

# Demand-based scheduling

Michel Bierlaire   Stefan Binder   Yousef Maknoon   Tomáš Robenek

Transport and Mobility Laboratory  
School of Architecture, Civil and Environmental Engineering  
Ecole Polytechnique Fédérale de Lausanne

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# Outline

- 1 Demand and supply
- 2 Measuring satisfaction
- 3 Ideal timetable
- 4 Disposition timetable
- 5 Conclusion

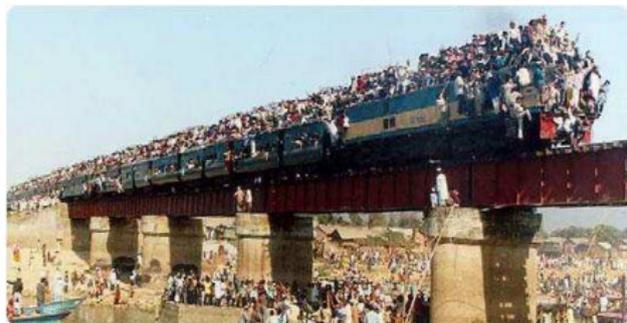


# Demand models



- Supply = infrastructure
- Demand = behavior, choices
- Congestion = mismatch

# Demand models



- Usually in OR:
- optimization of the supply
- for a given (fixed) demand

# Aggregate demand



- Homogeneous population
- Identical behavior
- Price ( $P$ ) and quantity ( $Q$ )
- Demand functions:  $P = f(Q)$
- Inverse demand:  $Q = f^{-1}(P)$

# Disaggregate demand



- Heterogeneous population
- Different behaviors
- Many variables:
  - Attributes: price, travel time, reliability, frequency, etc.
  - Characteristics: age, income, education, etc.
- Complex demand/inverse demand functions.

# Demand-supply interactions

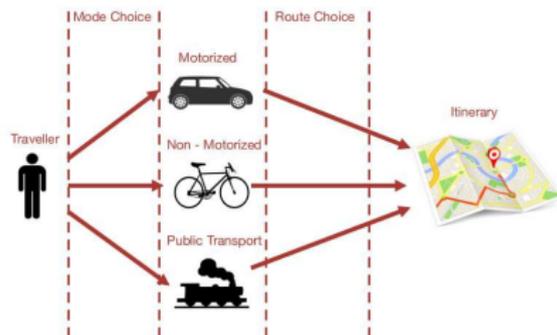
## Operations Research

- Given the demand...
- configure the system

## Behavioral models

- Given the configuration of the system...
- predict the demand

Johnson City Enterprise.	
Published Every Saturday,	
\$1. per year—Advance Payment.	
SATURDAY, APRIL 7, 1883.	
TIME TABLE	
E. T. V. & G. R. R.	
PASSENGER,	ARRIVES.
No. 1, West,	6:37, a. m.
No. 2, East,	9:45, p. m.
No. 3, West,	11:51, p.m.
No. 4, East,	3:56, a. m.
LOCAL FREIGHT,	ARRIVES.
No. 5,	7:20, a. m.
No. 8,	6:20, p. m.
Jno. W. EAKIN, Agent.	
E. T. & W. N. C. R. R.	
Passenger, leaves,	7, a. m.
" arrives,	6, p. m.
J. C. HARDIN, Agent.	



# Demand-supply interactions

Multi-objective optimization

Minimize costs



Maximize satisfaction

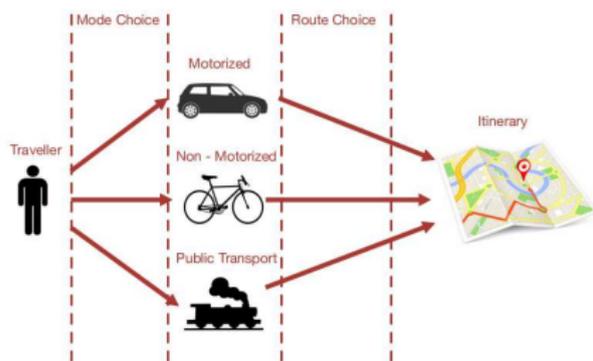


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# Measuring satisfaction



## Behavioral models

- Demand = sequence of choices
- Choosing means trade-offs
- In practice: derive trade-offs from choice models

# Choice models

## Theoretical foundations

- Random utility theory
- Choice set:  $C_n$
- Logit model:

$$P(i|C_n) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}}$$



2000



# Decision rules

## Neoclassical economic theory

Preference-indifference operator  $\succsim$

① reflexivity

$$a \succsim a \quad \forall a \in \mathcal{C}_n$$

② transitivity

$$a \succsim b \text{ and } b \succsim c \Rightarrow a \succsim c \quad \forall a, b, c \in \mathcal{C}_n$$

③ comparability

$$a \succsim b \text{ or } b \succsim a \quad \forall a, b \in \mathcal{C}_n$$



# Decision rules

## Utility

$$\exists U_n : \mathcal{C}_n \longrightarrow \mathbb{R} : a \rightsquigarrow U_n(a) \text{ such that}$$

$$a \succsim b \Leftrightarrow U_n(a) \geq U_n(b) \quad \forall a, b \in \mathcal{C}_n$$

## Remarks

- Utility is a latent concept
- It cannot be directly observed



# Example

## Two transportation modes

$$U_1 = -\beta t_1 - \gamma c_1$$

$$U_2 = -\beta t_2 - \gamma c_2$$

with  $\beta, \gamma > 0$

$$U_1 \geq U_2 \text{ iff } -\beta t_1 - \gamma c_1 \geq -\beta t_2 - \gamma c_2$$

