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

Figure: Crowded station

*International association for public transports

Context (cont.)

Examples of KPIs:

(a) Punctuality

(b) Regularity

$$P = \frac{|\#\text{ trips delayed by +than } x \text{ t.u.}|}{|\#\text{ trips}|} \quad ; \quad R = \frac{|\#\text{ deps. meeting ref. headways w/ precision of } x \text{ t.u.}|}{|\#\text{ departures}|}$$

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.

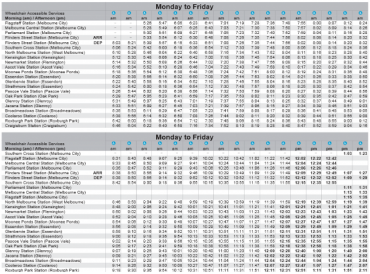
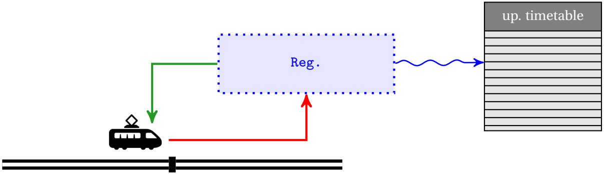
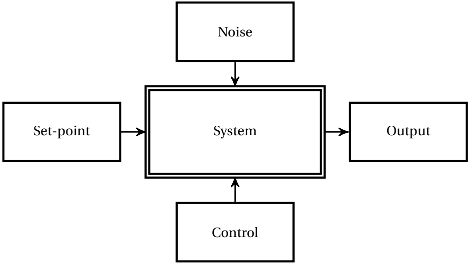


Figure: Example of a timetable



Objectives



Goals:

- evaluation of KPIs
- evaluation of regulation algorithms

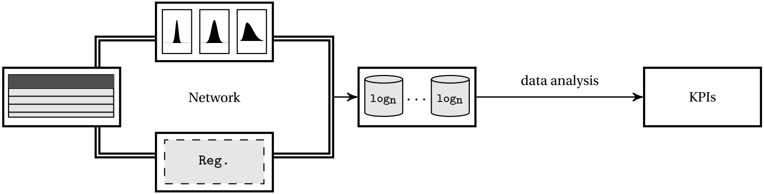
Needs :

- realistic model with a good level of abstraction:
  $\longrightarrow$ tracks, trains, time, constraints, stochasticity...
- integration of real traffic control algorithms
- fast simulations $\longrightarrow$ allow for Monte-Carlo

Outline

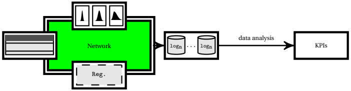
① a model for simulation of urban rail systems
② performed experiences and results
③ future work and improvements

Approach:

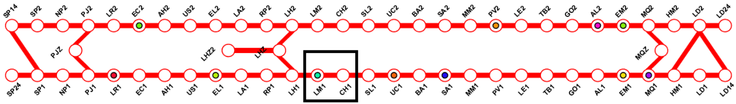


a framework for evaluation of regulation techniques through the measurement of KPIs

Modeling



Real topology:

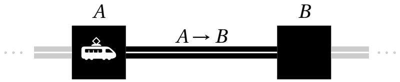


Portion of the network:

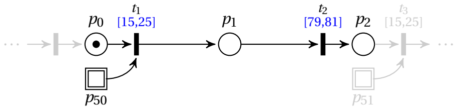
Assumptions:

- fixed-block policy
- consider network constraints: min. dwell/run times, interlockings...

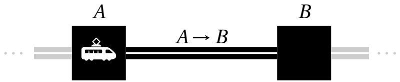
Network portion:



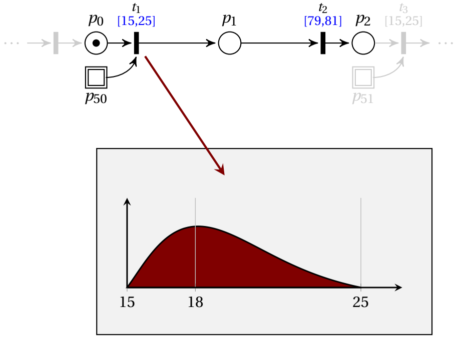
Model equivalent:



Network portion:

