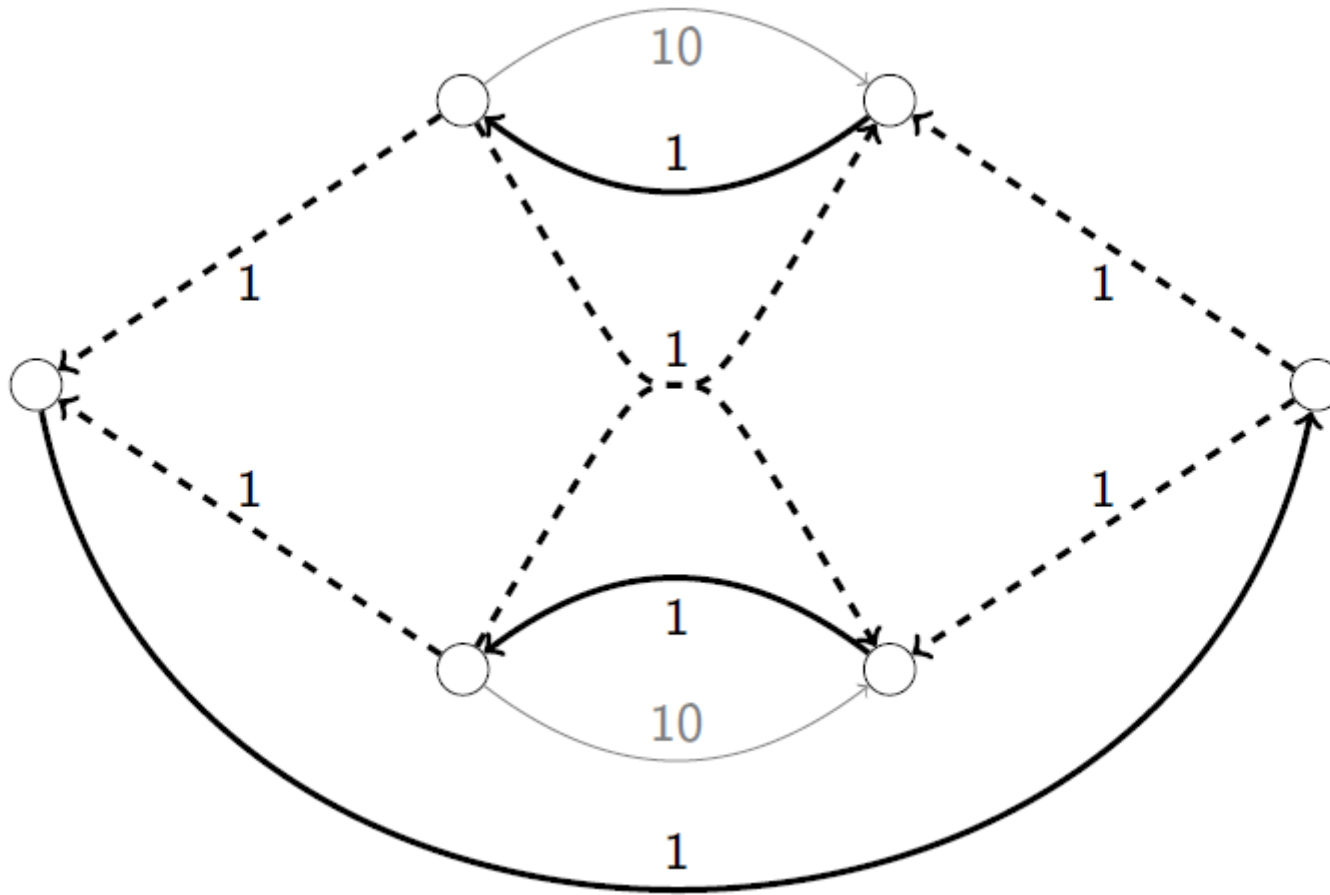
Theorem: The LP/IP gap of HAP can be arbitrarily large.



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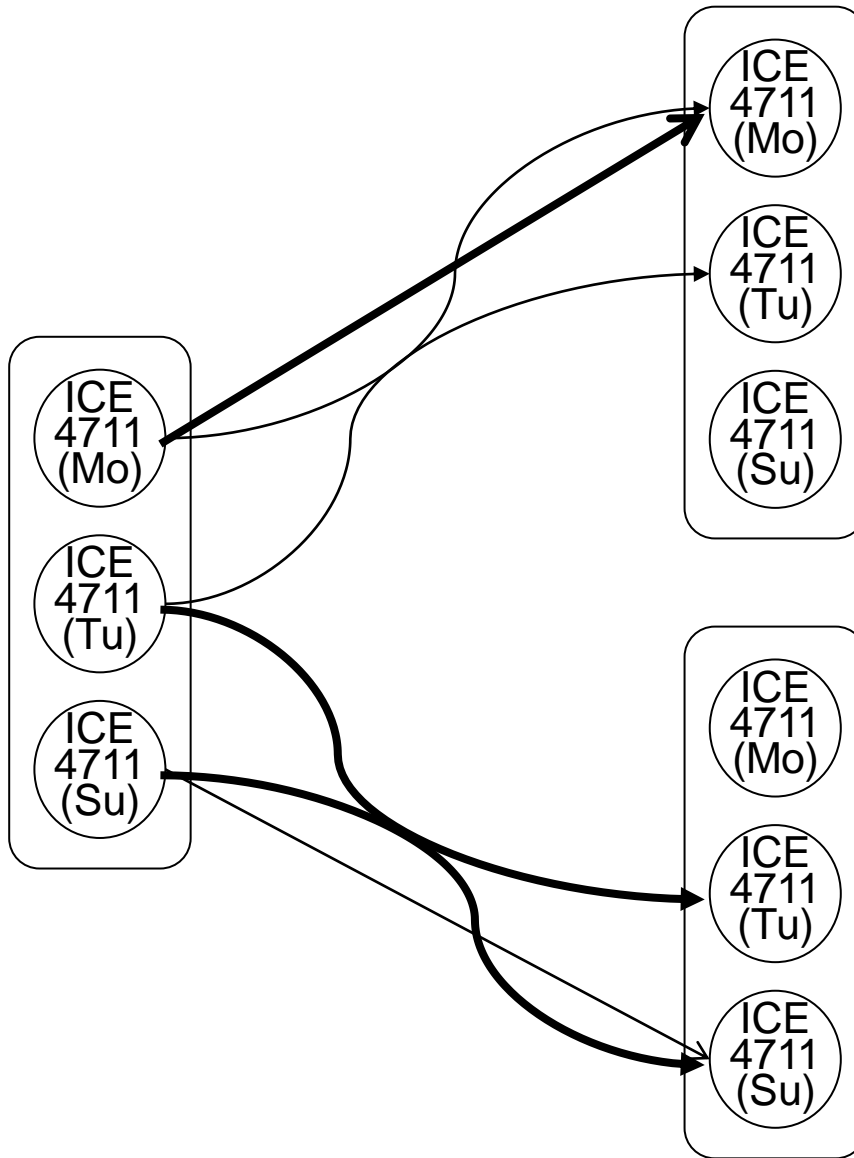
Theorem: The LP/IP gap of HAP can be arbitrarily large.

Proposition: The determinants of basis matrices of HAP can be arbitrarily large, even if all hyperarcs have head and tail size 2.

Proposition: HAP is APX-complete for hyperarc head and tail size 2 in general and for hyperarc head and tail cardinality 3 in the relevant cases.

# rows ($2 \cdot V $)	# columns ($ A $)	nonzeros	LP-IP gap	root gap	root improvement	# clique cuts	# other cuts	root run time (sec.)
534	52056	140081	11.16 %	6.81 %	4.90 %	160	14	8
620	80477	236020	8.72 %	0.00 %	9.54 %	120	2	29
812	102375	216566	0.38 %	0.18 %	0.20 %	24	16	40
1128	267542	732134	4.59 %	0.26 %	4.55 %	263	0	160
1310	363513	1006024	7.85 %	0.22 %	8.28 %	378	2	270
1496	469932	1369224	18.70 %	1.86 %	20.71 %	809	0	971
1696	618348	1787078	5.17 %	0.16 %	5.28 %	925	0	1705
1746	649525	1859898	7.52 %	4.88 %	2.86 %	563	0	1129
1798	647650	1822718	13.60 %	0.95 %	14.65 %	537	0	1099
1798	647650	1822718	13.35 %	0.62 %	14.69 %	604	0	873
2006	855153	2491372	5.76 %	0.68 %	5.39 %	1025	0	2490
2260	1079535	3138752	9.89 %	2.03 %	8.73 %	954	0	5483
2502	1290750	3680124	7.06 %	0.76 %	6.79 %	801	0	4583
2620	1432355	4187296	9.05 %	1.15 %	8.68 %	1068	0	7910
2624	1439453	4087042	14.17 %	5.23 %	10.41 %	951	0	(*) 14400

(*) = aborted



Theorem: There is an extended formulation of HAP with $O(V^8)$ variables that implies all clique constraints.

$$\begin{aligned}
 \min \quad & c^T x \\
 & x(\delta^+(v)) = 1 \quad \forall v \in V \\
 & x(\delta^-(v)) = 1 \quad \forall v \in V \\
 & x \in \{0,1\}^A \\
 & y(C^+(a)) = x_a \quad \forall a \in A \\
 & y(C^-(a)) = x_a \quad \forall a \in A \\
 & y \in \{0,1\}^C
 \end{aligned}$$