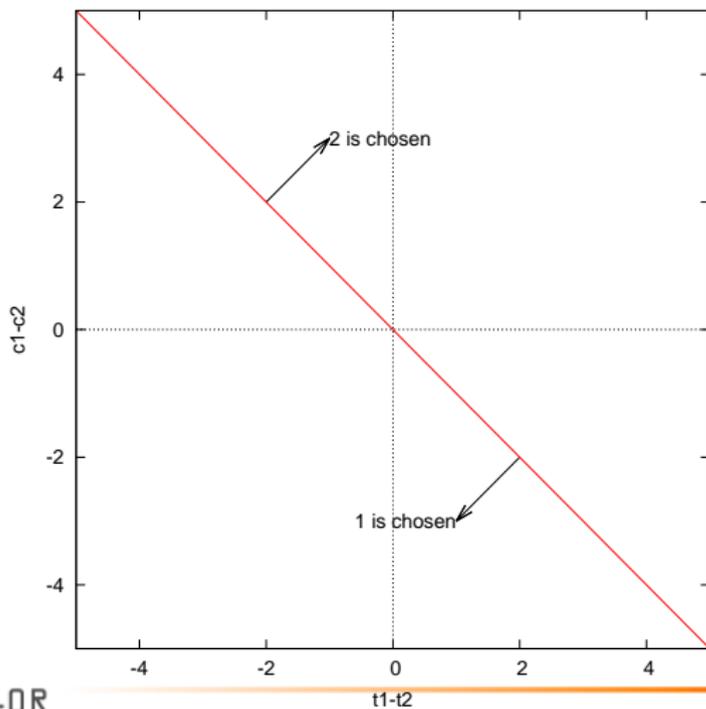
that is

$$-\frac{\beta}{\gamma} t_1 - c_1 \geq -\frac{\beta}{\gamma} t_2 - c_2$$

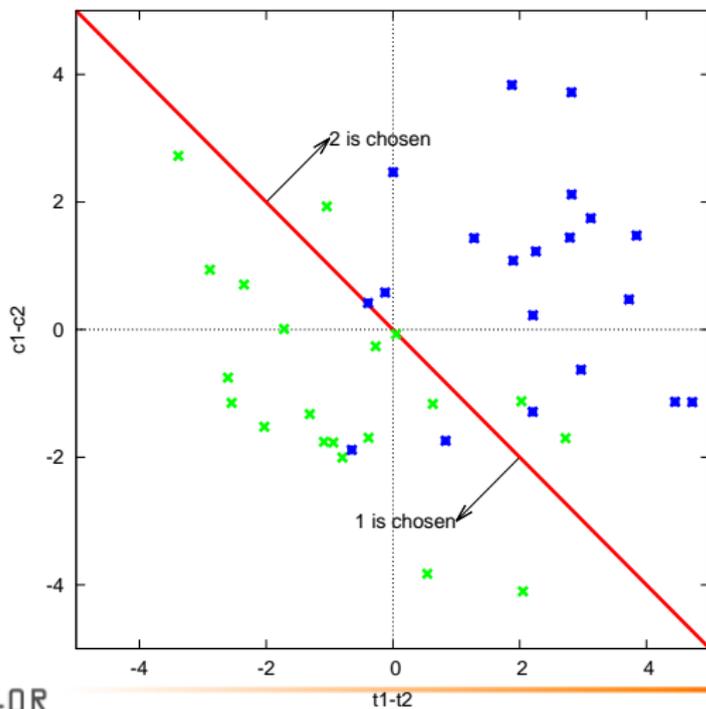
or

$$c_1 - c_2 \leq -\frac{\beta}{\gamma} (t_1 - t_2)$$

# Example



## Example



# Assumptions

## Decision-maker

- perfect discriminating capability
- full rationality
- permanent consistency

## Analyst

- knowledge of all attributes
- perfect knowledge of  $\succsim$  (or  $U_n(\cdot)$ )
- no measurement error

## Must deal with uncertainty

- Random utility models
- For each individual  $n$  and alternative  $i$

$$U_{in} = V_{in} + \varepsilon_{in}$$

and

$$P(i|C_n) = P[U_{in} = \max_{j \in C_n} U_{jn}] = P(U_{in} \geq U_{jn} \forall j \in C_n)$$

# Logit model

## Utility

$$U_{in} = V_{in} + \varepsilon_{in}$$

- Decision-maker  $n$
- Alternative  $i \in \mathcal{C}_n$

## Choice probability

$$P_n(i|\mathcal{C}_n) = \frac{e^{V_{in}}}{\sum_{j \in \mathcal{C}_n} e^{V_{jn}}}$$



Variables:  $x_{in} = (z_{in}, s_n)$

Attributes of alternative  $i$ :  $z_{in}$

- Cost / price
- Travel time
- Waiting time
- Level of comfort
- Number of transfers
- Late/early arrival
- etc.

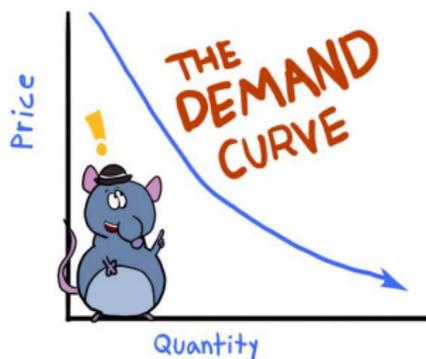
Characteristics of decision-maker  $n$ :

$s_n$

- Income
- Age
- Sex
- Trip purpose
- Car ownership
- Education
- Profession
- etc.



# Demand curve



Disaggregate model

$$P_n(i|c_{in}, z_{in}, s_n)$$

Total demand

$$D(i) = \sum_n P_n(i|c_{in}, z_{in}, s_n)$$

Difficulty

Inverse demand not analytically available

# Willingness to pay

## Attributes of alternative $i$ : $z_{in}$

- Cost / price
- Travel time
- Waiting time
- Level of comfort
- Number of transfers
- Late/early arrival
- etc.

## Willingness to pay for alternative $i$

- Value of travel time
- Value of waiting time
- Value of comfort
- Value of transfers
- Value of not being on time
- etc.

# Willingness to pay



## Utility

$$U_{in} = \beta_c c_{in} + \beta_t t_{in} + \dots$$

## Value of time

$$\text{VOT}_{in} = \frac{\partial U_{in} / \partial t_{in}}{\partial U_{in} / \partial c_{in}} = \frac{\beta_t}{\beta_c}$$

# Equivalence

## Utility

$$U_{in} = \beta_c c_{in} + \beta_t t_{in} + \beta_w w_{in} + \beta_{cft} cft_{in} + \beta_T T_{in} + \beta_e e_{in} + \beta_\ell \ell_{in} + \dots$$

### Willingness to pay: cost per unit

- Travel time:  $\beta_t/\beta_c$
- Waiting time:  $\beta_w/\beta_c$
- Comfort:  $\beta_{cft}/\beta_c$
- Transfers:  $\beta_T/\beta_c$
- Being early:  $\beta_e/\beta_c$
- Being late:  $\beta_\ell/\beta_c$

