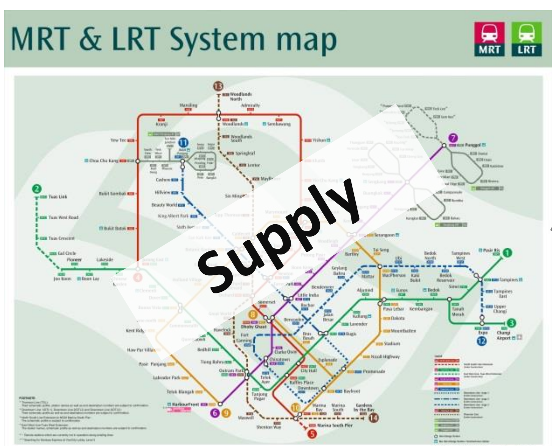
# Using public transport smart card data for large-scale, agent-based transport demand simulation using MATSim: the case of Singapore

Alex Erath, Sergio Ordonez, Artem Chakirov, Pieter Fourie

Future Cities Laboratory, Singapore ETH-Centre

# Idea: modelled Big Data for scenario forecast


MATSim

**Multi-Agent Transport Simulation**

**Insight**

# Using real demand to simulate public transport

**Derive travel demand from smart card transactions**

- Transactions recorded on Tuesday, 22nd April 2011
- 4 Mio journeys
- Boarding stop (journey level)
- Boarding time
- Alighting stop (journey level)


**Possible demand reactions**

- ✓ New routes (including transfers)
- ✓ Walk to other stops
- ✗ Mode switch (except for walk)
- ✗ Time of day
- ✗ Location of start/end stop
- ✗ Induced demand

SITCE 2013

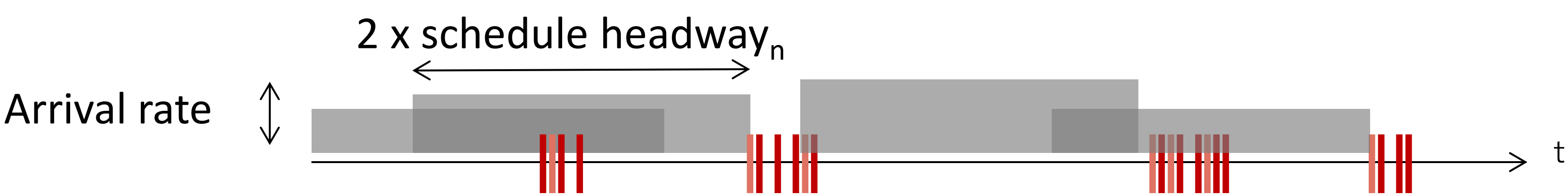
# Preparing demand data

**Challenges**

1. No infrmation about actual arrival time at bus stop
2. No information about actual origin and destination on building level

**Basic assumptions**

1. Uniform arrival rate between two scheduled services
2. Journey starts and ends at reported public transport stops




Boarding, alighting at stop x, bus line y

# Demand: behavioral parameters

**Public transport**

- Value of in-vehicle time: 8 SGD/h
- Value for waiting (start and transfer): 12.89 SGD/h
- Additional penalty for transfer: 0.65 SGD = 5 min in-vehicle time

**On foot (access/egress)**

- Walking speed: 4km/h
- Value of walking time: 16.92 SGD/h

**In future scenarios:**

- Value of a seat/crowdedness
- Preference for bus (anecdotal evidence)
- Agent specific preference

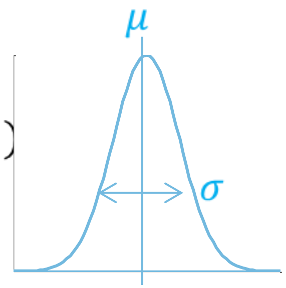
# Supply: stochastic nature of travel times

**Speed between stops**

$$v \sim N(\mu, \sigma)$$

$$\mu = f(\frac{f}{c}, v_f, tl, m, l \dots)$$

$$\sigma = f(\frac{f}{c}, v_f, tl, m, \dots)$$

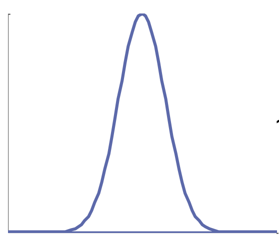



**Dwell time**

$$d \sim N(\mu, \sigma)$$

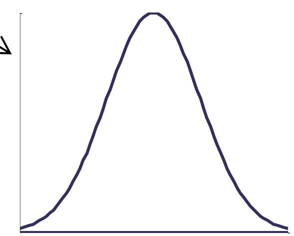
$$\mu = f(b, a, p, t)$$

$$\sigma = f(\mu)$$



**Simulation parameters**

**Trip speed**



$$v \sim N(\mu, \sigma)$$

$$\mu = f(\frac{f}{c}, v_f, tl, m, b, a, p, t, \dots)$$

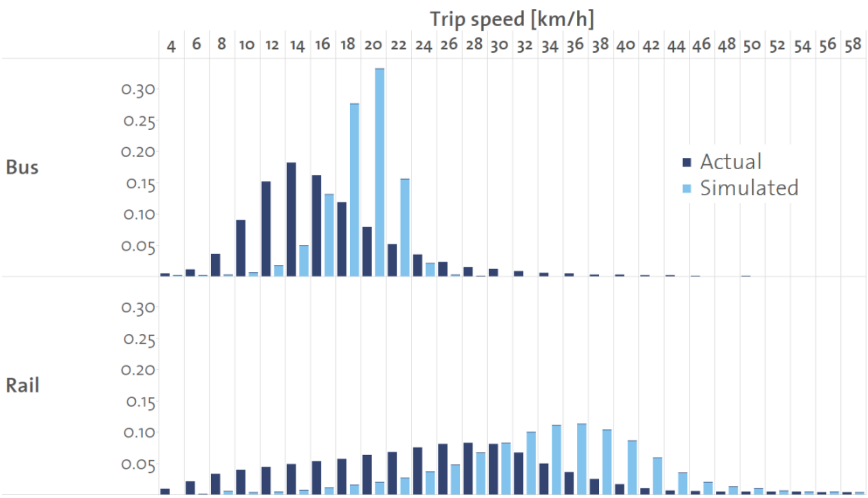
$$\sigma = f(\frac{f}{c}, v_f, tl, m, \mu_d)$$