Stochastic Scheduling



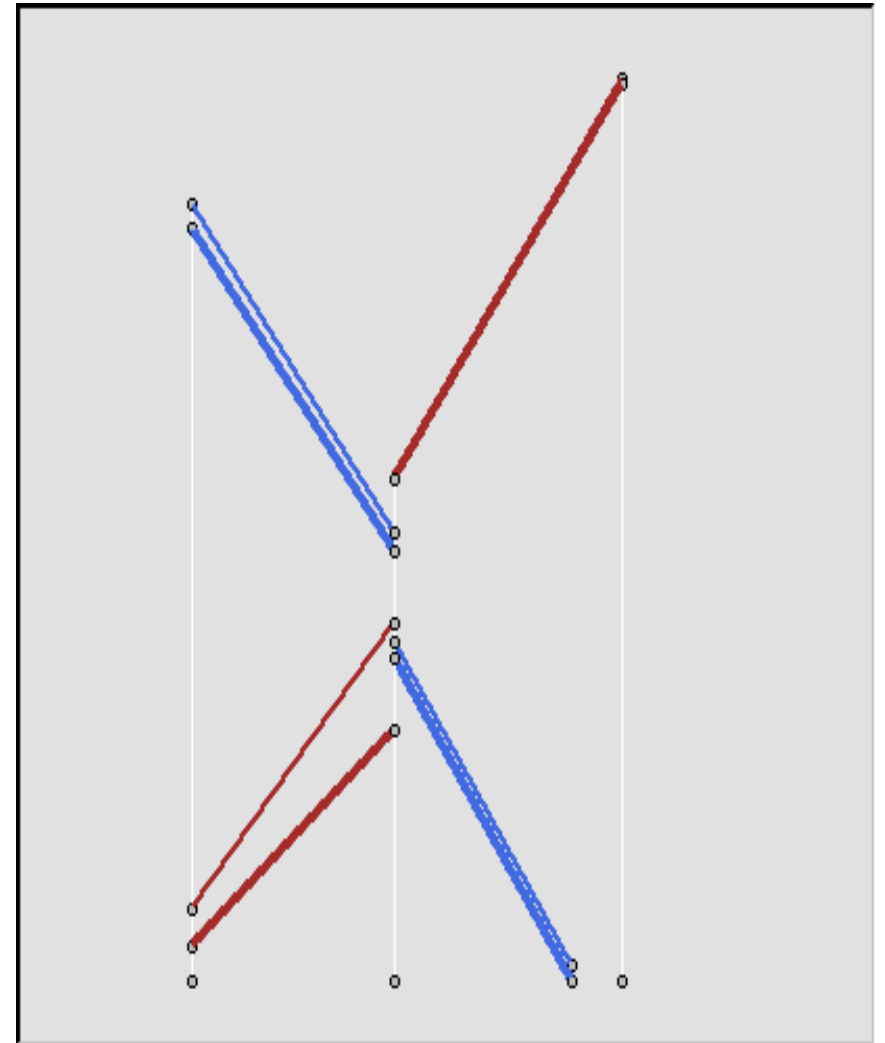
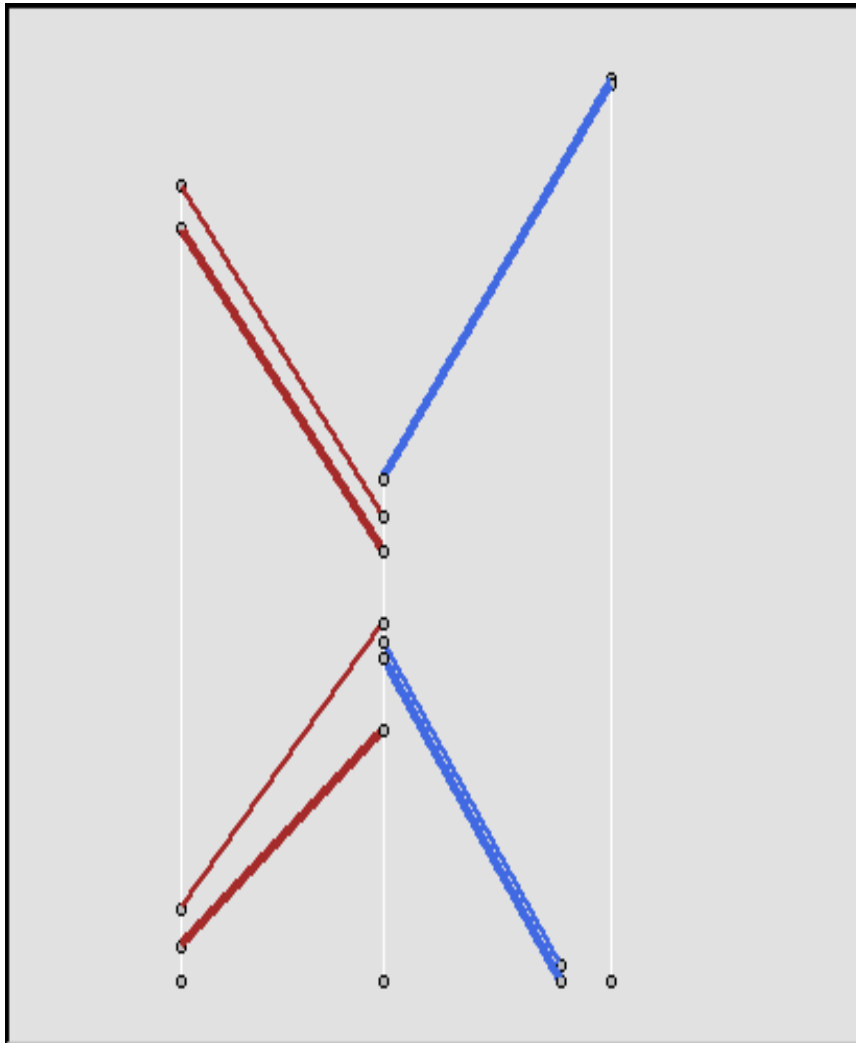
Cost of delays

- ▶ 72 €/minute average cost of gate delay over 15 minutes, cf. EUROCONTROL [2004]
- ▶ 840 – 1200 millions € annual costs caused by gate delays in Europe