### Travel time equivalent: hours per unit

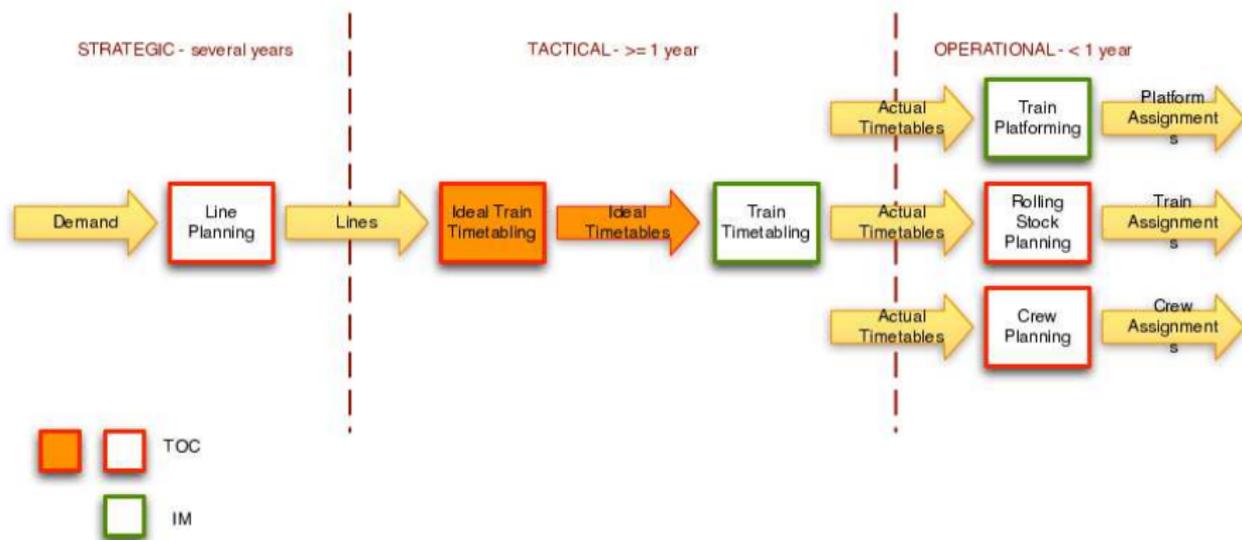
- Cost:  $\beta_c/\beta_t$
- Waiting time:  $\beta_w/\beta_t$
- Comfort:  $\beta_{cft}/\beta_t$
- Transfers:  $\beta_T/\beta_t$
- Being early:  $\beta_e/\beta_t$
- Being late:  $\beta_\ell/\beta_t$

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# Planning of railway operations





# Modeling elements

## Supply

- Line  $\ell$ : sequence of stations served by the same train
- Train  $v \in V_\ell$ : service of a line at a given departure time

## Demand

- Origin / destination  $i$
- Ideal arrival time  $t$
- Path  $p \in P_i$ : sequence of portions of lines to reach  $d$  from  $o$ 
  - Access/egress time for path  $p$  (OD  $i$ )
  - Travel time for path  $p$
  - Waiting time for path  $p$

# Model

## Decision variables

- $x_i^{tp}$ : 1 – if passenger with ideal time  $t$  between OD pair  $i$  chooses path  $p$ ; 0 – otherwise
- $y_i^{tp/v}$ : 1 – if a passenger with ideal time  $t$  between OD pair  $i$  on the path  $p$  takes the train  $v$  on the line  $l$ ; 0 – otherwise
- $d_v^l$ : the departure time of a train  $v$  on the line  $l$  (from its first station)
- $u_v^l$ : number of train units of a train  $v$  on the line  $l$
- $\alpha_v^l$ : 1 – if a train  $v$  on the line  $l$  is being operated; 0 – otherwise



# Model

## Calculation variables

- $C_i^t$ : total cost of a passenger with ideal time  $t$  between OD pair  $i$
- $w_i^t$ : total waiting time of a passenger with ideal time  $t$  between OD pair  $i$
- $s_i^t$ : value of the scheduled delay of a passenger with ideal time  $t$  between OD pair  $i$
- $z_v^l$ : dummy variable modeling the cyclicity corresponding to a train  $v$  on the line  $l$
- $o_{vg}^l$ : occupation of train  $v$  of line  $l$  on segment  $g$



# Model

## Problem constraints

- passenger cost  $\leq \varepsilon$
- everyone uses at most one path
- link between path and trains: everyone boards one train of each line in the path
- cyclicity
- everyone uses only trains that are actually running
- train capacity
- maximum number of train units



# Model

## Calculation constraints

- Scheduled delay
- Waiting time
- Overall cost



# Models

## Current model

Departure times of trains are fixed, current values are used (cyclic).

## Cyclic model

Departure times are optimized, cyclicity is enforced.

## Non-cyclic model

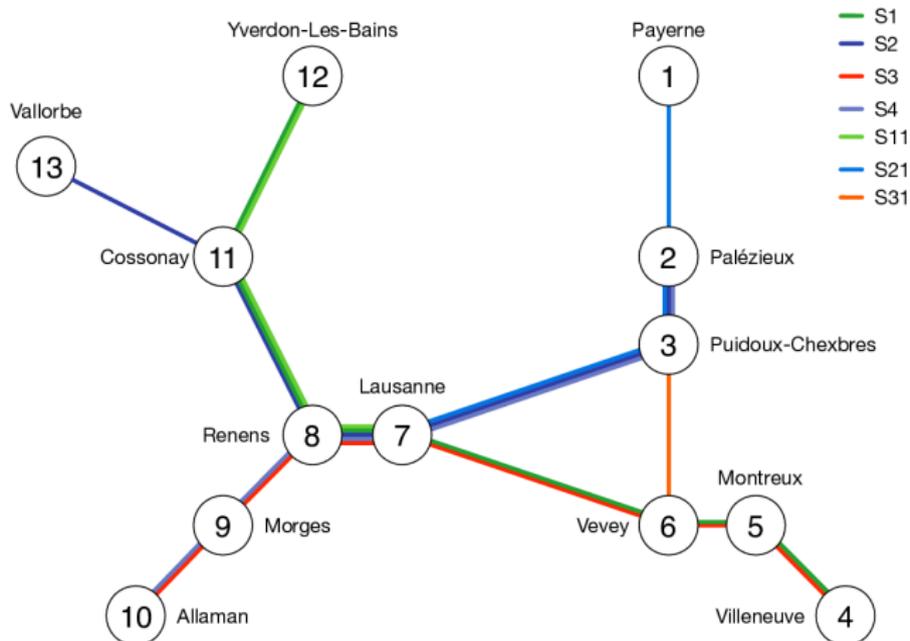
Departure times are optimized, cyclicity is not enforced.



