AN EFFICIENT EVALUATION SCHEME FOR KPIs IN REGULATED URBAN TRAIN SYSTEMS

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Context

Rail systems are subject to **disturbances**.

(a) Signaling sys. failure  
(b) Passenger blocking doors  
(c) Bad weather cond.

**Bad QoS:**
- trains are **delayed** and **more crowded**
- 😊 **passengers**

QoS requirements:
**UITP** * defines
**Key Performance Indicators (KPIs)**
Non-compliance → financial penalties

*International association for public transports

**Figure:** Crowded station
Examples of KPIs:

(a) Punctuality

\[ P = \frac{\text{# trips delayed by } + \text{than } x \text{ t.u.}}{\text{# trips}} \]

(b) Regularity

\[ R = \frac{\text{# deps. meeting ref. headways w/ precision of } x \text{ t.u.}}{\text{# departures}} \]

Figure: Traffic regulators
Timetables

A timetable: an **idealized** representation of an execution of the system.

**Timetable:**
- departures
- arrivals

**Uses:**
- Passenger information
- Regulation
- Logs

**Objective of regulation:**
→ stick to a reference timetable.

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**Figure:** Example of a timetable

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Objectives

Goals:
- evaluation of KPIs
- evaluation of regulation algorithms

Needs:
- realistic model with a good level of abstraction:
  - tracks, trains, time, constraints, stochasticity…
- integration of real traffic control algorithms
- fast simulations —— allow for Monte-Carlo
Outline

1. a model for simulation of urban rail systems
2. performed experiences and results
3. future work and improvements

Approach:

a framework for evaluation of regulation techniques through the measurement of KPIs
Modeling

Real topology:

Portion of the network:

Assumptions:
- fixed-block policy
- consider network constraints: min. dwell/run times, interlockings
Modeling (cont.)

Network portion:

Model equivalent:
Modeling (cont.)

Network portion:

Model equivalent:
Semantics of STPNs:
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Semantics

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Block occupation constraints:
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Block occupation constraints:
Construction:
Expolynomial functions

\[ f(x) = \begin{cases} 
\sum_{k=1}^{K} c_k \cdot x^{a_k} \cdot e^{-\lambda_k x} & \alpha < x < \beta \\
0 & \text{otherwise}
\end{cases} \]
Construction:

Expolynomial functions

\[ f(x) = \left\{ \begin{array}{ll}
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\end{array} \right. \]

Inverse transform sampling:
Several timetables:

- **reference timetable**: target
- **active timetable**: execution + future
Several timetables:
- reference timetable: target
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- reference timetable: target
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Regulation module

■ Regulation mode:
ASAP with change of dwell times
**Regulation mode:**
ASAP with change of dwell times
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- **Regulation mode:**
  ASAP with change of dwell times

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**KPIs**

**data analysis**

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Regulation mode:
ASAP with change of dwell times
Regulation module

- **Regulation mode:**
  ASAP with change of dwell times

```
10  16  29  35  41  47

5   7   6   9   5   3

n_{1ai-2}  n_{1ai-1}  n_{1ai}  n_{1ai+1}  n_{1ai+2}  n_{1ai+3}
```

```
23  31  38  44  54  60

5   7   6   9   5   3

n_{2ai-2}  n_{2ai-1}  n_{2ai}  n_{2ai+1}  n_{2ai+2}  n_{2ai+3}
```
**Regulation mode:**

ASAP with change of dwell times

\[ n_{1ai-2} \]
\[ n_{1ai-1} \]
\[ n_{1ai} \]
\[ n_{1ai+1} \]
\[ n_{1ai+2} \]
\[ n_{1ai+3} \]

\[ n_{2ai-2} \]
\[ n_{2ai-1} \]
\[ n_{2ai} \]
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Regulation module

- **Regulation mode:**
  ASAP with change of dwell times
### Real case: Santiago’s metro, line 1

- interwined loops topology
- 27 stations
- 50 trains

#### Time-space graph:
**Real case:** Santiago’s metro, line 1

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**Real case:** Santiago’s metro, line 1

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**Time-space graph:**
Evolution of deviation (1 simulation - all stations)

Simulation speed: 1 simulation in approx. 35s (w/o display).
Monte-Carlo method

Monte-Carlo simulation method:
→ an experimental method to estimate a value.

$X$: random variable

$f_X(x)$: probability density function (PDF) of $X$

$F_X(x) = \mathbb{P}[x \leq X]$: cumulative distribution function of $X$

Central Limit Theorem:

For $X_1, X_2, \ldots, X_n$ experiments when $n \to +\infty$,

then the empirical mean $\bar{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i$ tends towards $E[X]$.

Can compute:

• a satisfactory empirical mean $\bar{X}_n$

• a confidence interval $[\alpha_n, \beta_n]$
  
  w/ $\alpha_n$ and $\beta_n$ resp. upper and lower bounds of the interval

• a probability $\mathbb{P}[E[X] \in [\alpha_n, \beta_n)]$ (precision)
Simulation campaign

- **n = 100** stochastic simulation runs:

  - mean deviations between reference and observed departure dates for all stations

  - stochastic simulation → different values
  - calculating mean value is not sufficient
Performance evaluation

- **Estimated parameter:**
  - the mean headway deviation, a regularity indicator.

- **Results:**
  - substantial disturbances $\rightarrow$ regulation failed to cope with delay
  - observation of bunching phenomena

Confidence intervals for deviation between reference and observed mean headways per station
Future work

- Moving blocks:

- Distributions:
  - learning from real data
  - taking into account the non-markovian aspect of delays

- Regulation techniques:
  - headway equalizing regulation,
  - mixed regulation (punctuality + regularity)
  - progressive delay compensation,
  - objective regulation,
  - etc.
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