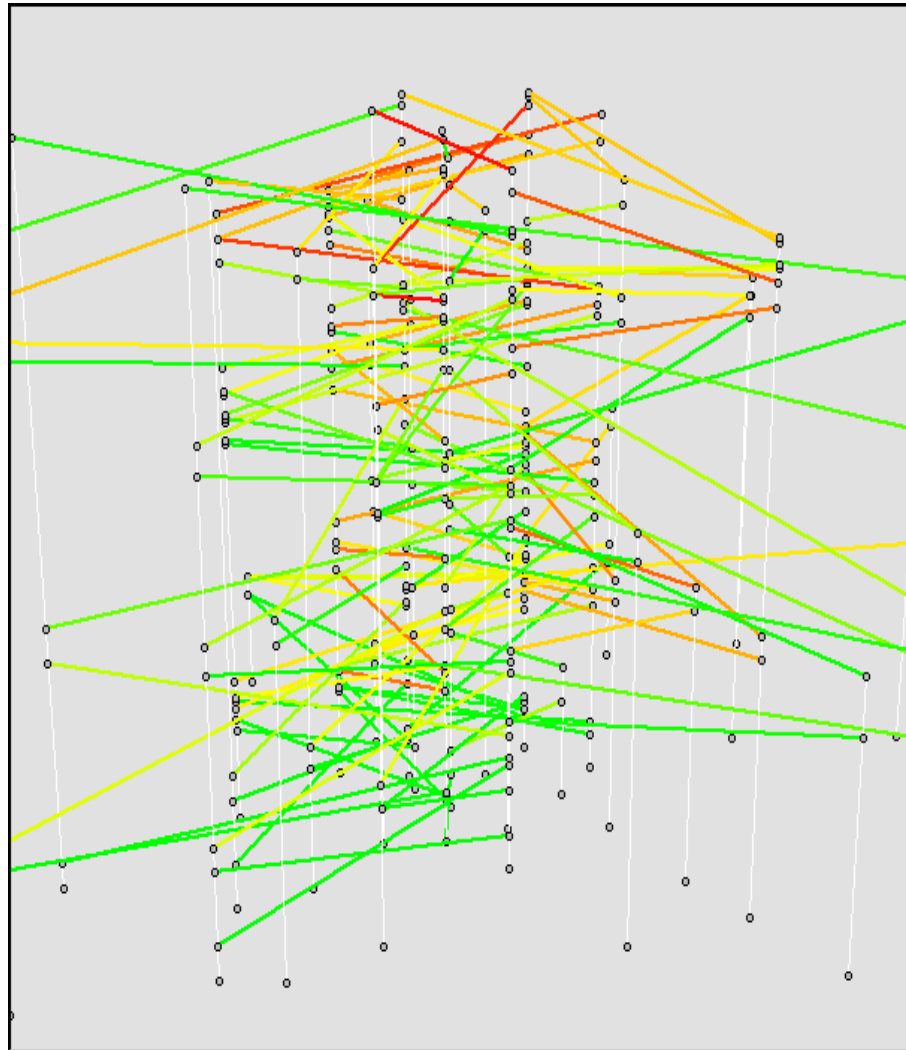
Benefits of robust planning

- ▶ Cost savings
- ▶ Reputation
- ▶ Less operational changes

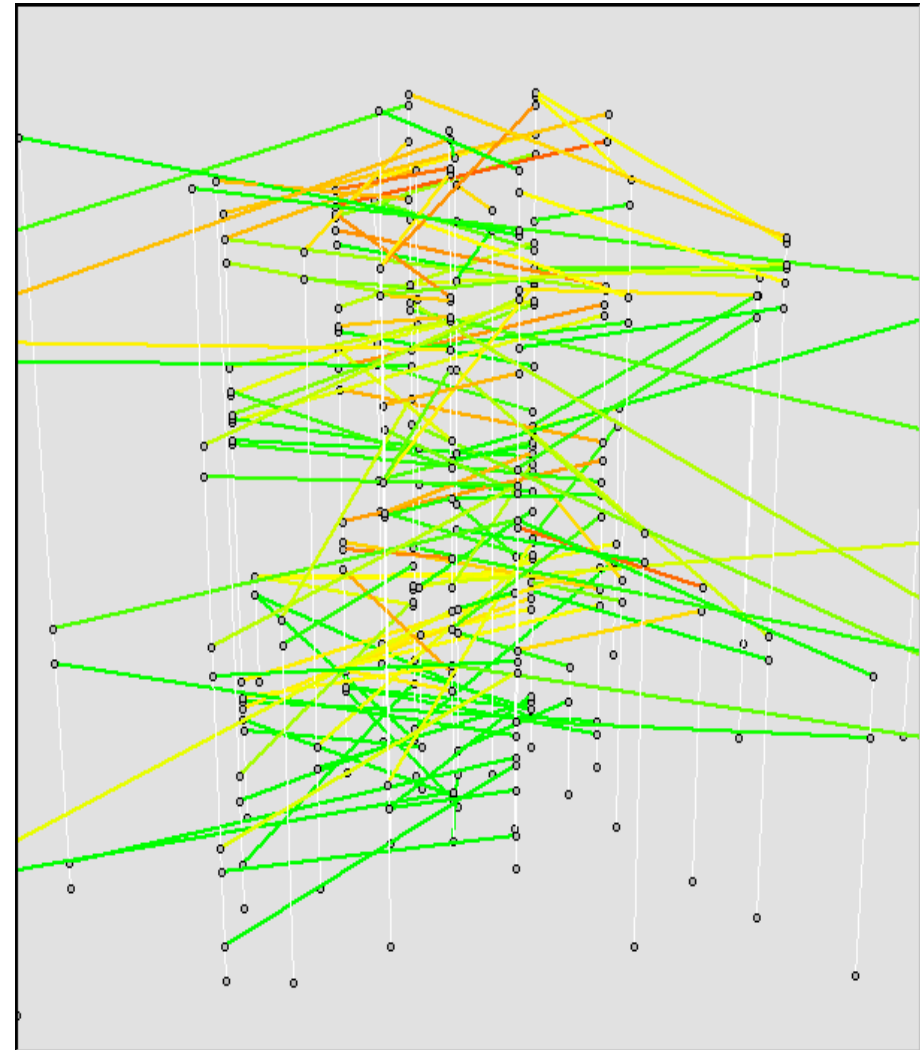
The Tail Assignment Problem – assign legs to aircraft in order to fulfill operational constraints such as preassignments, maintenance rules, airport curfews, and minimum connection times between legs, cf. Grönkvist [2005]



EDP (bad)



EDP (good)





Goal: Decrease impact of delays

- ▶ Primary delays: genuine disruptions, unavoidable
- ▶ Propagated delays: consequences of aircraft routing, **can be minimized**

Rule-oriented planning

- ▶ Ad-hoc formulas for buffers
- ▶ These rules are costly and it is uncertain how efficient they are
- ▶ Calibrating these rules is a balancing act: supporting operational stability, while staying cost efficient

Goal-oriented planning

- ▶ Minimize occurrence of delay propagation on average



Delay distribution

- ▷ Delays are not homogeneously spread in the network
- ▷ Stochastic model must captures properties of individual airports and legs

Structure of the stochastic model

- ▷ Gate phase, representing time spent on the ground
- ▷ Flight phase, representing time spent en-route

Phase durations are modelled by probability distribution

- ▷ G_j is random variable for delay of gate phase of leg j
- ▷ F_j is random variable for duration of flight phase of leg j



Mathematical model:

$$\min \sum_k \sum_{r \in R_k} d_r x_r^k$$

▷ Minimize non-robustness

$$\sum_k \sum_{r: l \in r, r \in R_k} x_r = 1 \quad \forall l \in L$$

▷ Cover all legs

$$\sum_k \sum_{p \in R_k} a_{bp} x_p^k \leq r_b \quad \forall b \in B$$

▷ Fulfill side constraints

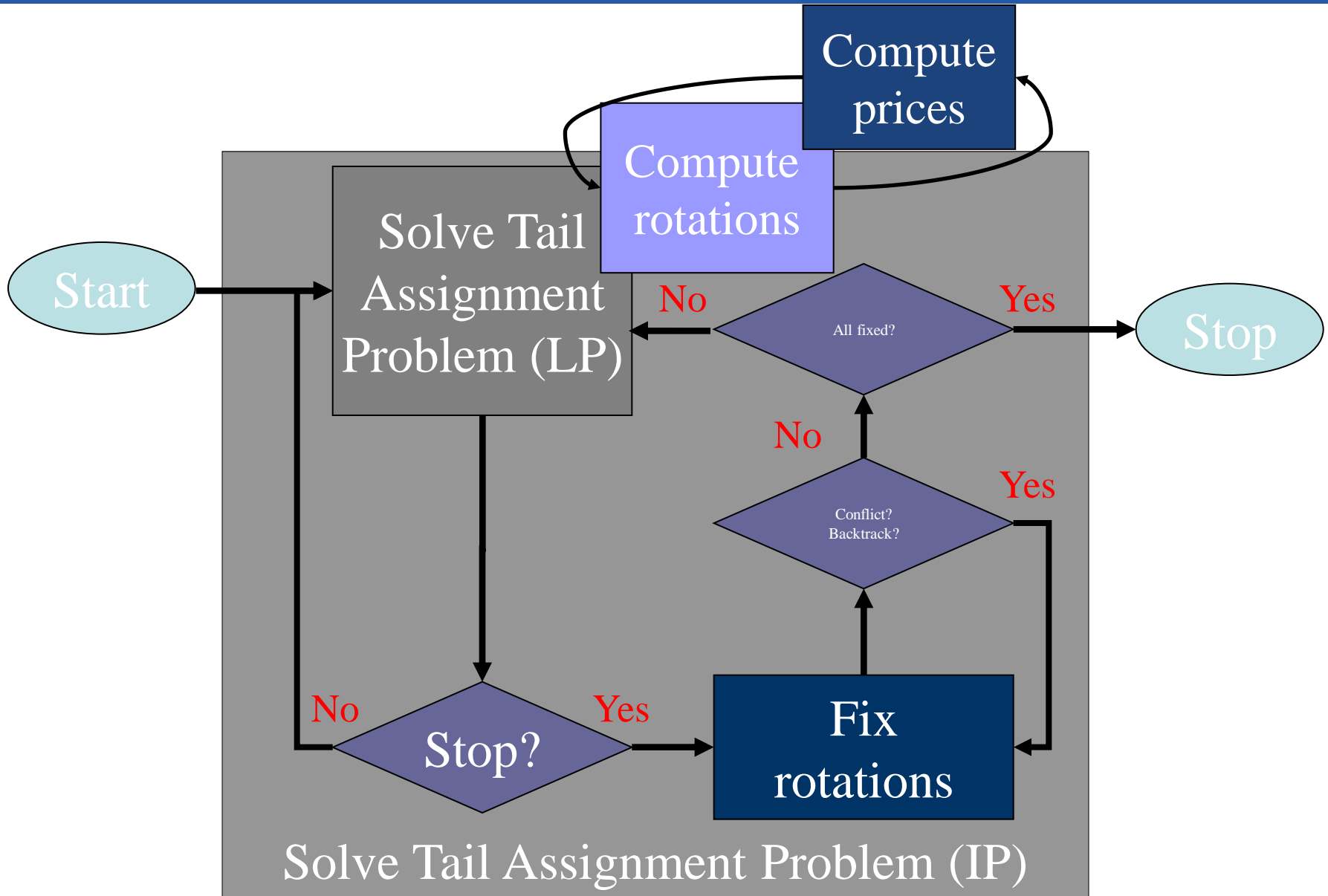
$$\sum_{j \in R_k} x_j^k = 1 \quad \forall k$$