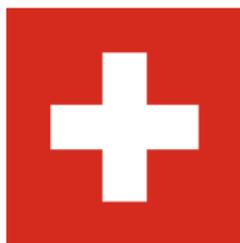
# Case Study – Switzerland



# S-Train Network Canton Vaud, Switzerland



# Case study: Switzerland



## Context

- SBB 2014 (5 a.m. to 9 a.m.)
- OD Matrix based on observation and SBB annual report
- 13 Stations
- 156 ODs
- 14 (unidirectional) lines
- 49 trains
- Min. transfer – 4 mins

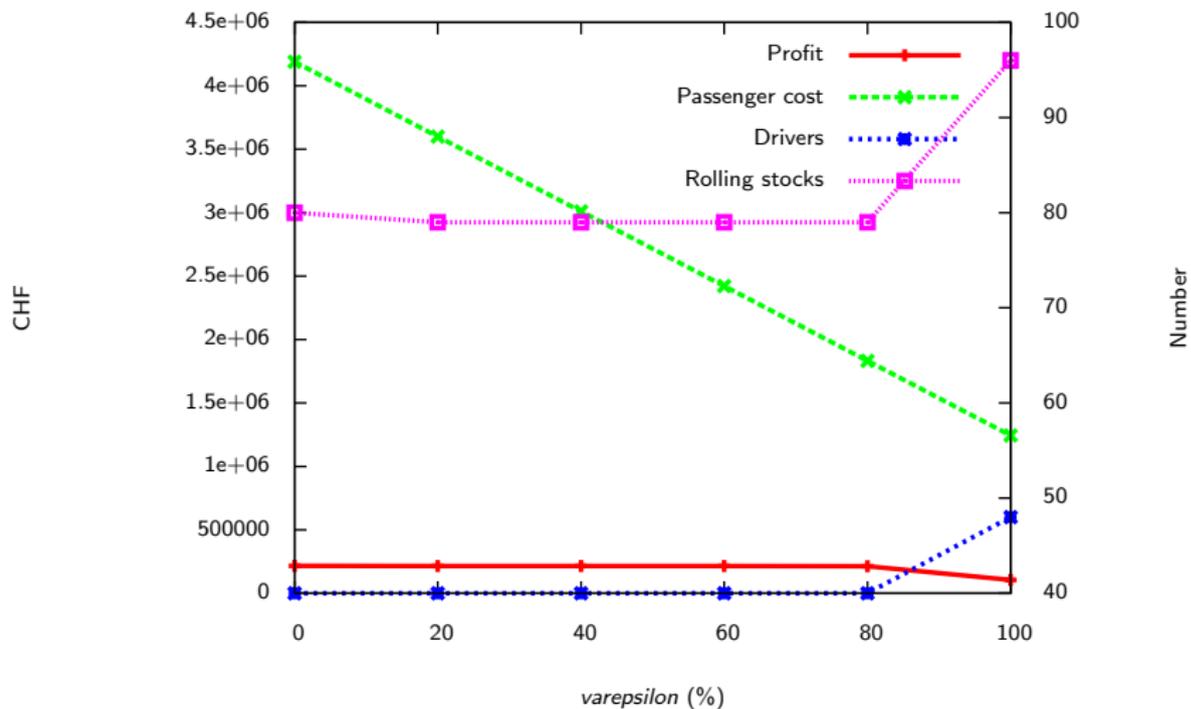
# Case study: Switzerland

## Willingness to pay from the literature

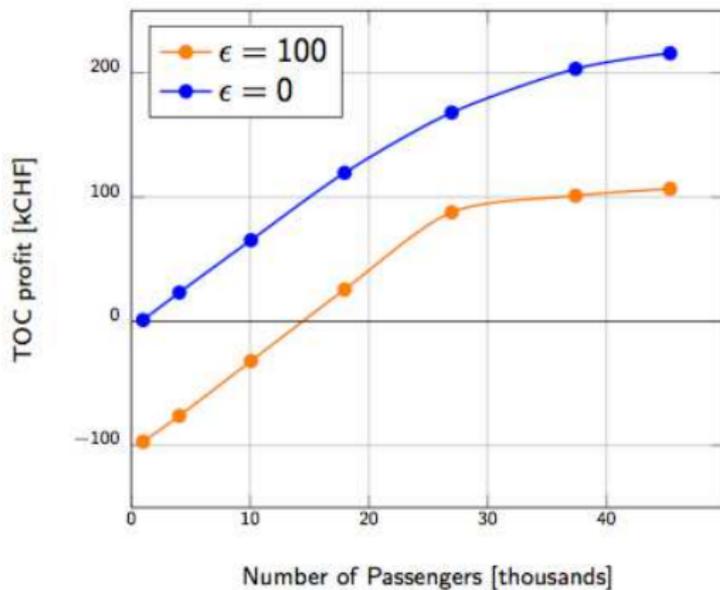
- Value of travel time: 27.81 CHF / hour
- Value of waiting time: 69.5 CHF /hour
- Value of comfort: —
- Value of transfers: 4.6 CHF / hour (10 min. travel time)
- Value of being late: 27.81 CHF / hour
- Value of being early: 13.9 CHF / hour
- etc.