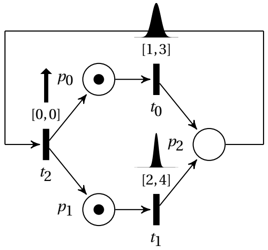


Model equivalent:



Semantics

Semantics of STPNs:



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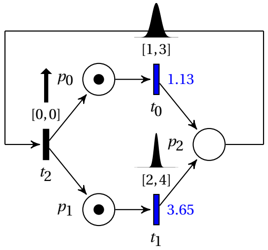

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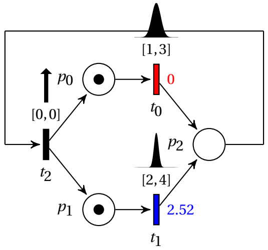

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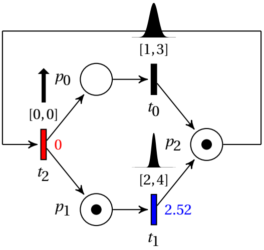

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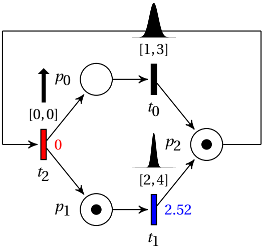
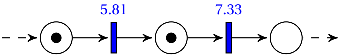


Block occupation constraints:



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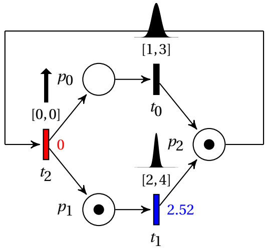

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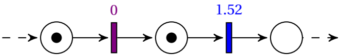

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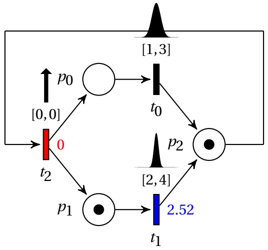

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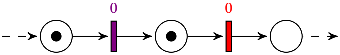

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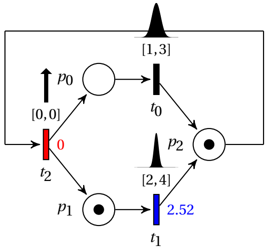

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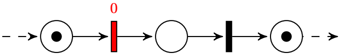

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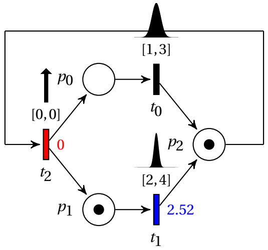

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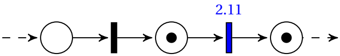
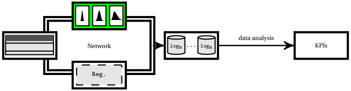
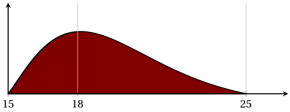


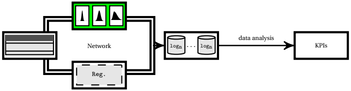


Construction:

Expolynomial functions

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





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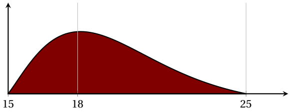
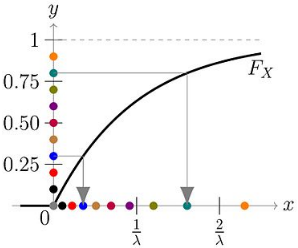
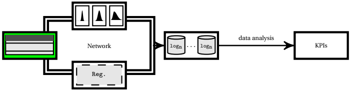


Inverse transform sampling:

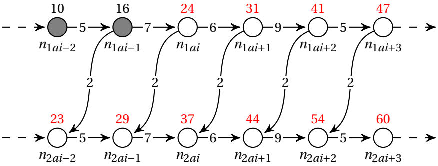


Timetables



Several timetables:

- reference timetable: target
- active timetable: execution + future



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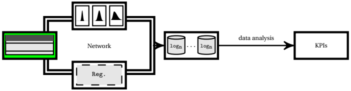

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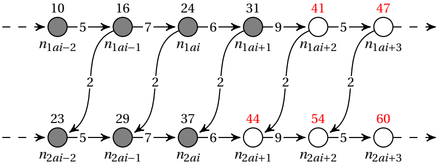

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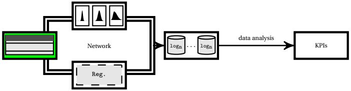