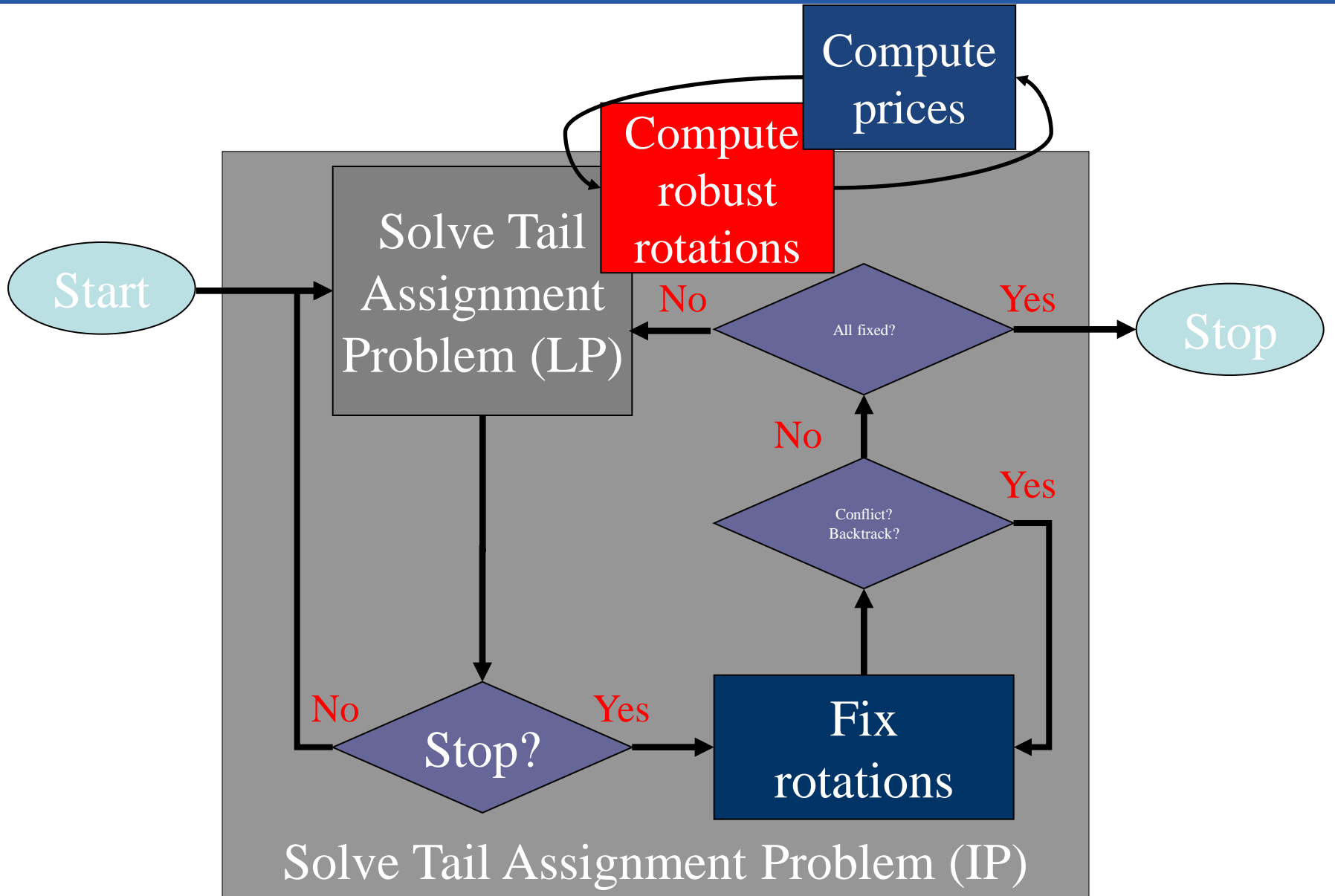
▷ One rotation for each aircraft

$$x_r^k \in \{0, 1\} \quad \forall k, \forall r \in R_k$$

▷ Integrality

- ▷ Set partitioning problem with side constraints
- ▷ Problem has to be resolved daily for period of a few days
- ▷ Solved by Netline/Ops Tail xOPT (state-of-the-art column generation solver by Lufthansa Systems)





Solve Tail Assignment Problem (IP)



- ▶ Robustness measure: total probability of delay propagation (PDP)

$$d_r = \sum_{i \in r} \mathbb{P}[PD_i^r > 0]$$

- ▶ Resource constraint shortest path problem

$$\min_{r \in R^k} d_r - \sum_{i \in r} \pi_i + \sum_{b \in B} a_{br} \mu_b - \nu_k$$

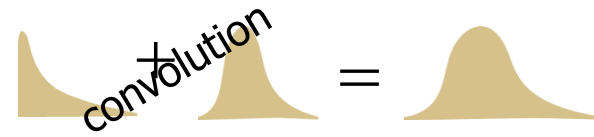
where PD_i^r is random variable of delay propagated to leg i in rotation r and π_i, ν_k, μ_b are dual variables corresponding to cover, aircraft, and side constraints

$$\min_{r \in R^k} \sum_{i \in r} \mathbb{P}[PD_i^r > 0] - \sum_{i \in r} \pi_i + \sum_{b \in B} a_{br} \mu_b - \nu_k$$

To solve this problem one must compute PD_i^r along rotations

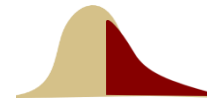
Delay distribution H_j of leg j

▷ $H_j = G_j + F_j$



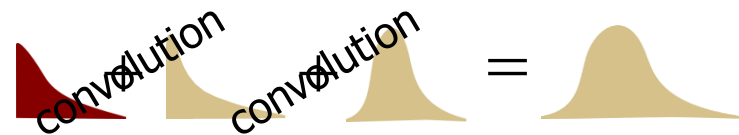
Delay propagation from leg j to leg k via buffer b_{jk}

▷ $PD_k = \max(H_j - b_{jk}, 0)$



Delay distribution H_k of next leg k

▷ $H_k = PD_k + G_k + F_k$



and so on...

Convolution

- ▶ $H = F + G$ and f, g and h are their probability density functions

$$h(t) = \int_0^t f(x)g(t-x)dx$$

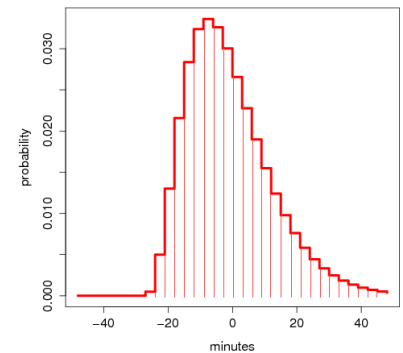
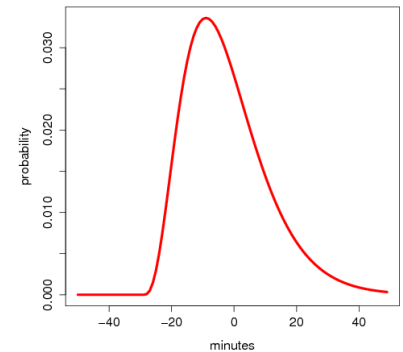
Numerical convolution based on discretization

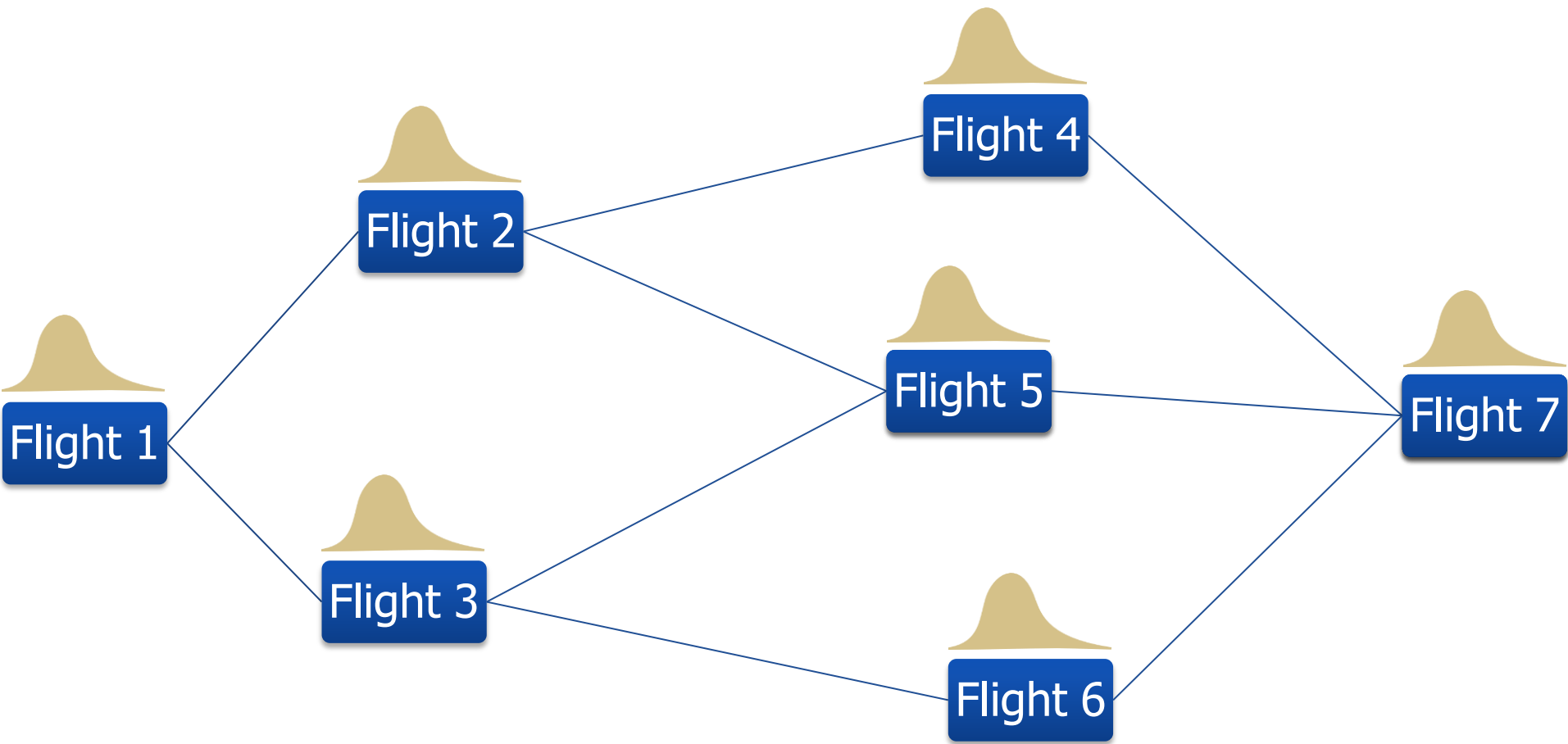
$$\bar{h}_t = \sum_{i=1}^t \bar{f}_i (\bar{g}_{t-i} + \bar{g}_{t-i-1}) / 2$$