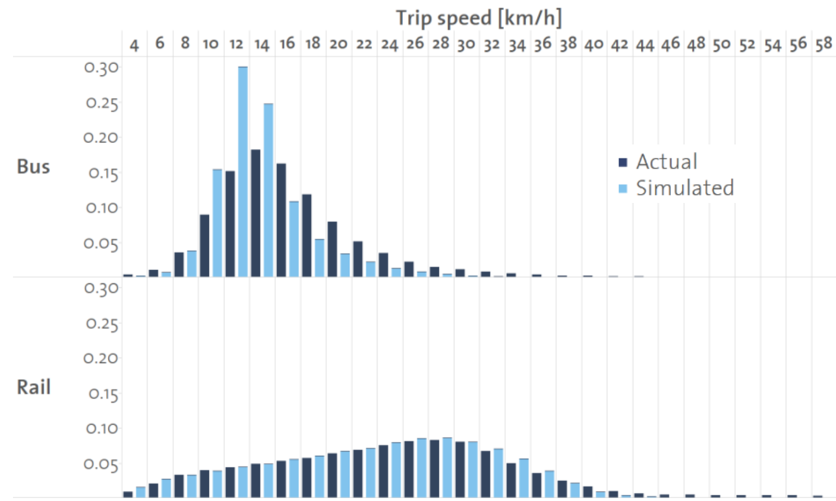
**Observation**



6

# Calibration of simulation




## **Starting** values

$$v_{bus,trunk} = 26\ km/h$$
$$v_{bus,exp} = 50\ km/h$$
$$\sigma_{bus}(v) = 0.2 \cdot v_{bus}$$
$$v_{train} = 72\ km/h$$
$$\sigma_{train}(v) = 0$$

Bus stops: sequential operations
Rail: access and waiting time **not included** in MATSim

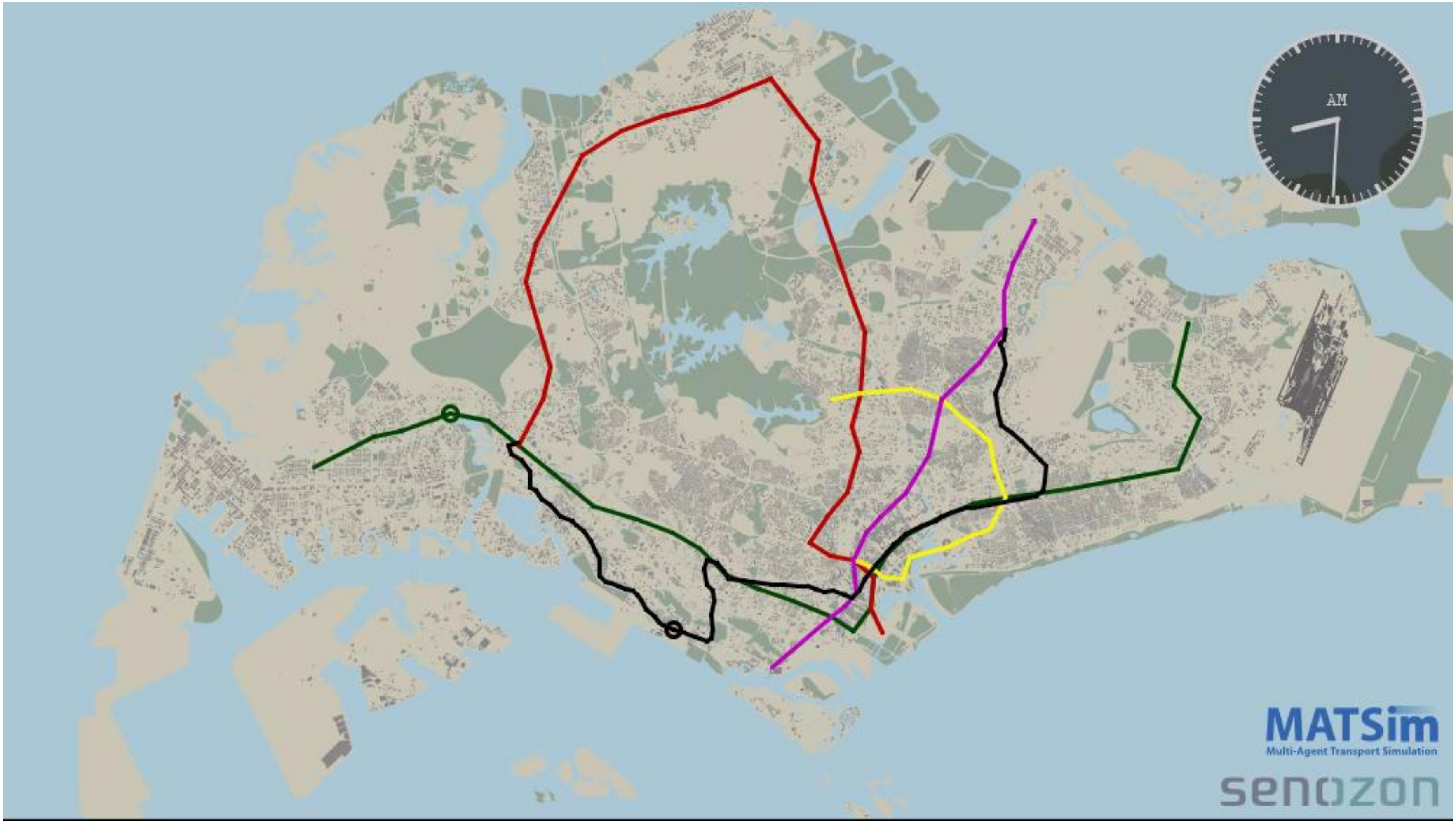
**Dozens of calibration runs** →

## **Calibrated** values

$$v_{bus,trunk} = 22\frac{km}{h} \pm f(h)$$
$$v_{bus,exp} = 50\ km/h \quad v_{bus,art} = 40\ km/h$$
$$\sigma_{bus}(v) = 1.1 \cdot \sigma_{bus,Cepas,h}$$
$$v_{train} = 72\ km/h$$
$$\sigma_{train}(v) = 0$$