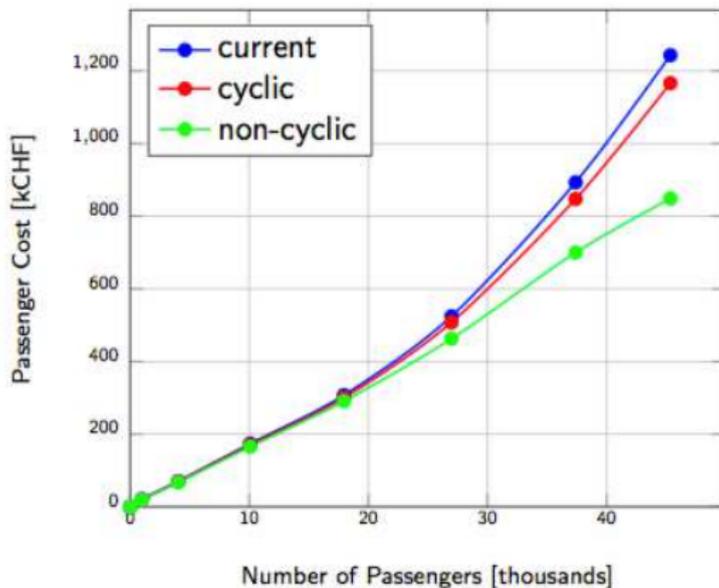
## Current model



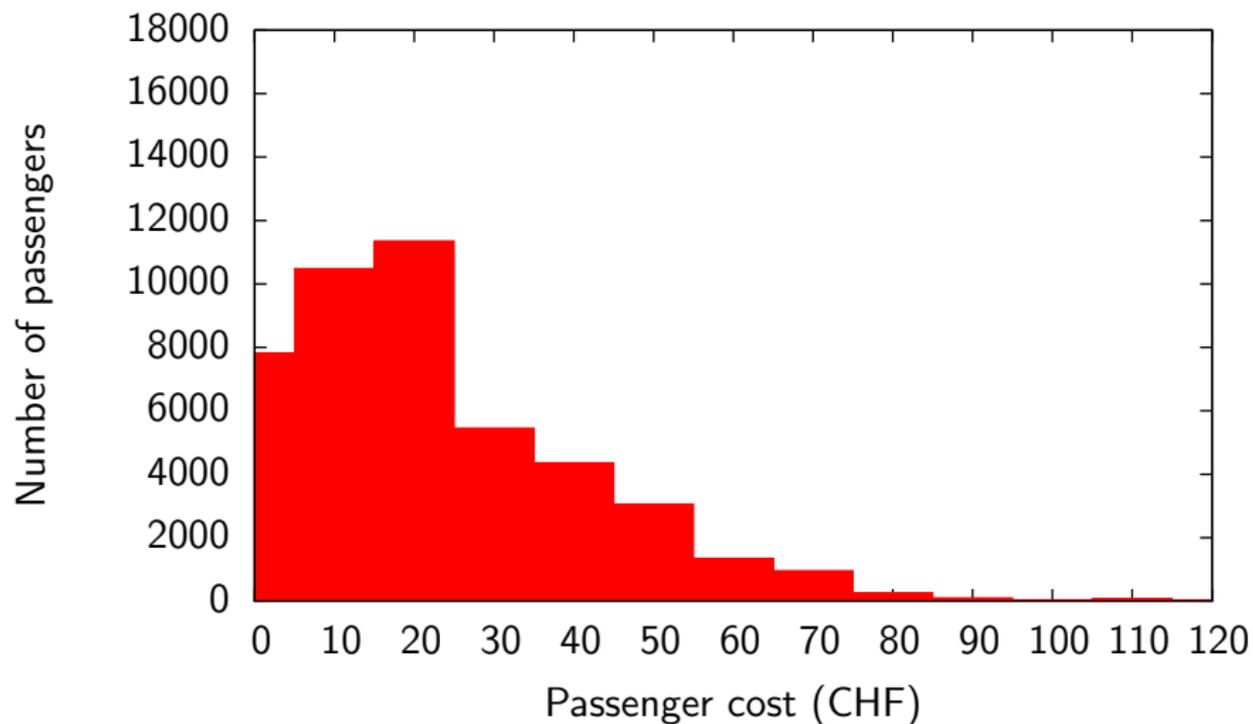
# Impact of congestion



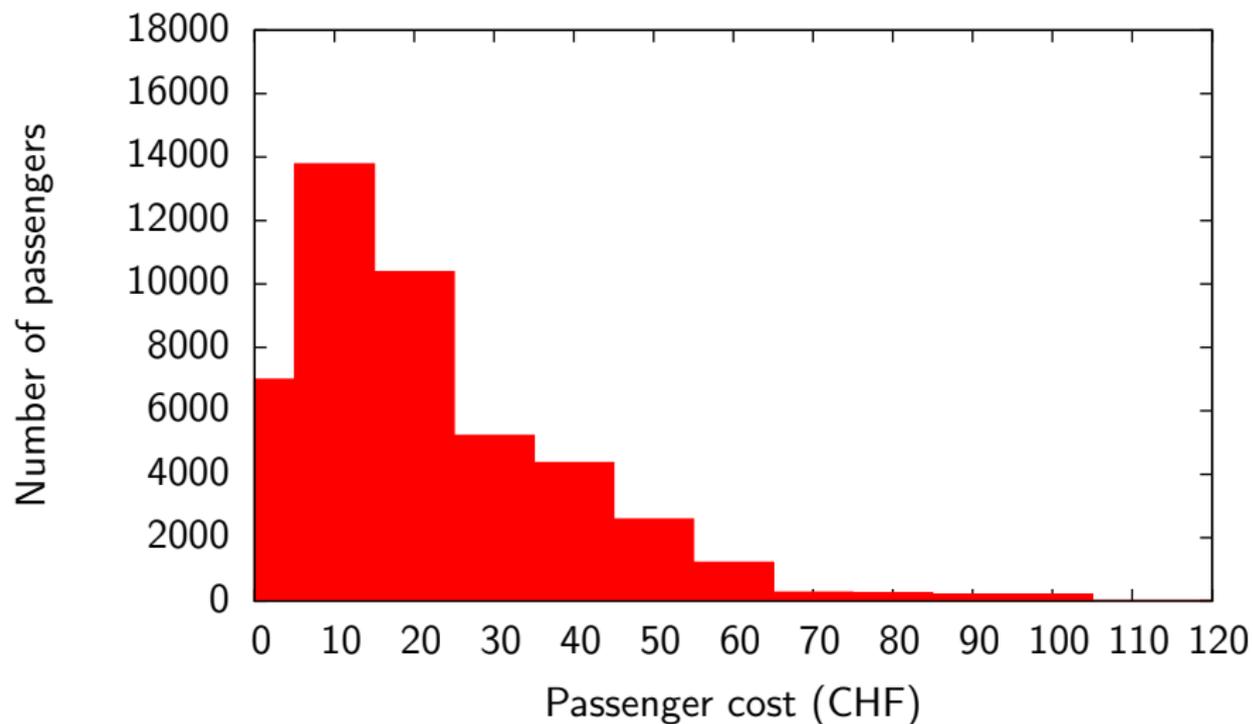
# Impact of congestion



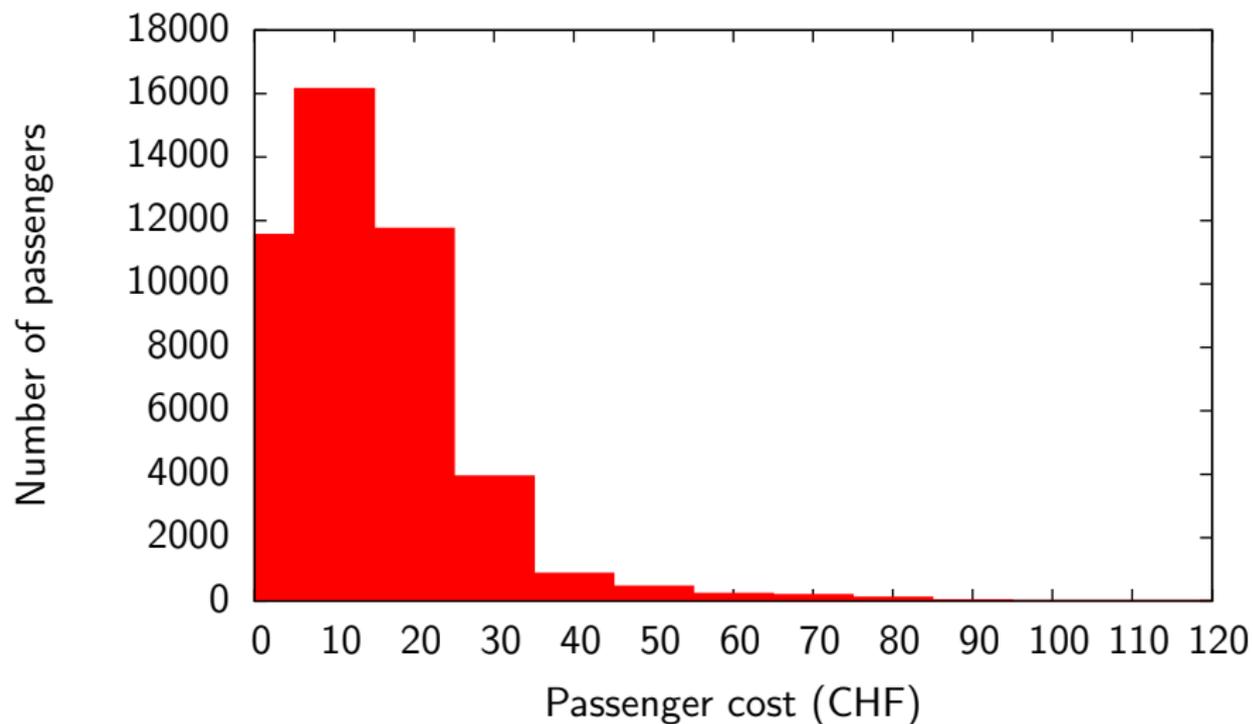
## Passenger cost: highest demand, current model