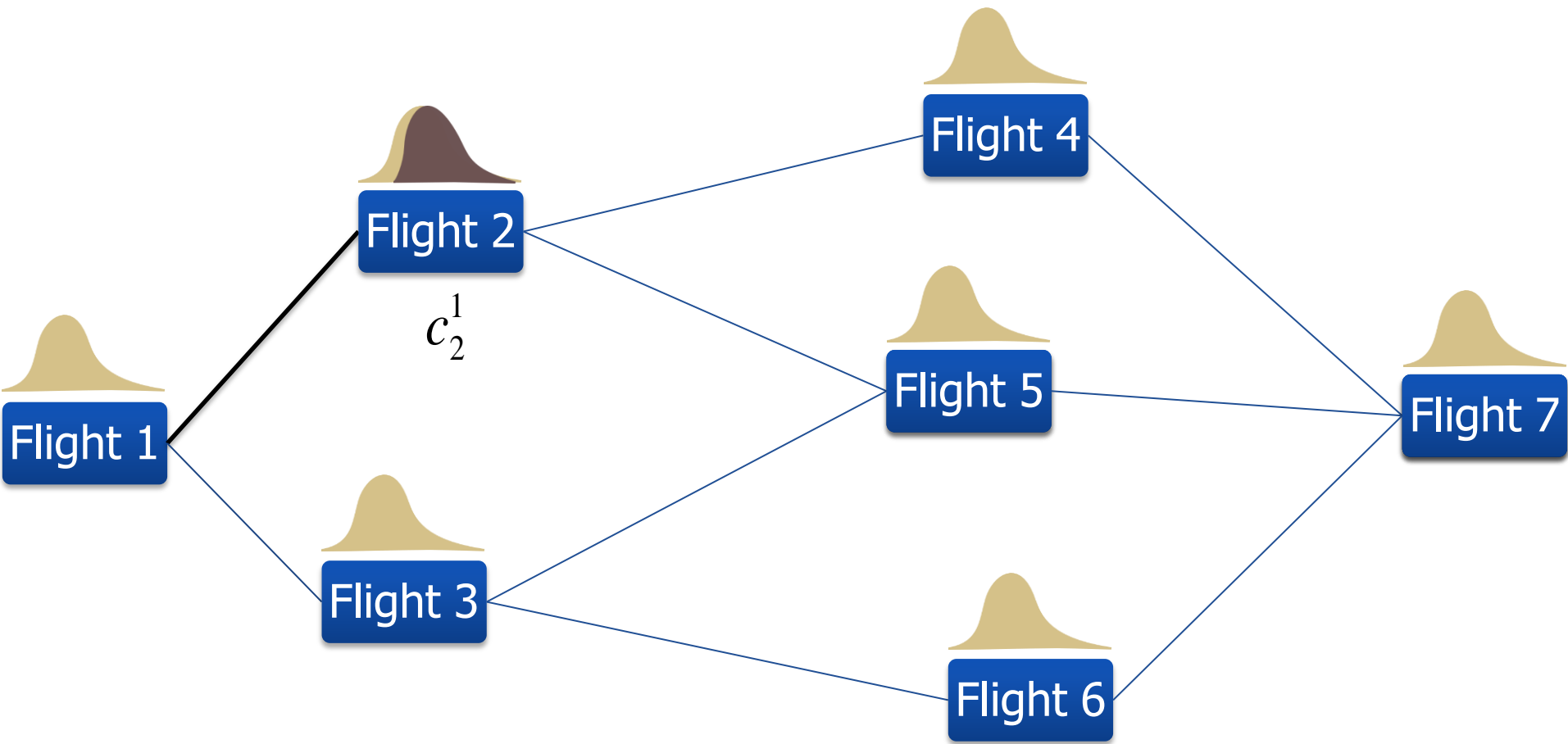
where \bar{f}, \bar{g} are stepwise constant approximations of functions f, g