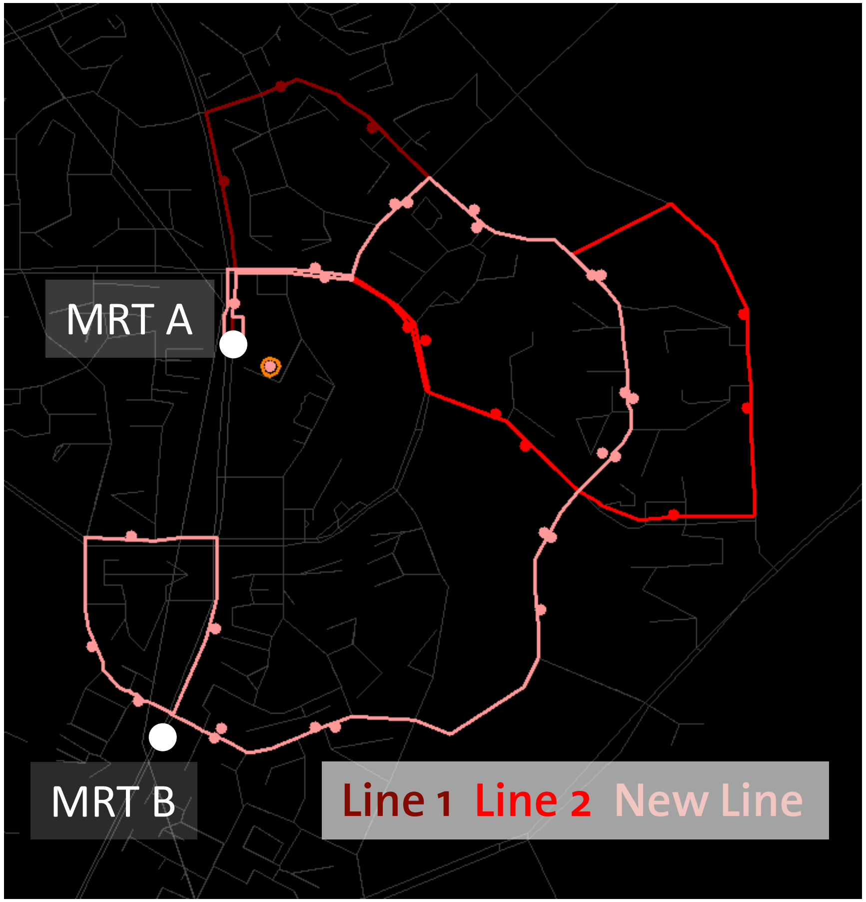
Bus stops: parallel boarding
Rail: access and waiting time **included**

# MATSim CEPAS




Erath, Alexander L. (2013). Modelled Big Data: Simulating 1 day of public transport smart card data with MATSim https://vimeo.com/76347080

# Case study I: Adding a new bus line




**Residential new town**

- **Tidal demand patterns**
- **Issues with overcrowding during peak hours**

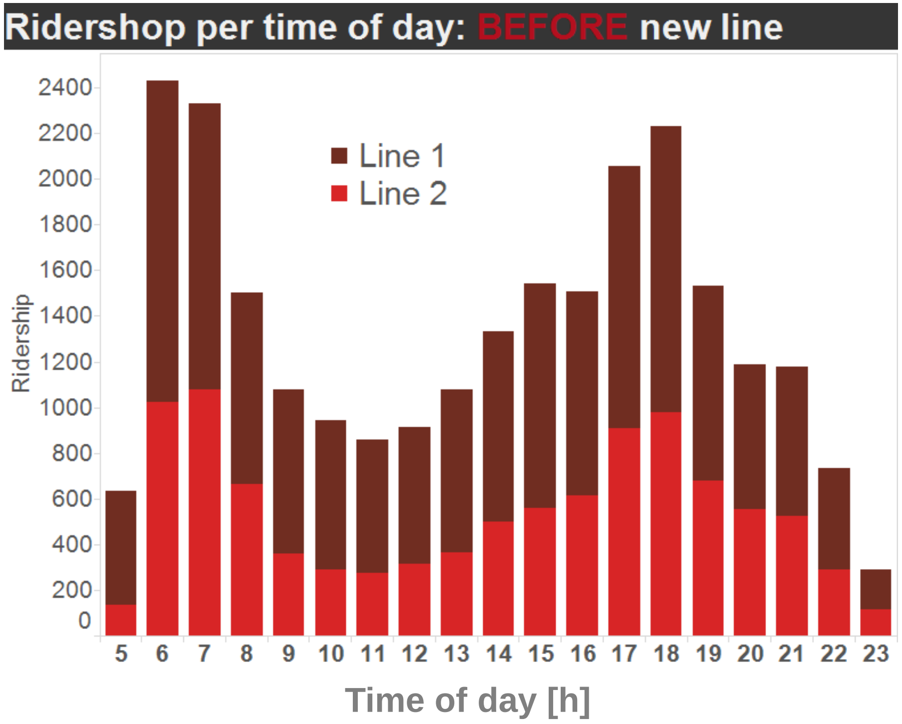
**New bus line:**

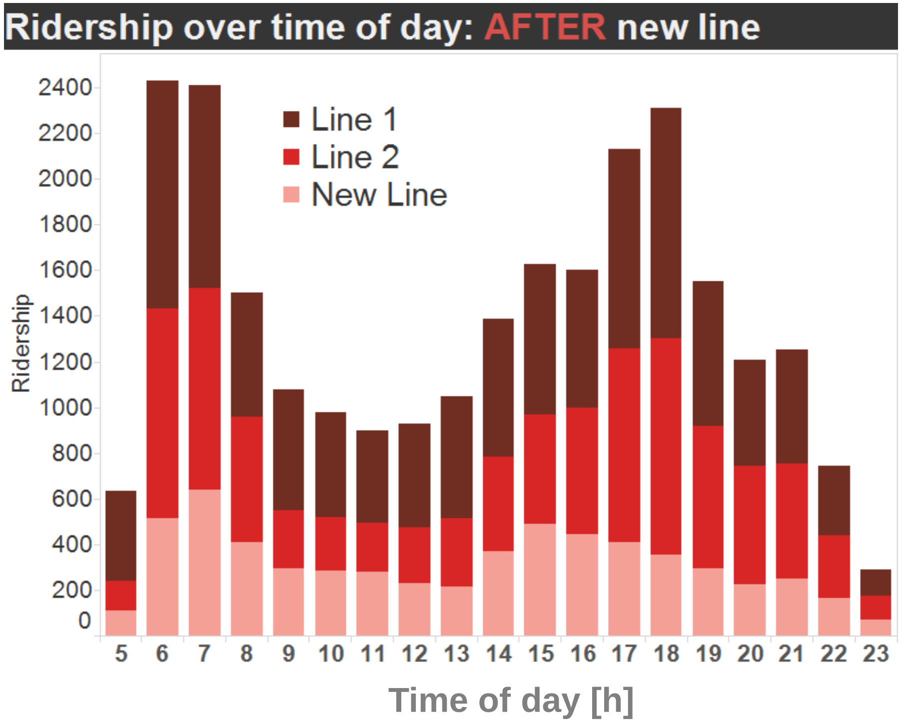
- **26 stops**
- **10km**
- **Loop from MRT A to MRT B and back**