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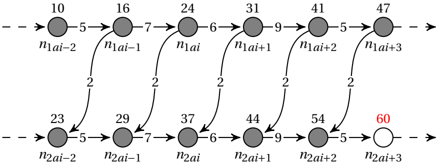
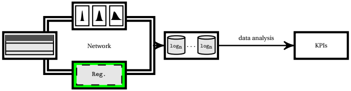
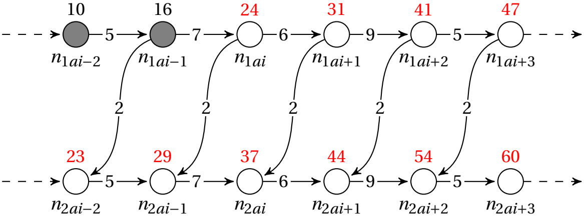
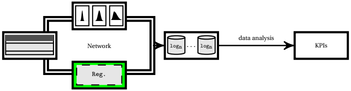


Regulation module



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





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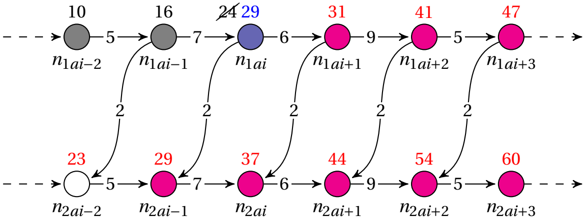

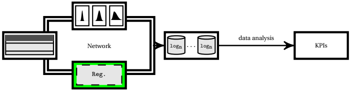

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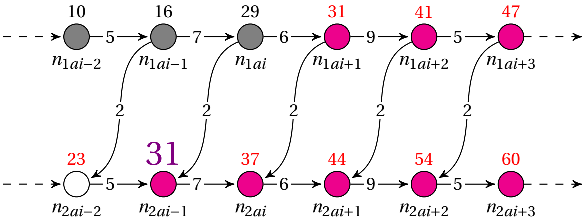

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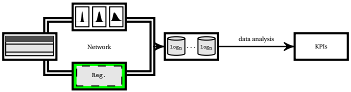

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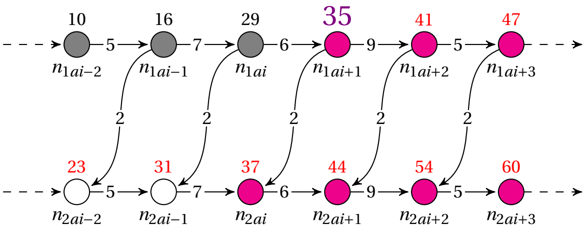

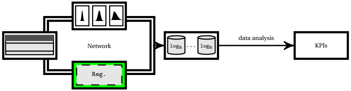

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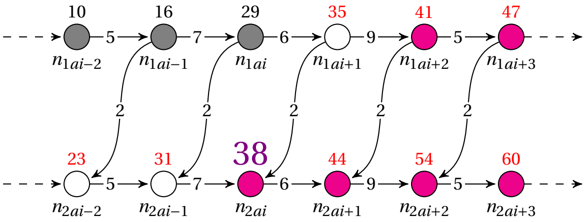

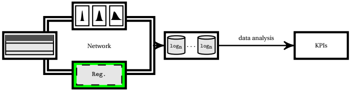

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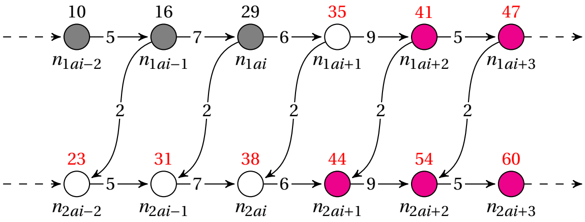