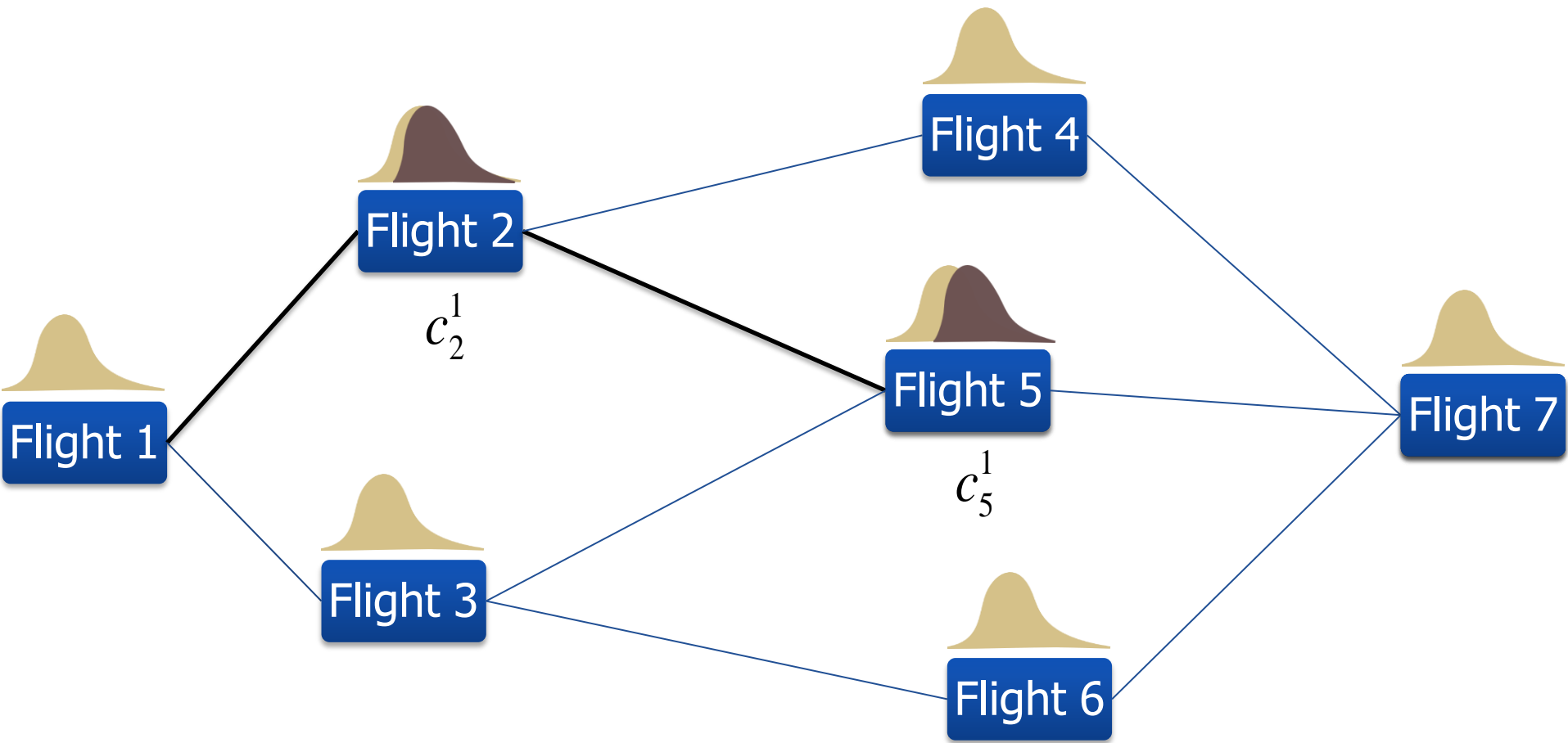
Alternative approaches

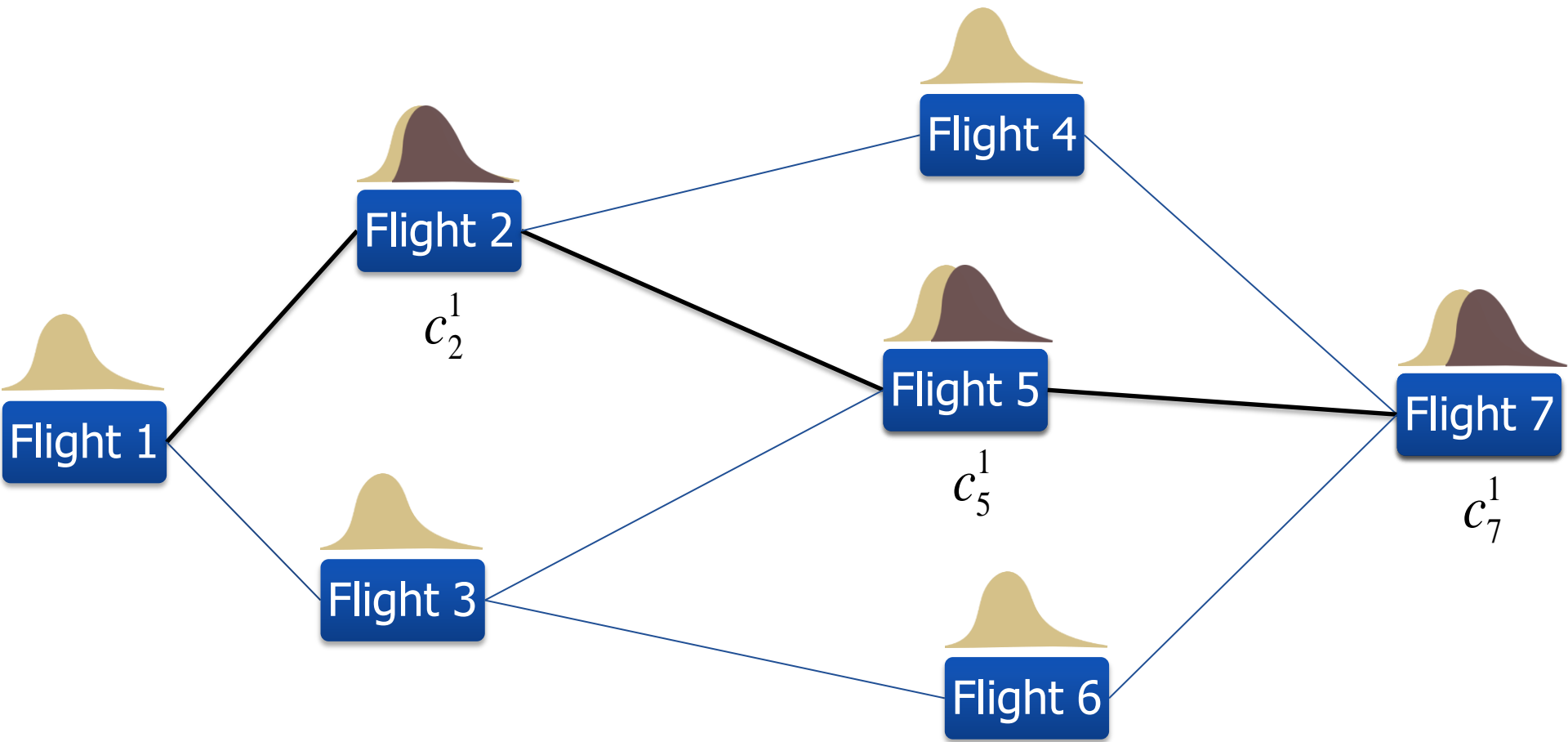
- ▶ Analytical convolution, cf. Fuhr [2007]