# Ridership: Line1, Line 2 and new line

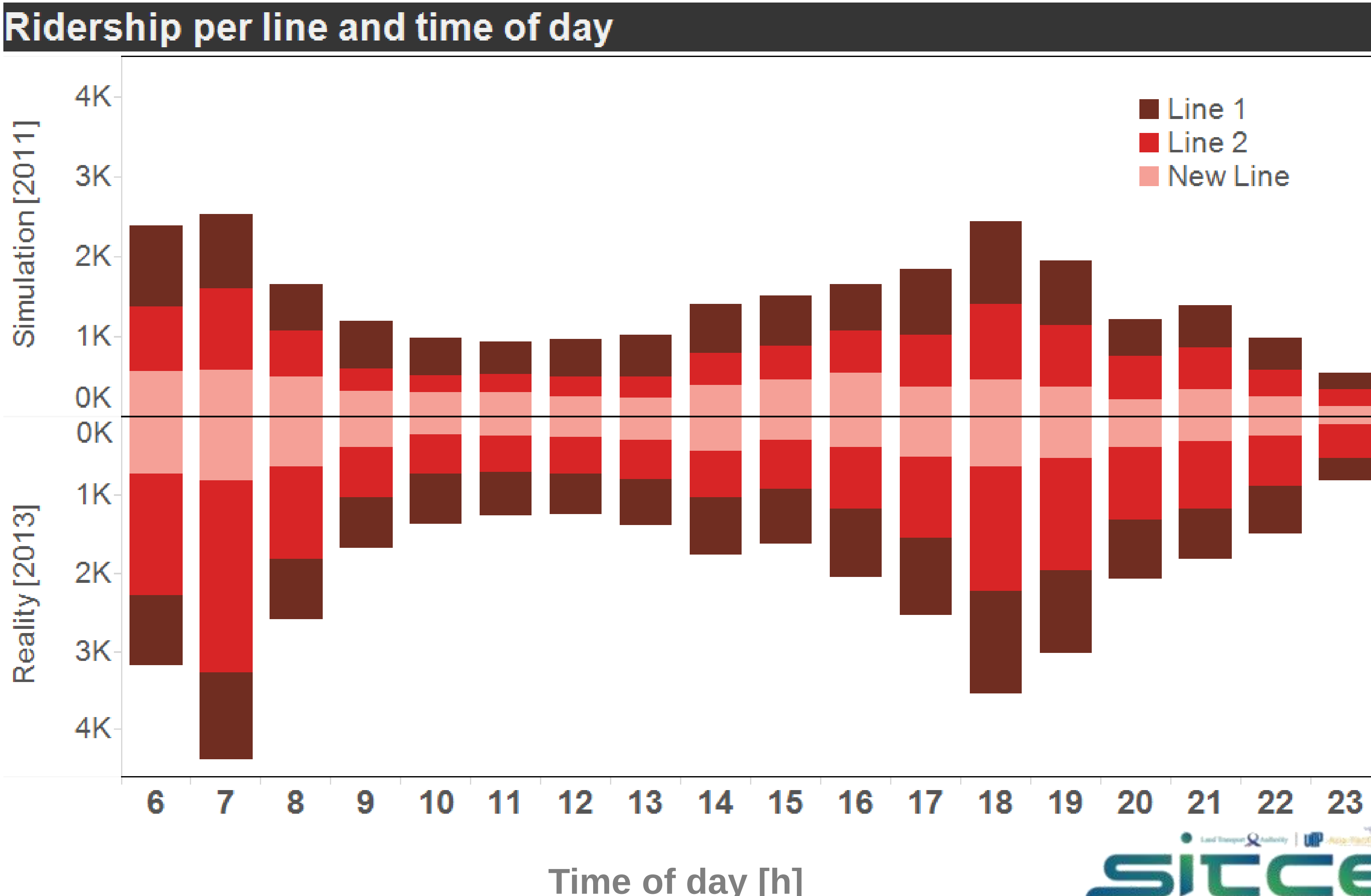
before

after

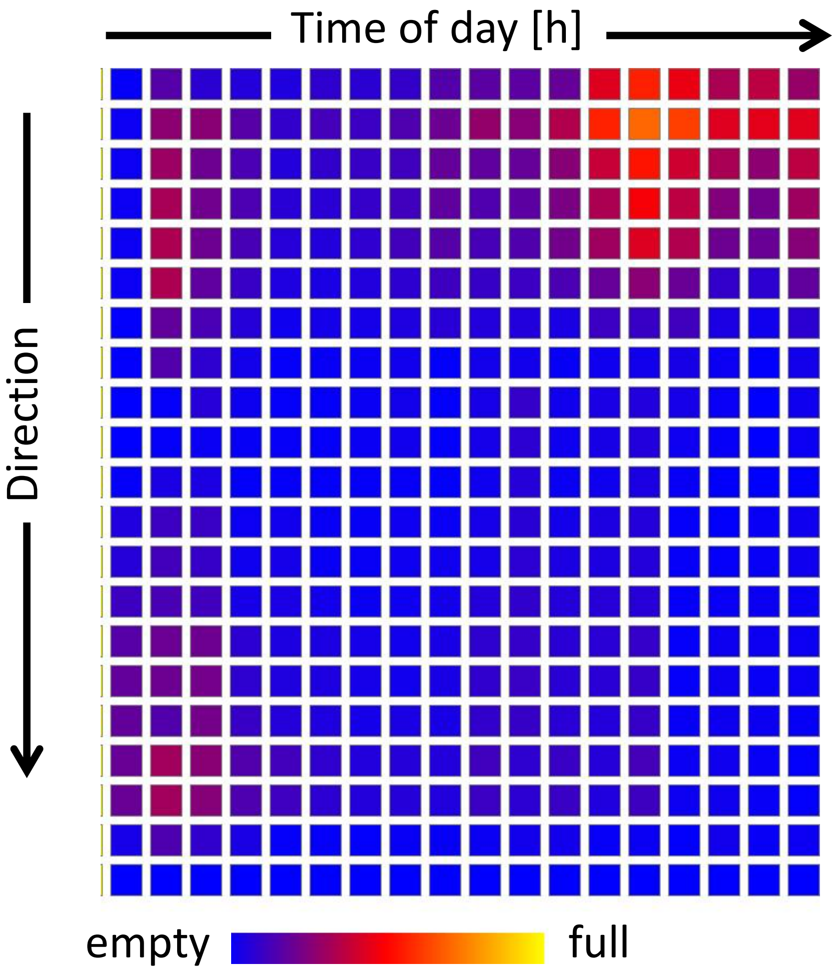


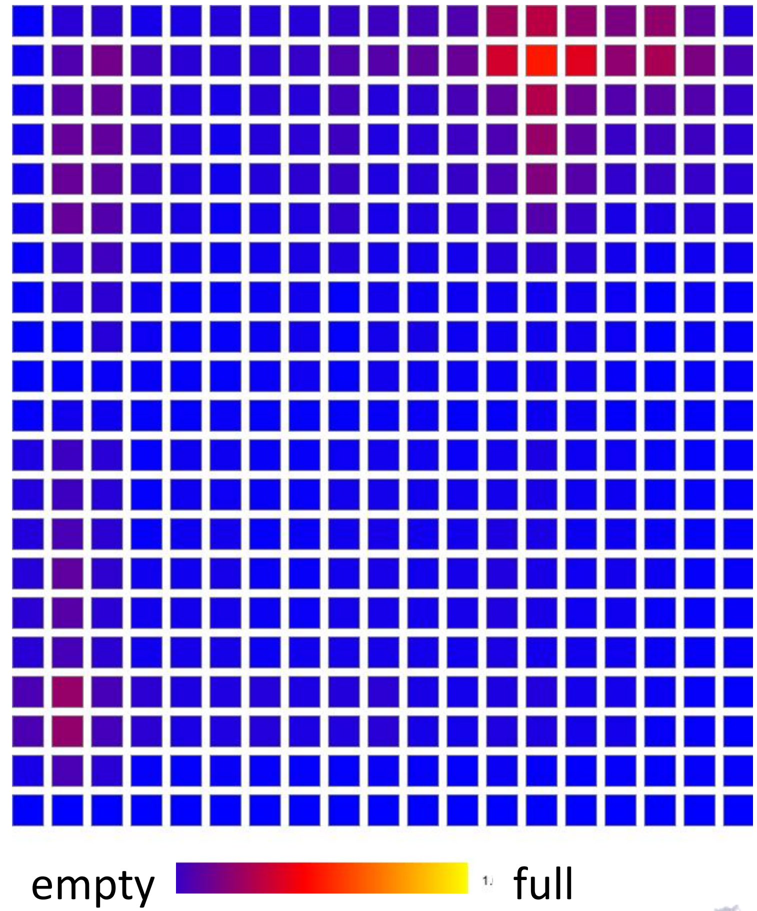