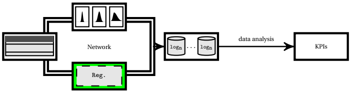

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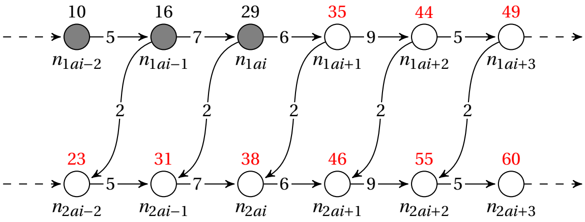
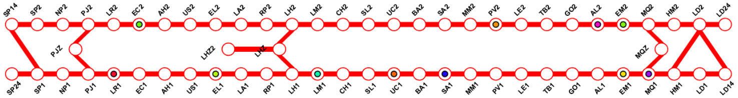
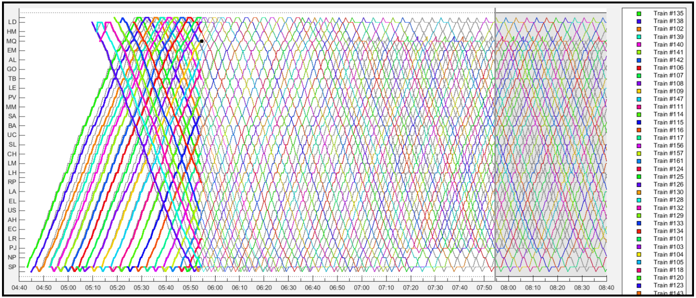


- **Real case:** Santiago's metro, line 1



- interwined loops topology
- 27 stations
- 50 trains

Time-space graph:



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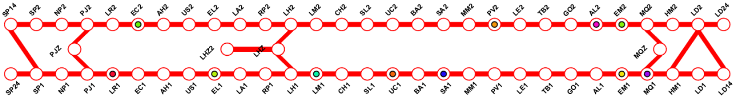

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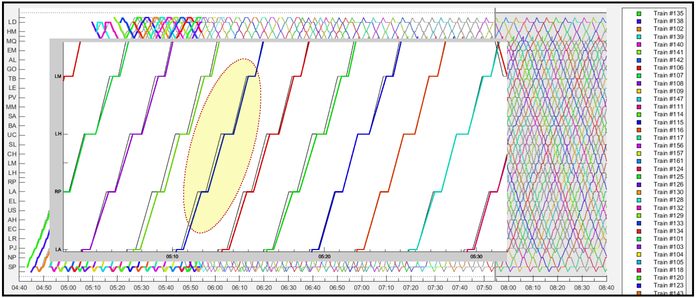
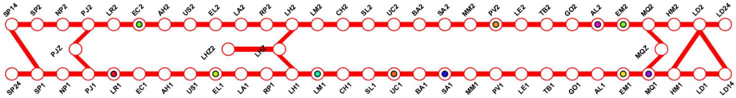


Simulation

- **Real case:** Santiago's metro, line 1



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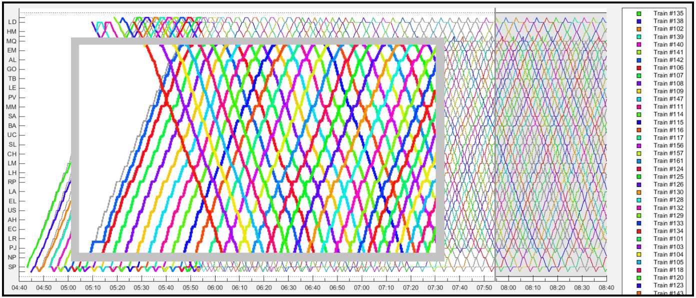
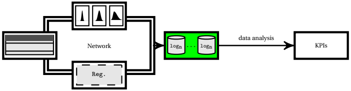
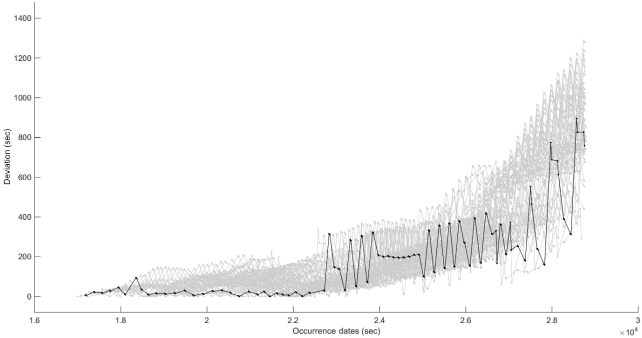




Evolution of deviation (1 simulation - all stations)



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

Monte-Carlo simulation method:

$\longrightarrow$ an experimental method to estimate a value.