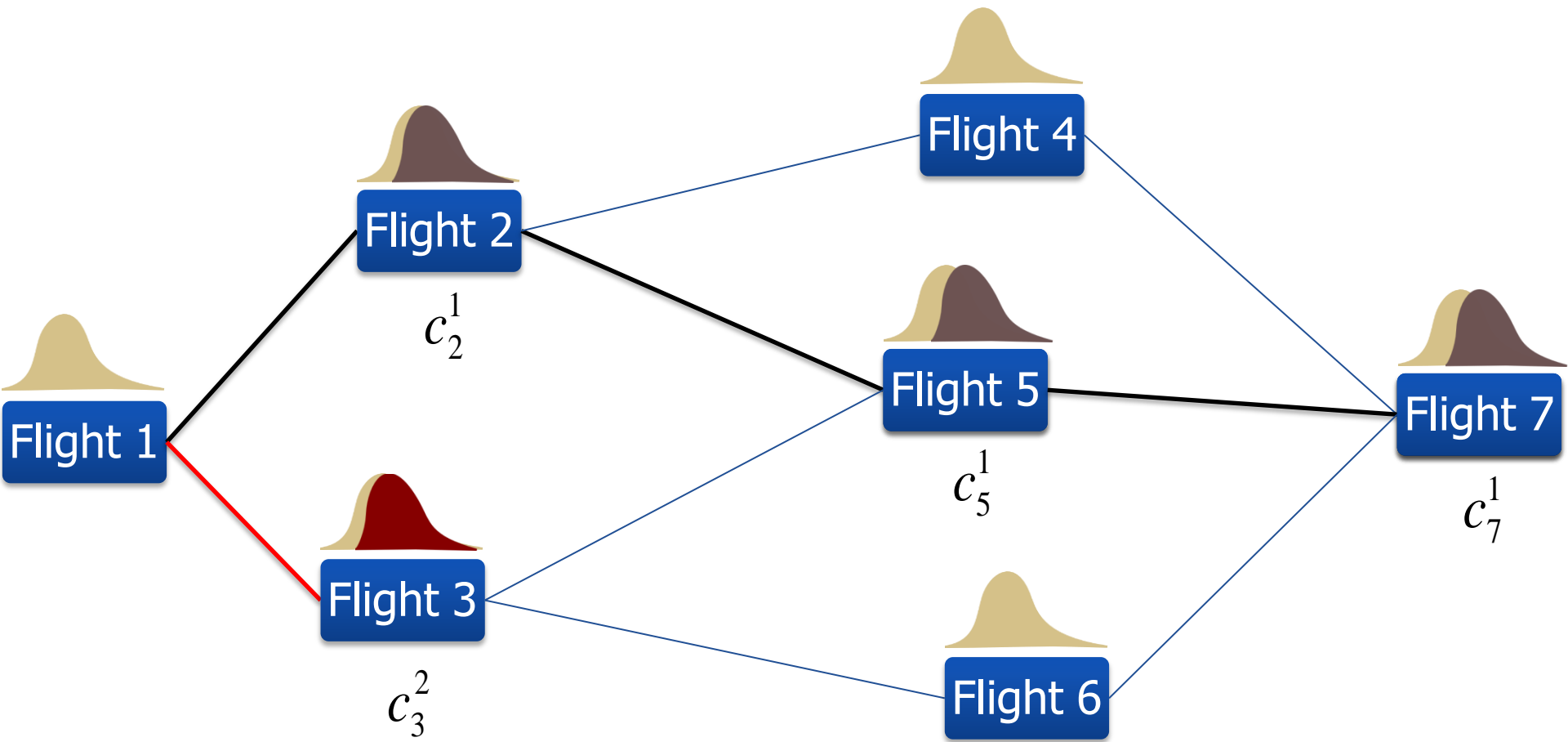


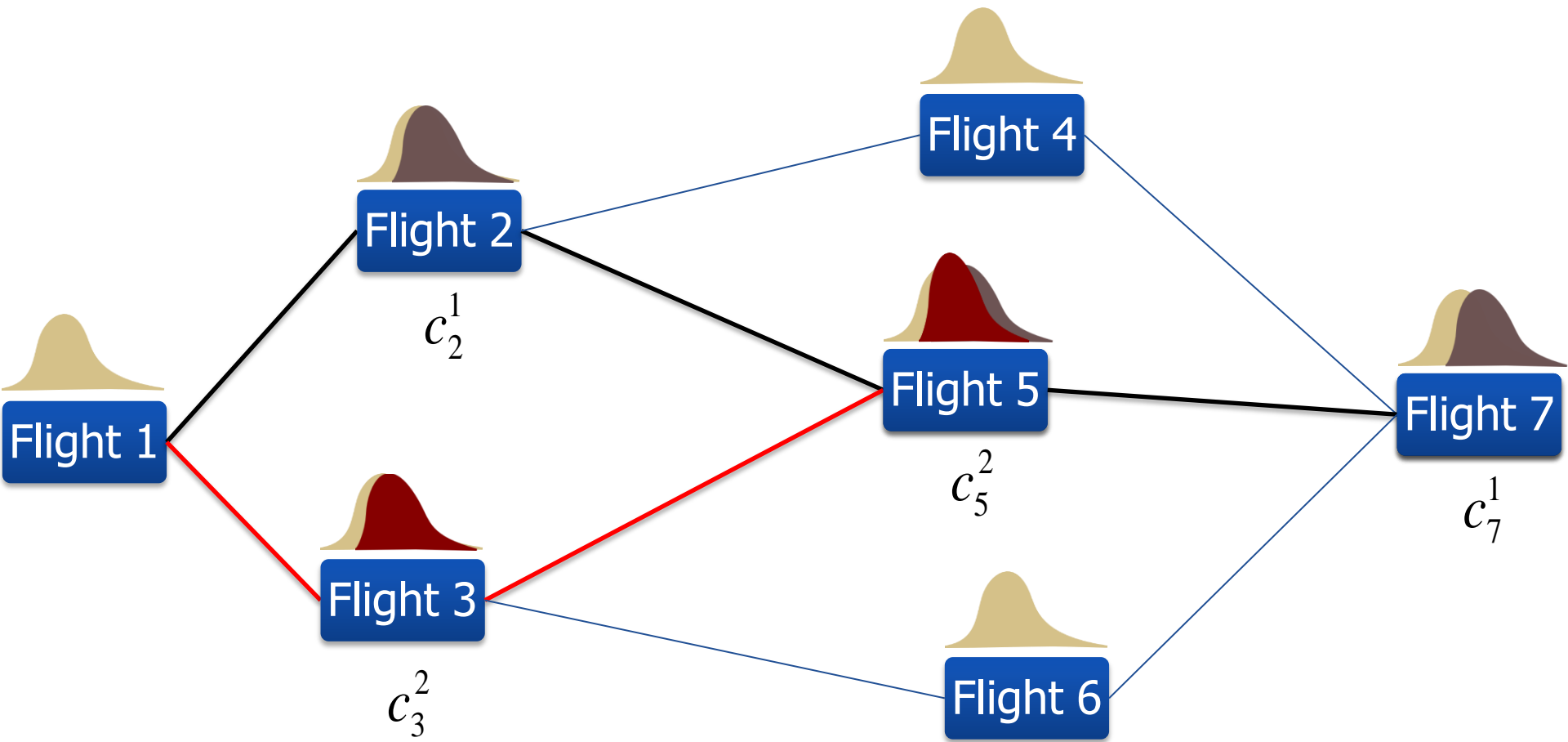


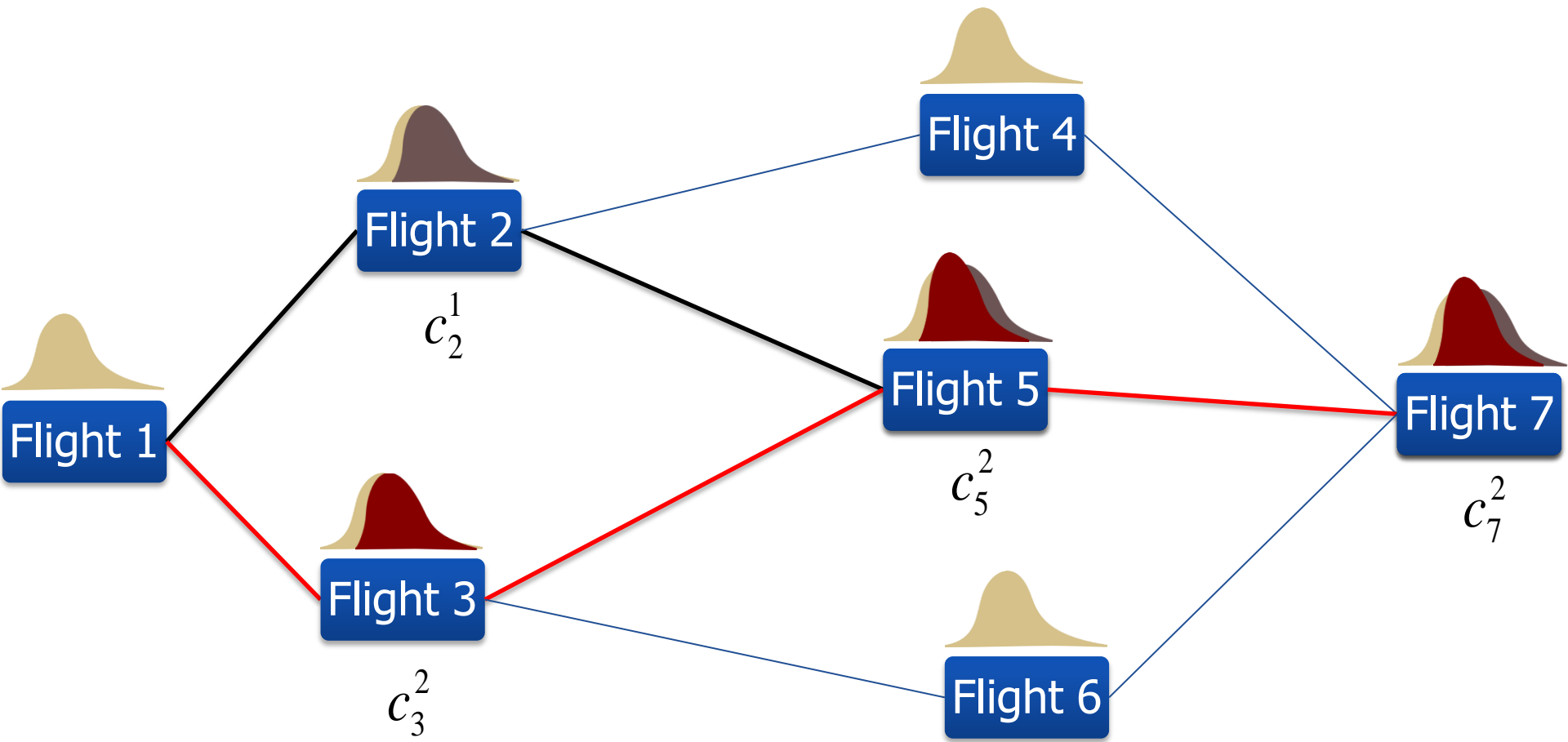












Instance SC1: reference solution

- ▶ 100 legs, 16 aircraft, no preassignments, no maintenance
- ▶ Optimizer produces the same solution for each step size
- ▶ CPU time differs only in computation of the convolutions
- ▶ PDP values differ because of approximation error

	step size [min]	CPU [s]	PDP	error [%]
SC1	0.1	15.4	25.0586	0.11
SC1	0.5	1.0	25.0672	0.15
SC1	1	0.5	25.0917	0.25
SC1	2	0.4	25.2227	0.77
SC1	3	0.4	25.4775	1.79
SC1	4	0.3	25.7667	2.94
Simulation*			25.0303	

Instance SC1: optimized solution

- ▷ Different discretization step sizes may produce different solutions
- ▷ CPU time and PDP are not straightforward to compare

	step size [min]	PDP optimized	CPU [s]	PDP simulated*
SC1	0.1	19.7268	4450	19.7469
SC1	0.5	19.7362	231	19.7382
SC1	1	19.7450	70	19.7239
SC1	2	19.8693	45	19.7313
SC1	3	20.0651	29	19.7239
SC1	4	20.3353	31	19.7562

Analyzed data

- ▷ approx. 350000 flights / 300 – 650 flights per day
- ▷ 28 months, 4 subfleets
- ▷ European airline with hub-and-spoke network

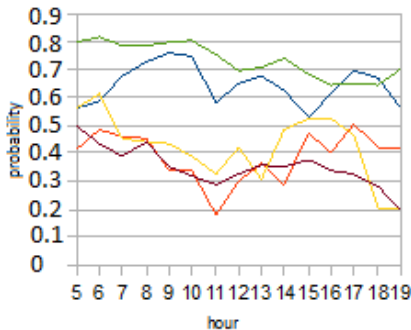
Test instances

- ▷ We optimize single day instances of one subfleet
- ▷ Data for 4 months, no maintenance rules and preassignments

		min			max			avg		
	#days	Legs	aircraft	flight time [min]	legs	aircraft	flight time [min]	legs	aircraft	flight time [min]
January	26	44	12	3840	105	17	8830	88	15	7447
February	22	94	15	8295	118	17	10065	109	16	9339
March	21	94	15	7900	121	17	10390	110	16,3	9483
April	27	93	15	7080	118	18	9750	103	16	8648

Probability of delay

- ▷ Depends on day time and departure airport



probability of departure delay during the day on various airports

Gate phase

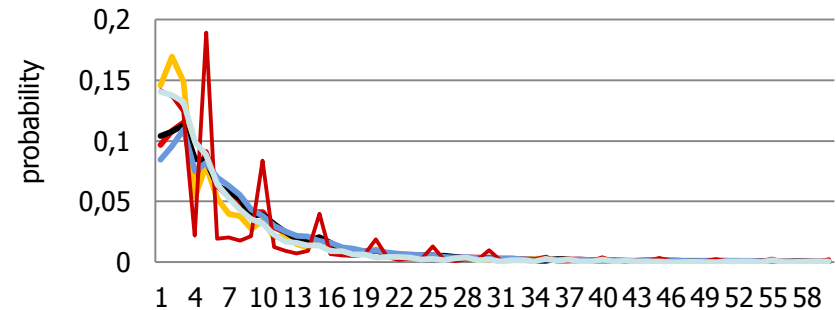
- ▷ gate delay distribution G_j of flight j

$$\Pr[G_j = x] = \begin{cases} 1 - p_j & x = 0 \\ p_j \text{Ln}(x, \mu, \sigma) & x > 0 \end{cases}$$

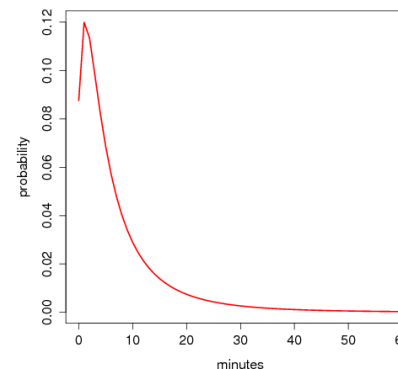
where $\text{Ln}()$ is probability density function of Log-normal distribution with Power-law distributed tail and $p_j = c(t(j), a(j))$, $t(j)$ is departure time of flight j and $a(j)$ is departure airport of flight j

Distribution of delay

- ▷ Independent of daytime and departure airport

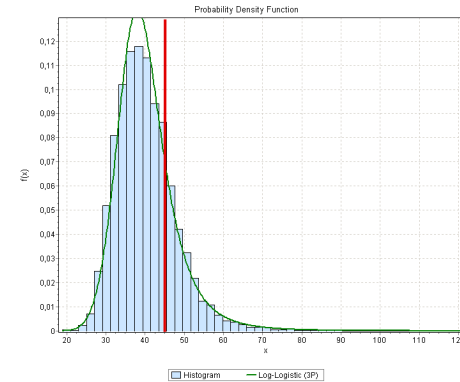
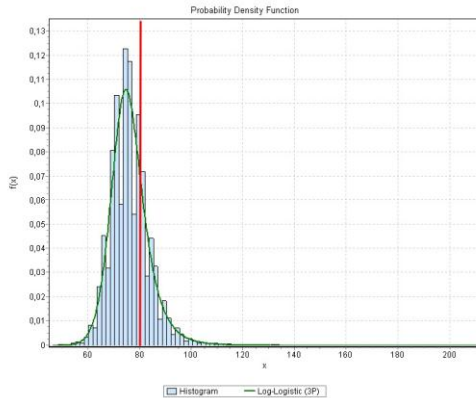


distribution of the length of gate primary delays on various airports



Distribution of deviation from scheduled duration

- ▷ Depends on scheduled leg duration



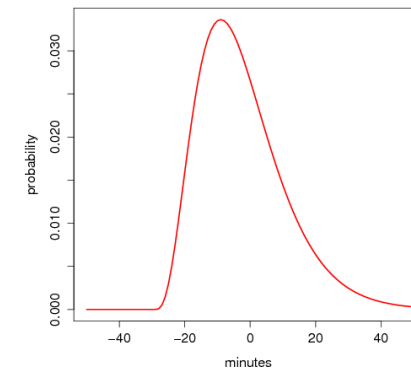
Histogram of the flight duration and its representation by random variable. left: scheduled flight duration 80 minutes, right: scheduled flight duration 45 minutes