# Reality check



# Load factor: **Line 1**



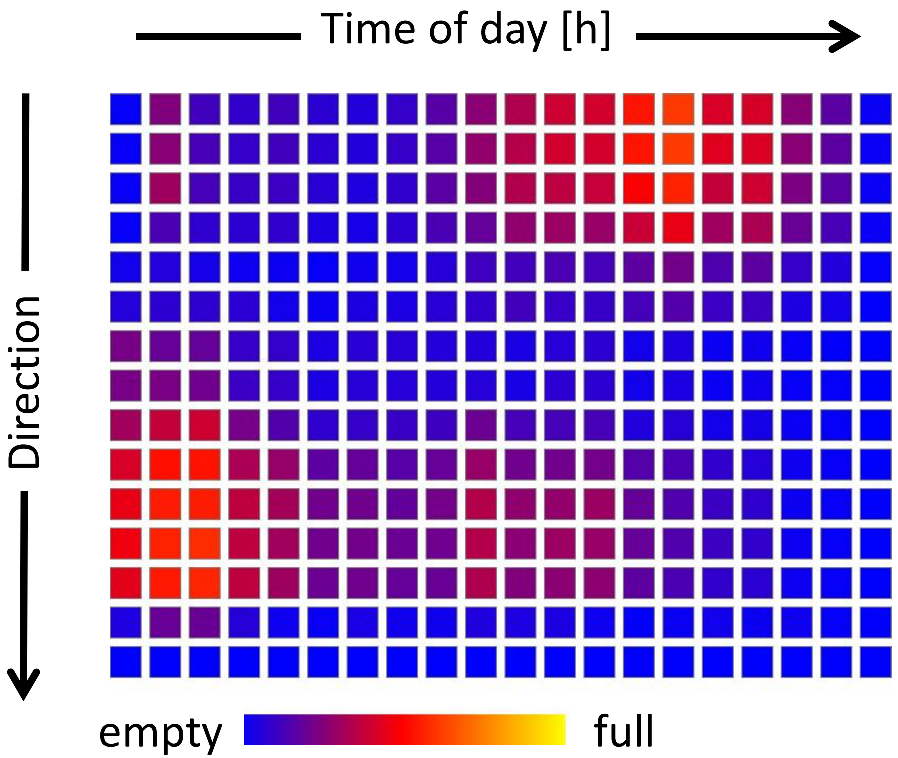

BEFORE



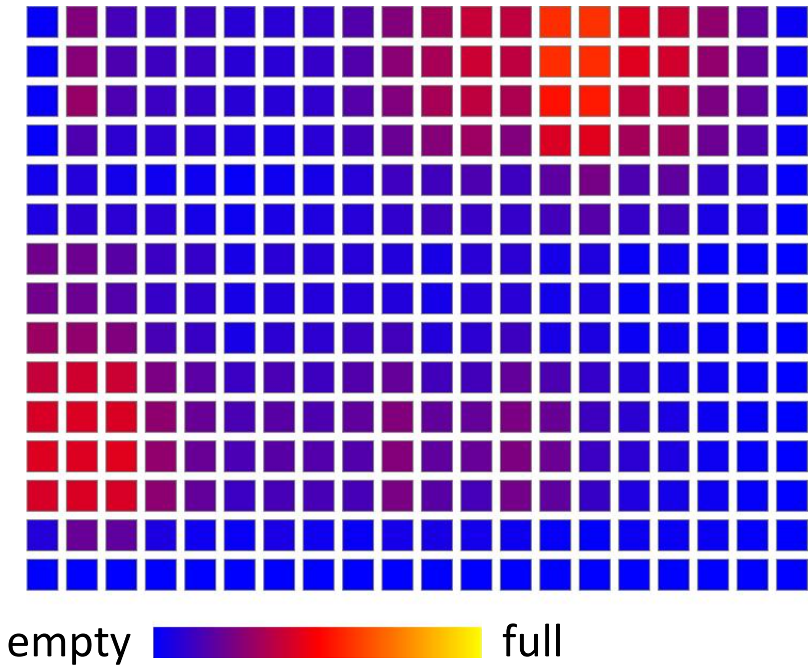

AFTER

# Load factor: **Line 2**

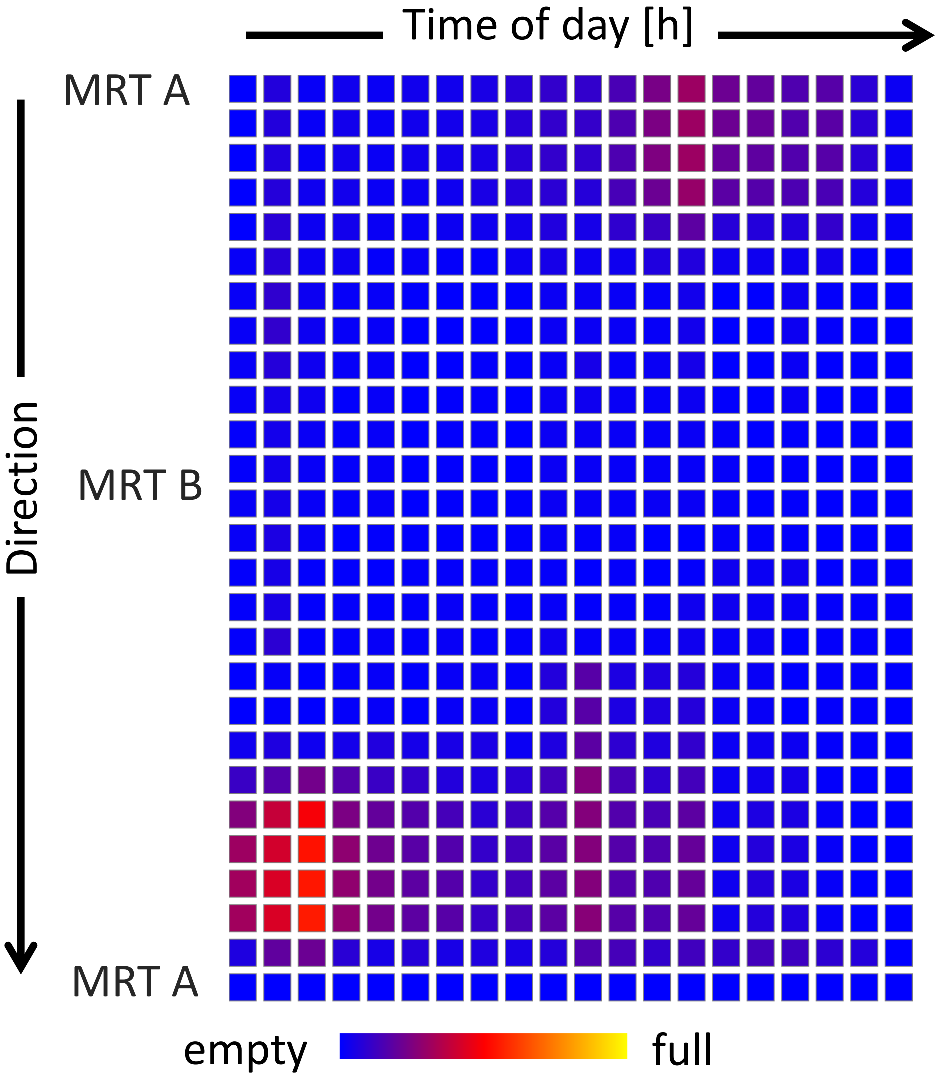