## Passenger cost: highest demand, cyclic model



## Passenger cost: highest demand, non-cyclic model



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# Motivation



Figure: Bray Head, Railway Accident, Ireland, 1867. The Liszt Collection.

# Recovery

## Research question

What are the impacts, in terms of passenger (dis-)satisfaction, of different recovery strategies in case of a severe disruption in a railway network?

## Recovery strategies

- Train cancellation
- Partial train cancellation
- Global re-routing of trains
- Additional service (buses/trains)
- “Direct train”
- Increase train capacity



# Assumptions

## Supply side

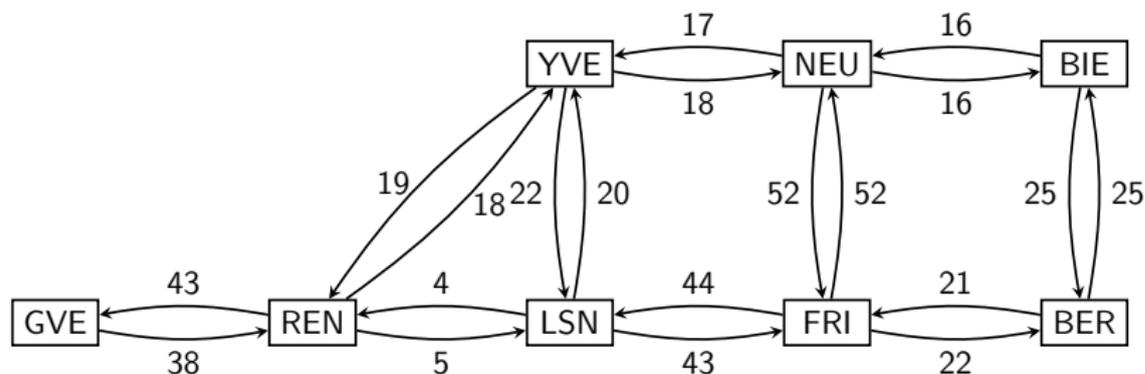
- Homogeneity of trains
- Passenger capacity of trains / buses
- Depots at stations where trains can depart

## Demand side

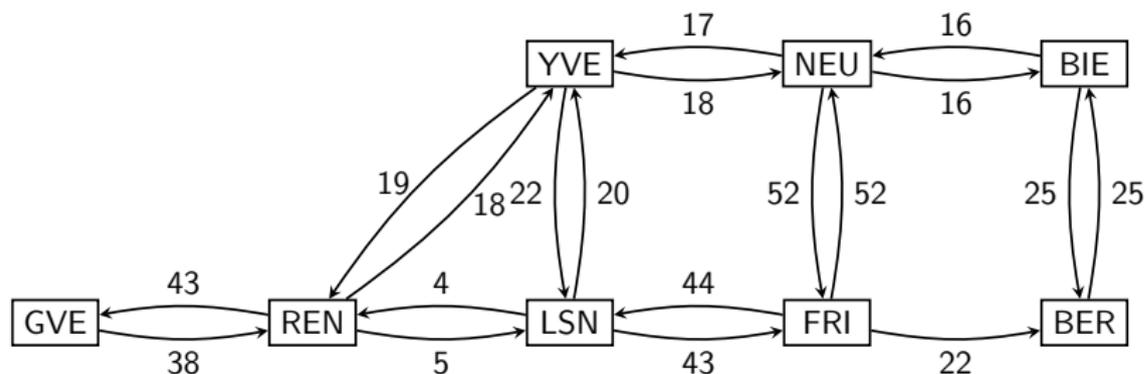
- Disaggregate passengers : origin, destination and desired departure time
- Path chosen according to generalized travel time (made of travel time, waiting time and penalties for transfers and early/late departure)
- Perfect knowledge of the system
- No en-route re-rerouting



# A sample network



# A disrupted sample network



# Time-expanded network

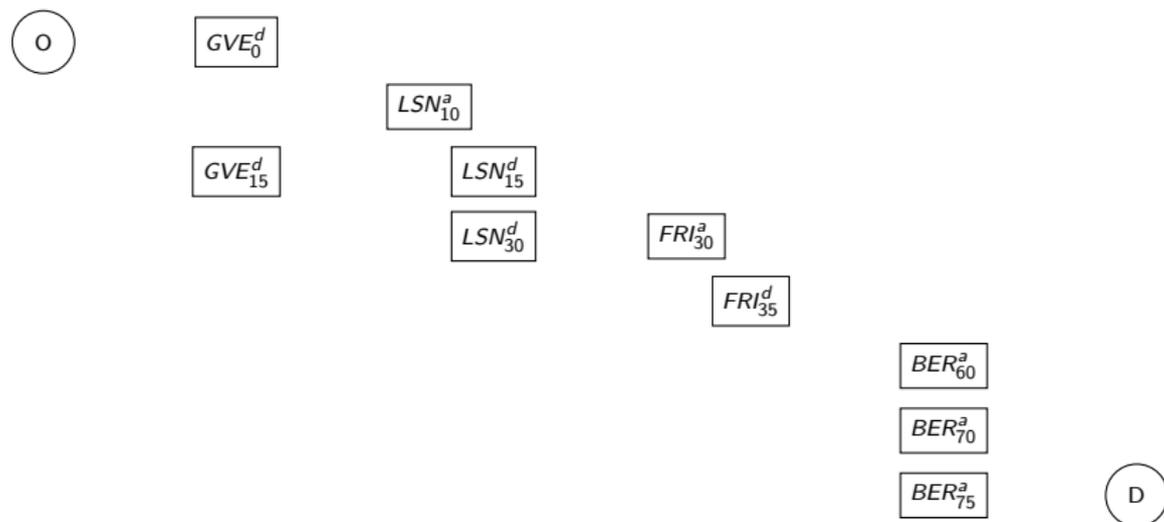
## Nodes ( $N$ )