Flight phase

- ▷ flight delay distribution F_j of flight j

$$\Pr[F_j = x] = \text{Llg}(x + l_j, \alpha_{l_j}, \beta_{l_j}) \quad x \in R$$

where $\text{Llg}()$ is probability density function of Log-logistic distribution and l_j is scheduled flight duration of leg j



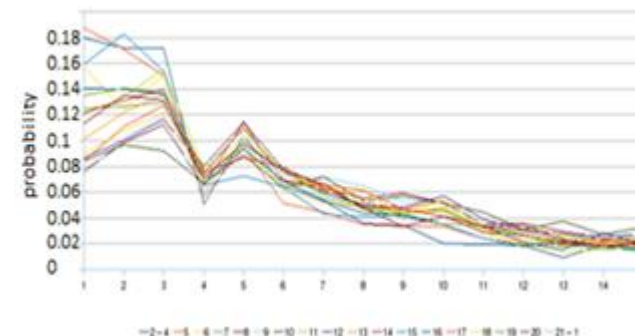
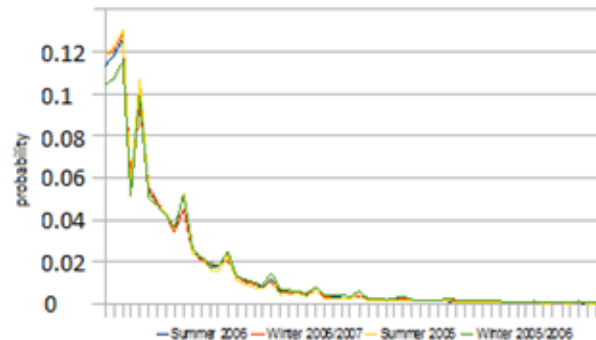
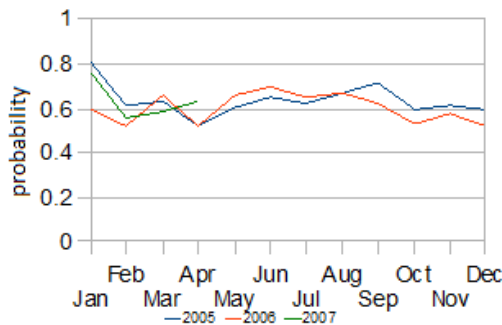
Parameters of the model:

- ▷ p for every airport and day hour
- ▷ μ, σ
- ▷ α, β for every flight length
- ▷ Parameters are estimated by automatic scripts in R and quality is proofed by Chi-Square test.

Model applied to South American airline data

Validation of various assumptions of the model

- ▷ Stability of parameters over time, ...



ORC

- ▷ Standard KPI method
- ▷ Bonus for ground buffer minutes
- ▷ Threshold value for maximal ground buffer time (15 minutes)

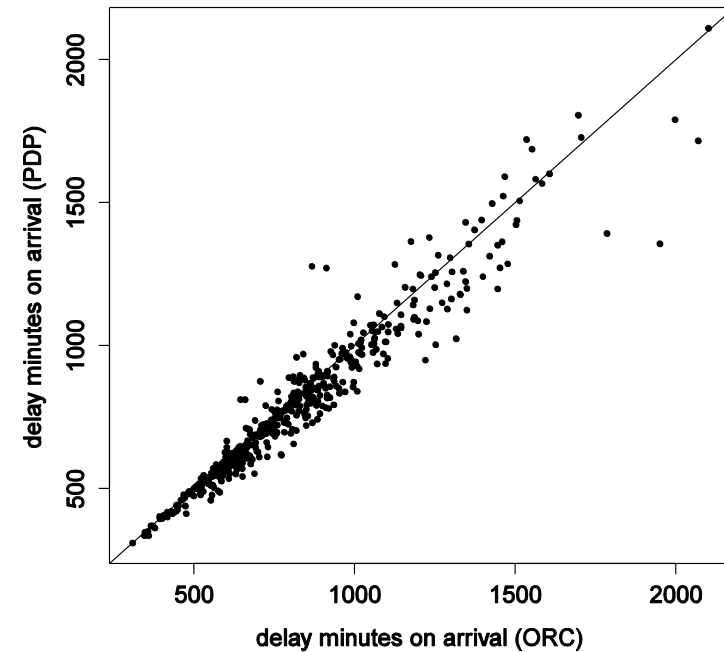
PDP

- ▷ Total probability of delay propagation

	#days	ORC			PDP			Savings	
		PDP	EAD [min]	CPU [s]	PDP	EAD [min]	CPU [s]	PDP	EAD [min]
January	26	414,51	28488	28	395,46	28085	66	19,05	403
February	22	540,48	31870	31	530,42	31652	89	10,06	218
March	21	516,69	30363	31	507,91	30174	75	8,78	189
April	27	465,48	34453	42	449,16	34159	71	16,51	294

ORC vs. PDP on a single disruption scenario

- ▷ ORC outperforms PDP only in 21% of cases
- ▷ PDP saves on average 29 minutes of arrival delay
- ▷ For more disrupted days, PDP saves on average 62 minutes of arrival delay

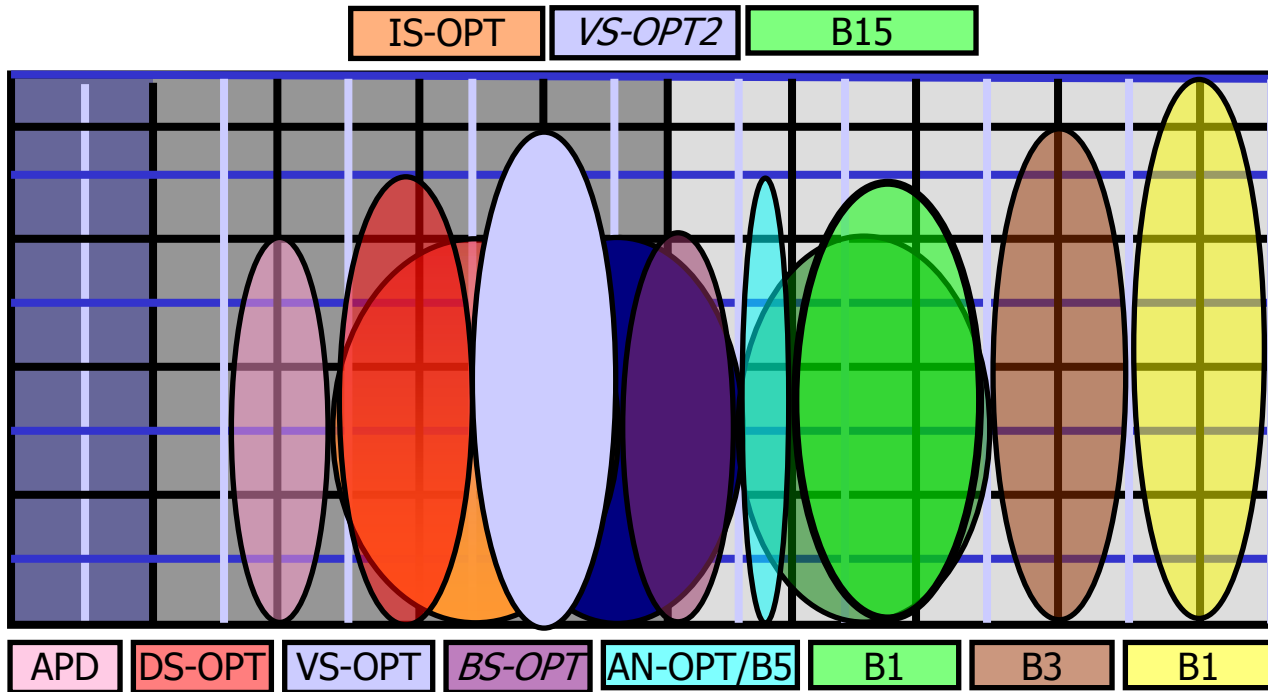


Estimation of monetary savings by the cost model developed based on EUROCONTROL [2004]

Lufthansa Systems estimates annual saving of the method in the tail assignment to 300,000 € for short haul carrier with 30 aircraft

Application in other planning stages may increase the benefit

Cost Recovery
 Construction Costs
 Network Topology
 Velocities
 Lines
 Service Level
 Frequencies
 Connections
 Timetable
 Sensitivity
 Rotations
 Relief Points
 Duties
 Duty Mix
 Rostering
 Fairness
 Crew Assignment
 Disruptions
 Operations Control



multidepartmental
 Departments
 multidepotwise
 Depots
 multiple line groups
 Line Groups
 multiple lines
 Lines
 multiple rotations
 Rotations

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The 21st **International Symposium on Mathematical Programming** (ISMP) take place in Berlin, Germany from August 19 - 24 2012.

ISMP is a scientific meeting held every 3 years on behalf of the Mathematical Optimization Society. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed diam nonummy nibh euismod tincidunt ut laoreet dolore magna aliquam erat volutpat.

GENERAL INFORMATIONS



WE MEET IN BERLIN

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ANOTHER HEADLINE

2012/08/19

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