## BEFORE




## AFTER



# Load factor: New line

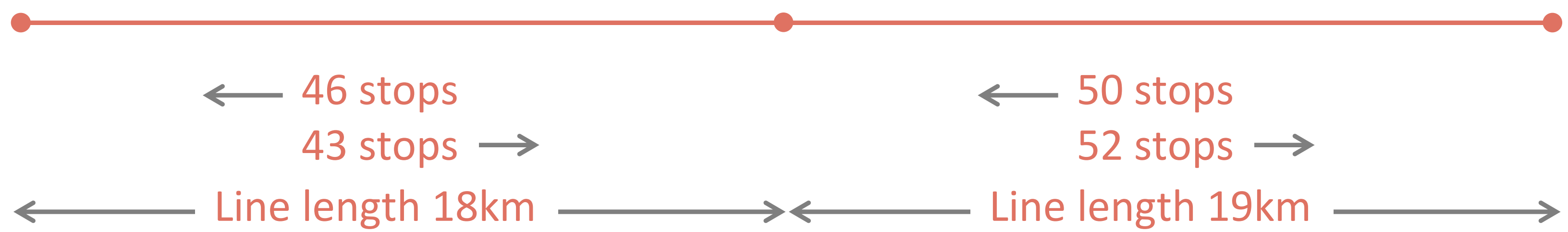



AFTER

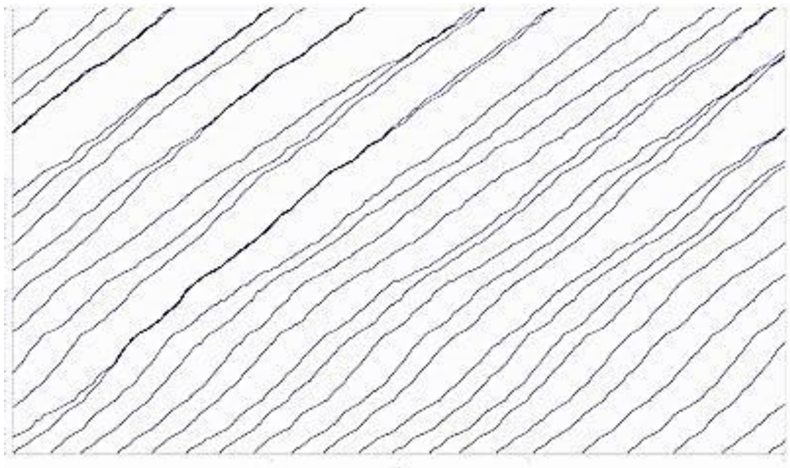
# Case study II: split bus line in two parts