- $s_t^a$ : train arrival event from station  $s$  at time  $t$
- $s_t^d$ : train departure event from station  $s$  at time  $t$

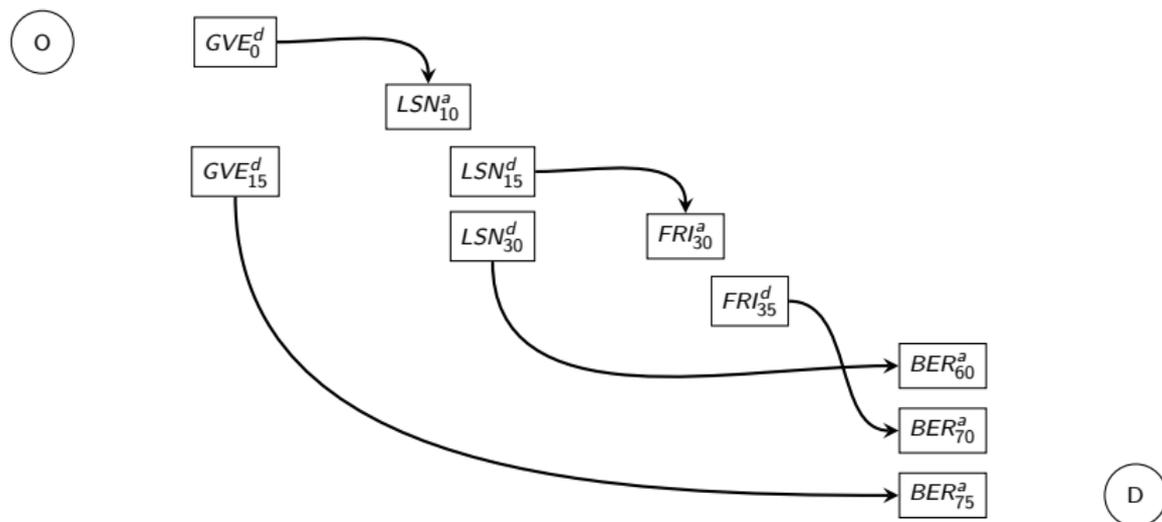
## Arcs ( $A$ )

- Train driving arcs
- Train waiting arcs
- Connection arcs
- Access & egress arcs