X: random variable

$f_X(x)$: probability density function (PDF) of X
$F_X(x) = \mathbb{P}\left[x \leq X\right]$: cumulative distribution function of X

Central Limit Theorem:

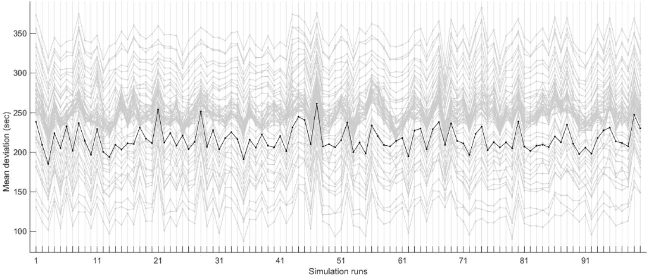
For $X_1, X_2, \ldots, X_n$ experiments when $n \longrightarrow +\infty$,
then the empirical mean $\overline{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i$ tends towards $E[X]$.

Can compute:

- a satisfactory empirical mean $\overline{X}_n$
- a confidence interval $[\alpha_n, \beta_n]$
  w/ α_n and β_n resp. upper and lower bounds of the interval
- a probability $\mathbb{P}\left[E[X] \in [\alpha_n, \beta_n]\right]$ (precision)

Simulation campaign

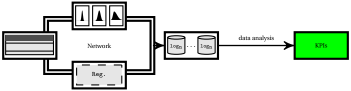
- n = 100 stochastic simulation runs:



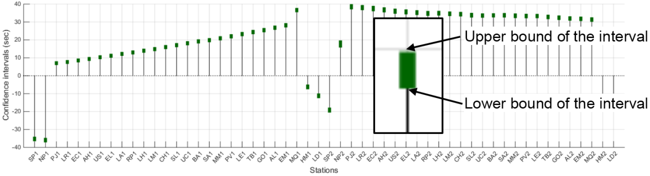
mean deviations between reference and observed departure dates for all stations

- stochastic simulation ⟶ different values
- calculating mean value is not sufficient

Performance evaluation



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



confidence intervals for deviation between reference and observed mean headways per station

- **Results:**

• substantial disturbances ⟶ regulation failed to cope with delay
• observation of bunching phenomena

Future work

- **Moving blocks:**

Future work

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Future work

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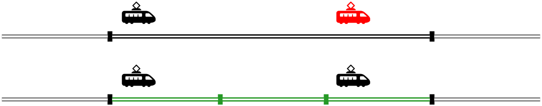
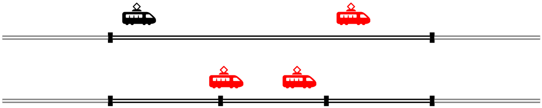


Future work

- **Moving blocks:**



Future work

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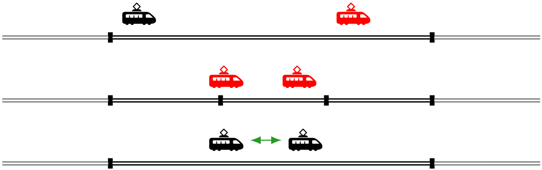
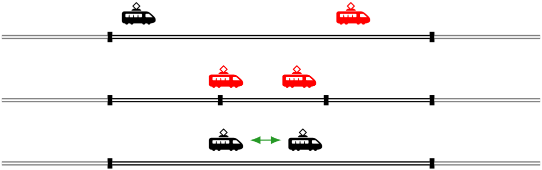
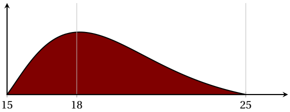


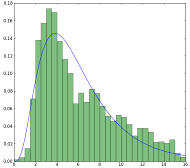
Moving blocks:



Distributions:

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





Future work

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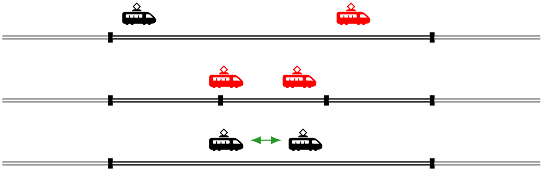

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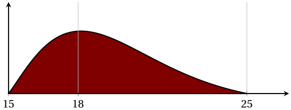

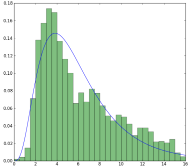

Regulation techniques:

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