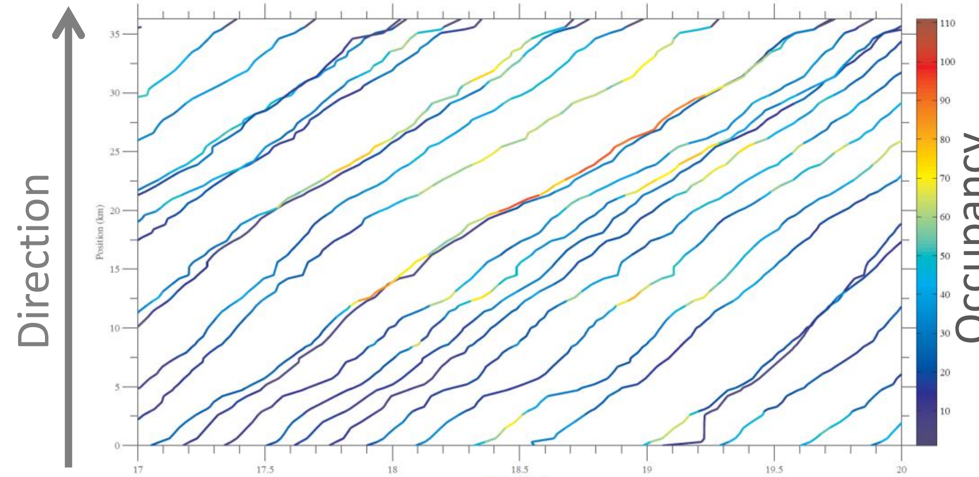
**BEFORE SPLIT**


**AFTER SPLIT**



# Reliablity before: Simulation vs. Observation





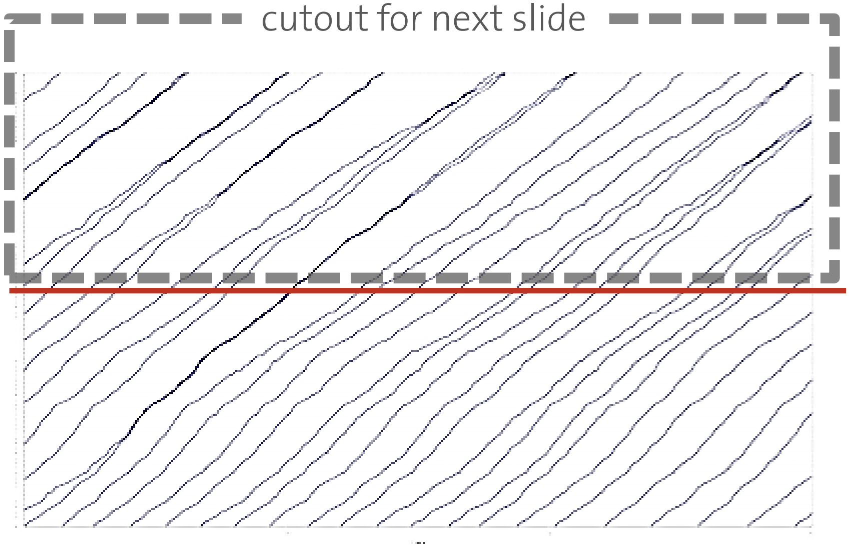

5pm 6pm 7pm 8pm

**Simulation**

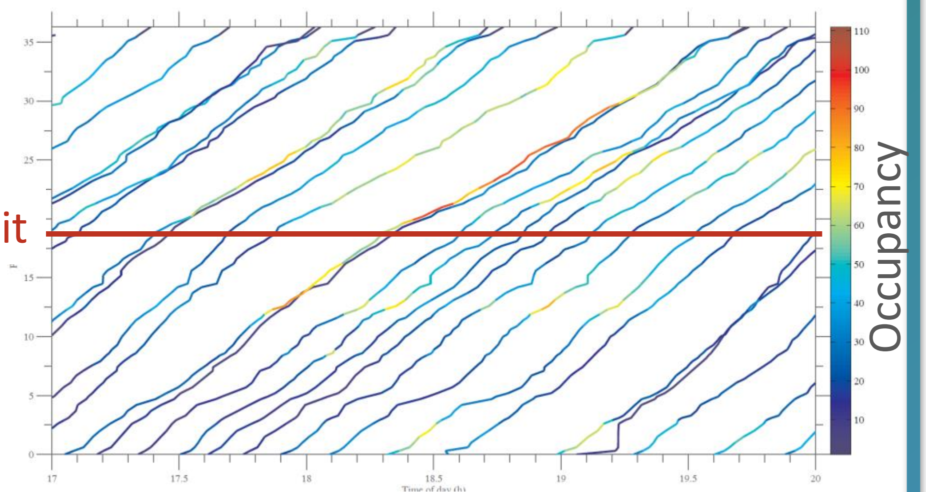
5pm 6pm 7pm 8pm

**Observation**

# Reliablity before: Simulation vs. Observation




Split




5pm 6pm 7pm 8pm

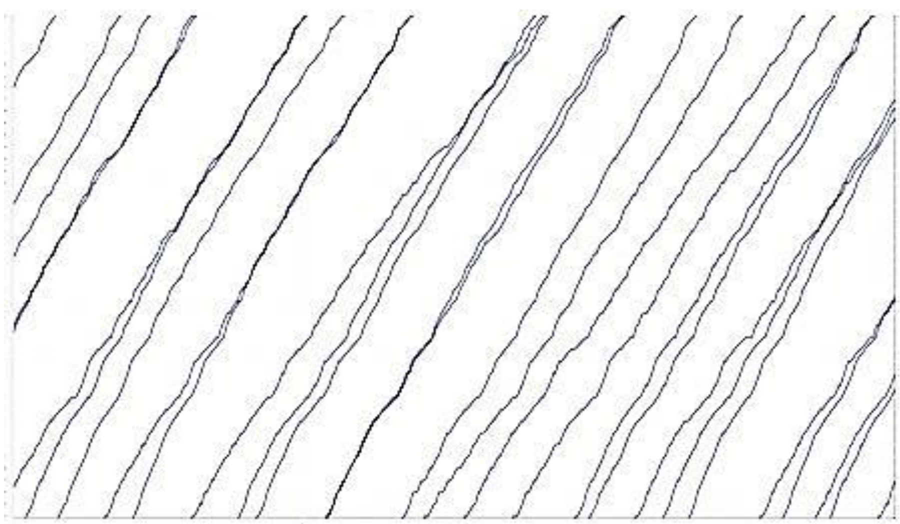
5pm 6pm 7pm 8pm

**Simulation**

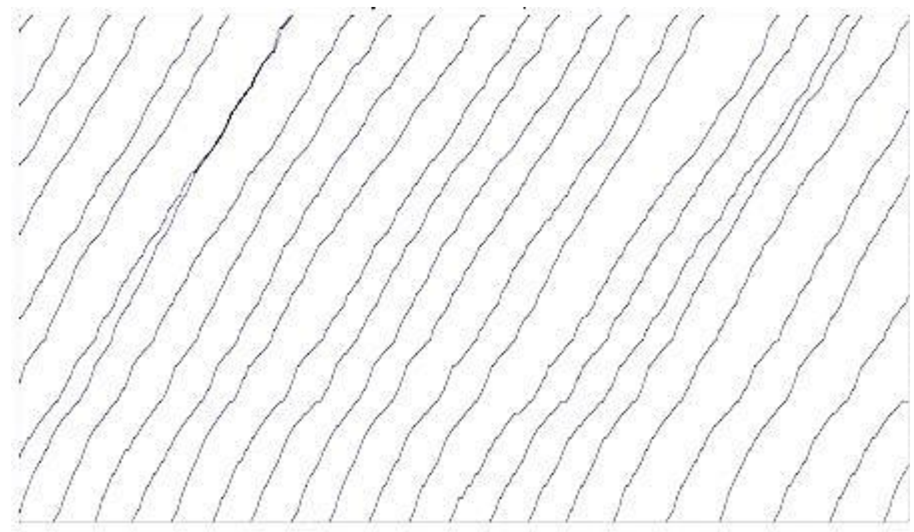
**Observation**

# Reliability: before and after split

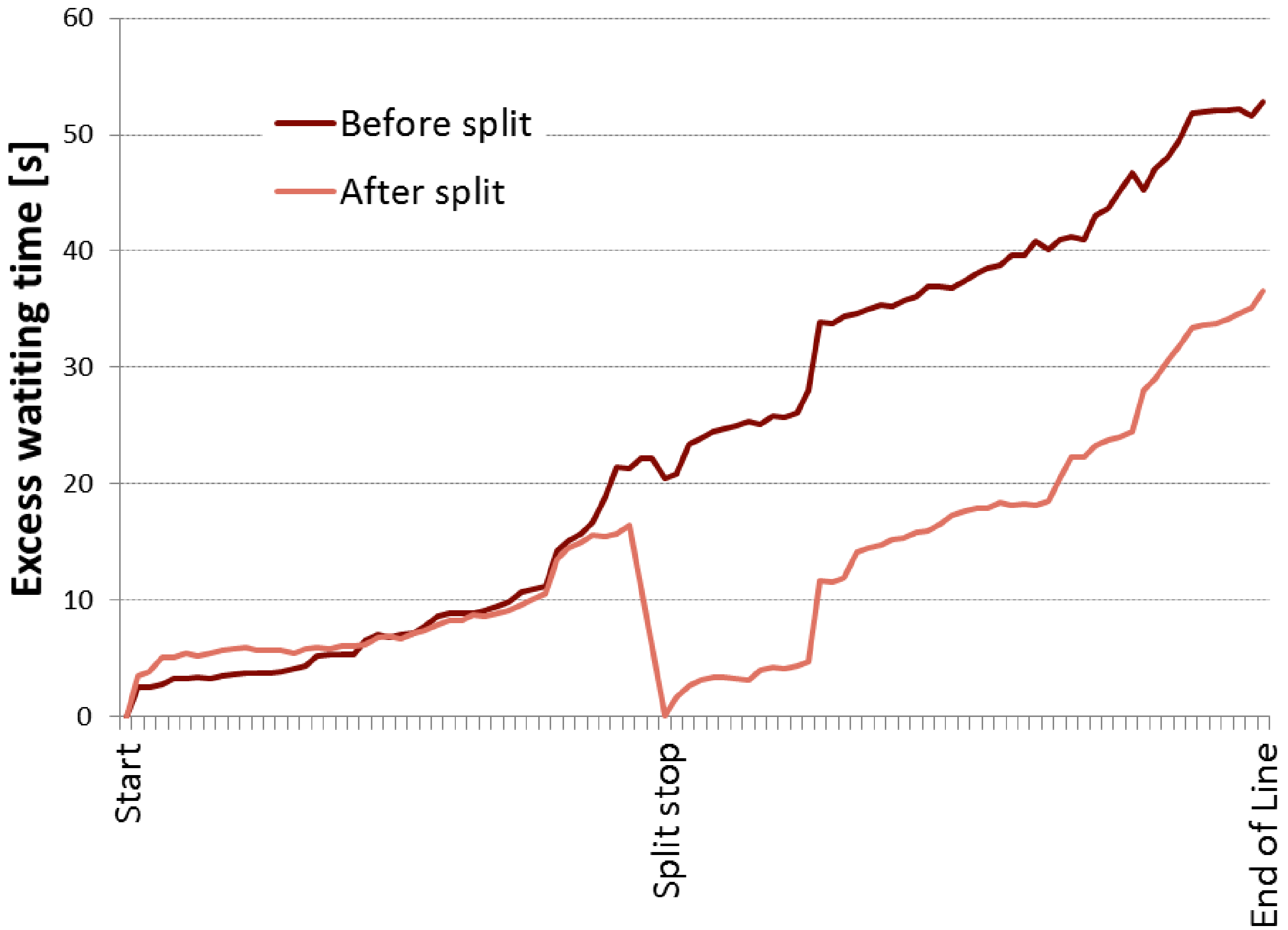
**Simulation: BEFORE line split**




**Simulation: AFTER line split**



# Reliability: Excess waiting time along line



# Computation: hardware and run times

**HPC setting**

- IBM System x3850 X5 featuring 4 Intel Xeon E7-4870
- 15 threads used for each simulation scenario
- Requires up to 80 Gb RAM for each simulation scenario

**1 iteration = simulation of all public transport lines in Singapore**

- 6 minutes  for simulation
- 2 minutes for finding new routes

**Number of iterations required to reach equilibrium**

- We computed 200 iterations -> 26h
- 50 iterations probably already sufficient -> 6.5h

# Conclusion

**Modeled Big Data**

- Public transport smart card data
- Scenario forecast (rather than pattern analysis)

**Use multi-agent transport simulation software MATSim to simulate CEPAS data**

- Observed demand as input
- Full temporal dynamics
- Demand reactions restricted to route choice

**Next steps**

- Demand: from stops to buildings
- Improving computational performance
- Make such scenario forecast accessible to planning practice