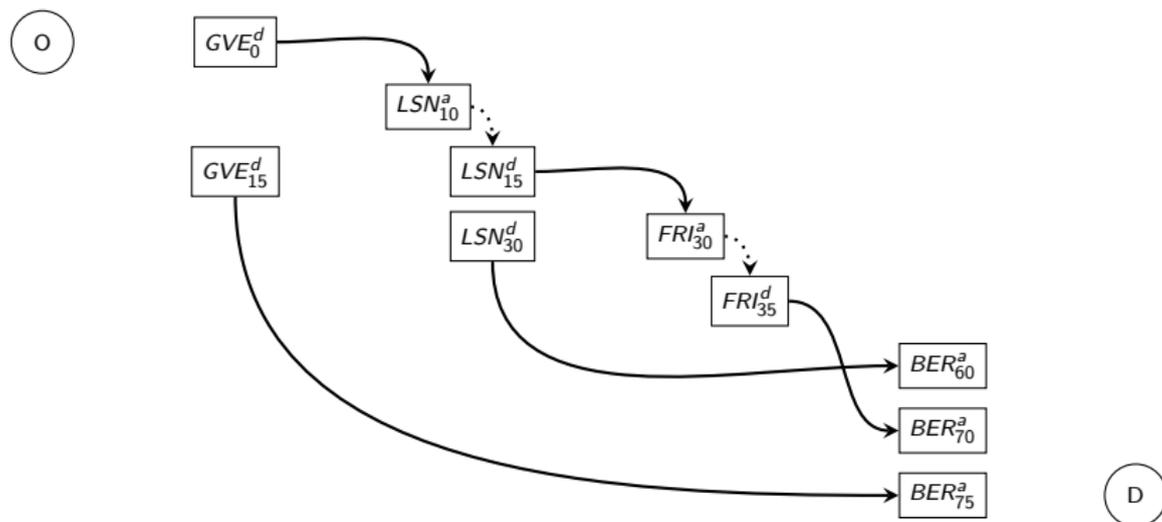
# Time-expanded network: an example



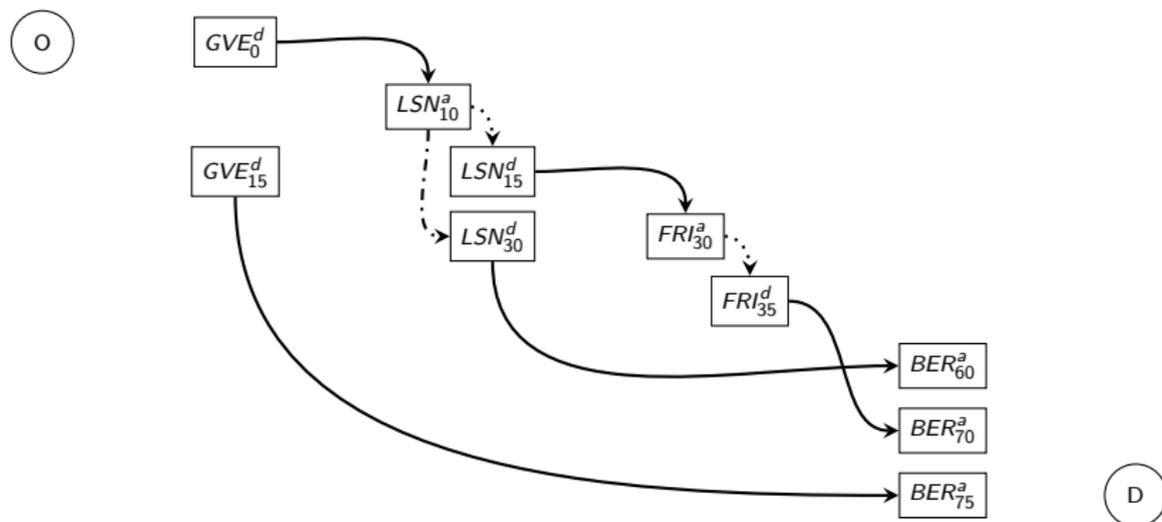
# Time-expanded network: an example



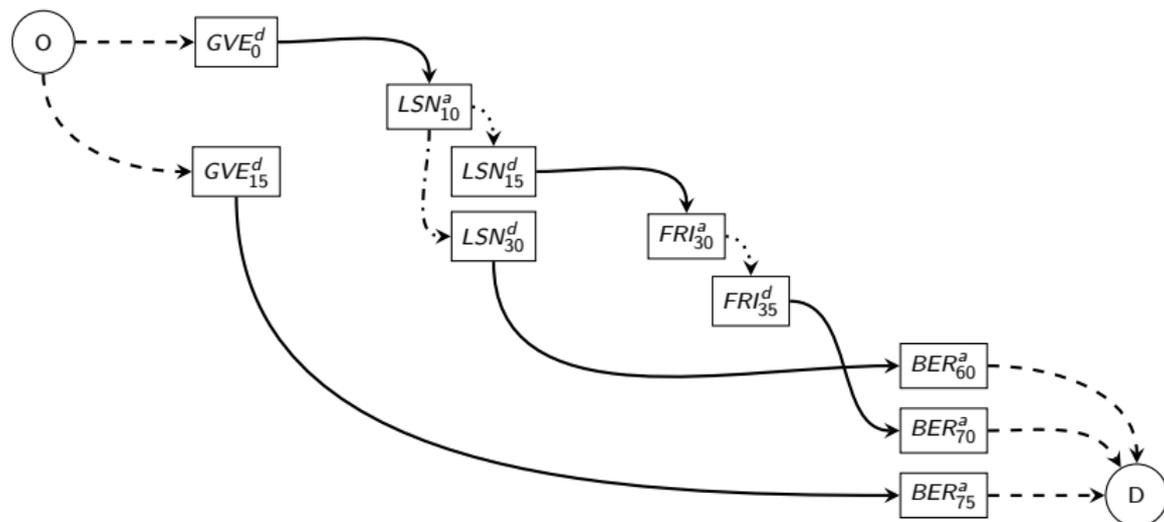
# Time-expanded network: an example



# Time-expanded network: an example



# Time-expanded network: an example



# Capacitated passenger assignment algorithm



- 1 Assign passengers on the least expensive path according to path disutility function.
- 2 If an arc capacity is exceeded, decide which passengers need to be re-assigned. Otherwise, stop.
- 3 Re-assign unassigned passengers on a reduced network, then go to Step 2.

# Decision variables

## Supply

$$x_{(i,j)} = \begin{cases} 1 & \text{if a train runs on arc } (i,j) \in A \\ 0 & \text{otherwise} \end{cases}$$

## Demand

$$w_{(i,j)}^p = \begin{cases} 1 & \text{if passenger } p \text{ uses arc } (i,j) \in A_p \\ 0 & \text{otherwise} \end{cases}$$



# Objective function

$$\min \sum_{p \in P} \sum_{(i,j) \in A_p} c_{(i,j)}^p \cdot w_{(i,j)}^p + \sum_{(i,j) \in A | i \in R} c_t \cdot X_{(i,j)}$$

## Passenger Cost $c_{(i,j)}^p$

- In-vehicle-time
- Waiting time
- Number of transfers
- Departure time shift



# Constraints

$$\sum_{j \in N} x_{(r,j)} \leq n_r \quad \forall r \in R$$

$$\sum_{i \in V} x_{(i,k)} = \sum_{j \in V} x_{(k,j)} \quad \forall k \in V$$

$$x_{(i,j)} = 0 \quad \forall (i,j) \in A_D$$

$$\sum_{(i,j) \in A_p | i=o_p} w_{(i,j)}^p = 1 \quad \forall p \in P$$

$$\sum_{(i,j) \in A_p | j=d_p} w_{(i,j)}^p = 1 \quad \forall p \in P$$

$$\sum_{i \in V_p} w_{(i,k)}^p = \sum_{j \in V_p} w_{(k,j)}^p \quad \forall k \in V_p, \forall p \in P$$

$$w_{(i,j)}^p \leq x_{(i,j)} \quad \forall p \in P, \forall (i,j) \in A \cap A_p$$

$$\sum_{p \in P} w_{(i,j)}^p \leq \text{cap}_{(i,j)} \cdot x_{(i,j)} \quad \forall (i,j) \in A \cap A_p$$

$$x_{(i,j)} \in \{0, 1\} \quad \forall (i,j) \in A$$

$$w_{(i,j)}^p \in \{0, 1\} \quad \forall (i,j) \in A_p, \forall p \in P$$



# Framework

## Adaptive large neighborhood search (ALNS)

It combines

- Simulated annealing
- Destroy and repair operators

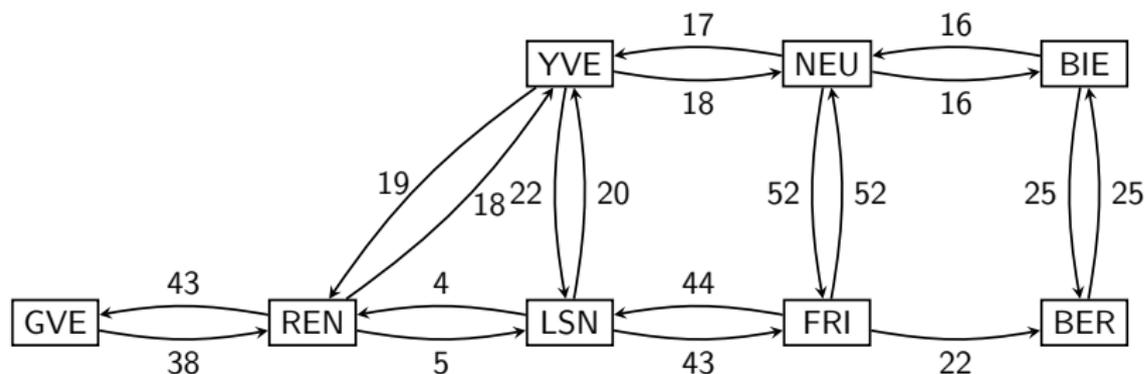


# Case study in Switzerland

- **8 stations** : GVE, REN, LSN, FRI, BER, YVE, NEU, BIE
- **207 trains** : All trains departing from any of the stations between 5am and 9am
- **40'446 passengers** : Synthetic O-D matrices, generated with Poisson process
- **Disruption** : Track unavailable between BER and FRI between 7am and 9am



## Case study network



# Results

	Total passenger disutility	# disrupted passengers
Before ALNS	2'666'630.49	2'847
After ALNS	2'539'605.59	1'508
Improvement	4.8 %	47.0 %

Substantial improvements.



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# Conclusions

## Importance of demand

- Passenger satisfaction
- Choice behavior
- Willingness to pay
- Heterogeneity

## Railway applications

- Ideal timetables
- Disposition timetables

