An improved approach for the sensitivity analysis of computationally expensive microscopic traffic models
-- a case study of the Zurich network in VISSIM

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Introduction

- Sensitivity Analysis (SA) is useful to identify influential parameters in model calibration.
- Problem: lack of formal procedures and few examples of SA in the calibration of microscopic traffic models, especially computationally expensive models.
- Our aim: to develop an efficient approach as a preliminary screening tool.

Review of SA Methods

- Derivative-based approach
- Regression-based approach
- Sampling-based approach
- Variance-based approach
- Metamodel-based approach
- Monte Carlo Filtering approach
- Screening approach: *Elementary Effects Method*

Definition of Elementary Effect

A model *Y* has *k* parameters **X**=[X_1, X_2, ..., X_k], the output is:

$$Y(\mathrm{X}) = Y(X_1, \ldots, X_{i-1}, X_i, \ldots X_k)$$

If X_i is changed by *Δ*, then the EE is:

$$EE_i = \frac{Y(X_1, \ldots, X_{i-1}, X_i + \Delta, \ldots, X_k) - Y(X_1, \ldots, X_{i-1}, X_i, \ldots, X_k)}{\Delta}$$

with $i \in [1, 2, 3, \ldots, k]$

Calculating the Sensitivity Index (SI) *μ*, *μ** and *σ* of EE by sampling different **X**:

1) Non-influential parameters: low *μ**
2) Linear and additive effects, no interaction: high *μ** but low *σ*
3) Non-linear effects and/or strong interactions: high *μ** and *σ*
4) Oscillating effects: low *μ* but high *μ**

Sampling Strategy (1/2)

- Two model runs are required to calculate one EE for X_i: with initial inputs $[X_1, X_2, \ldots, X_{i-1}, X_i, X_{i+1}, \ldots, X_k]$ and the varied inputs $[X_1, X_2, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k]$.

- A k-parameter model: if m EEs are required for each parameter, then ***2mk*** model runs are required.

e.g. k= 14, m=200, 30 min/run
Total computation time ≈ 116 days

Sampling Strategy (2/2)

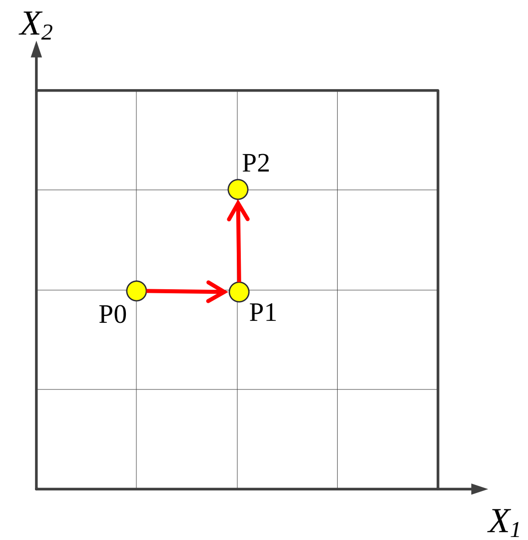
A model with 2 parameters $[X_1 , X_2]$

	X_1	X_2

$EE(X_1) = [Y(P_1) - Y(P_0)] / \Delta$

$EE(X_2) = [Y(P_2) - Y(P_1)] / \Delta$

k+1 points



k+1 points = one **trajectory**

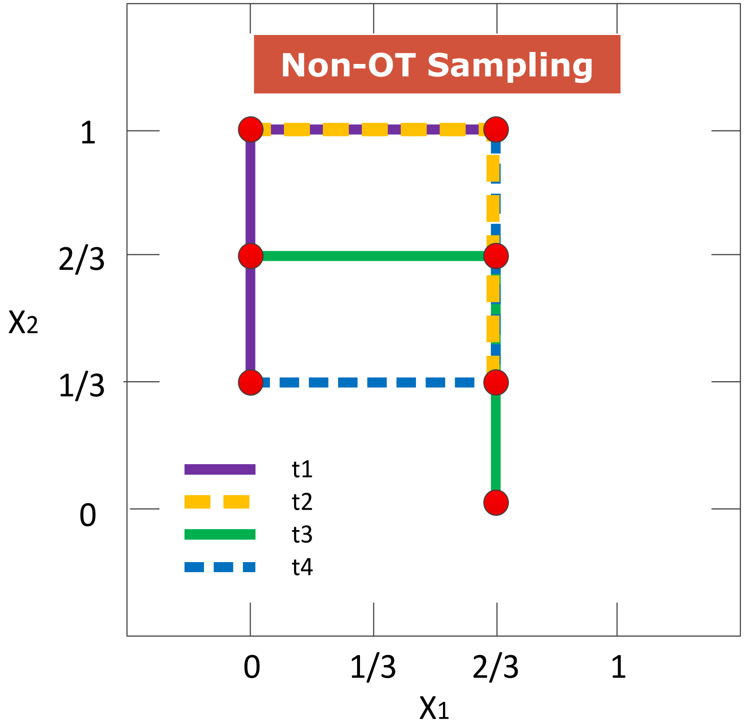
If randomly sampling *m* trajectories, same results only need ***m(k+1)*** runs.

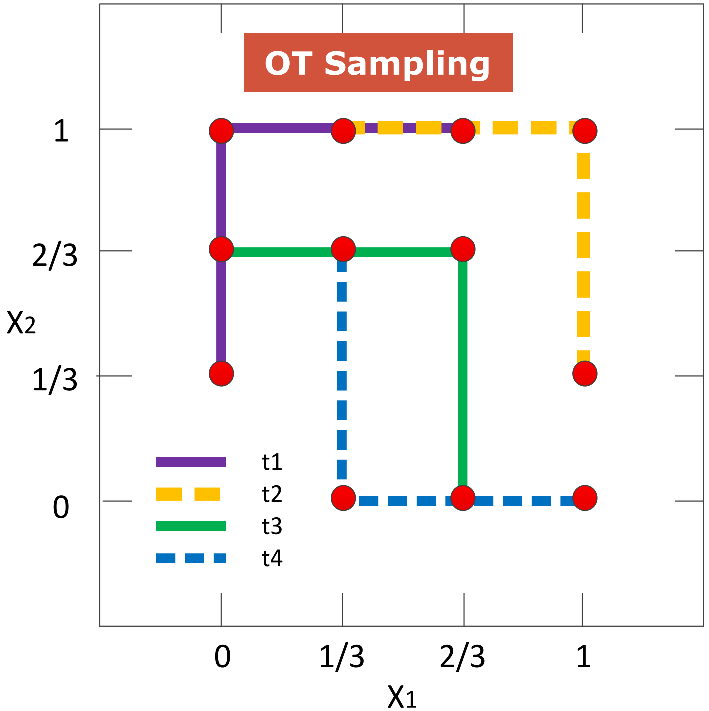
e.g. *k*= 14, *m*=200, 30 min/run
Total computation time ≈ 62 days

Optimized Trajectories (1/2)

Solution:

Find an optimized set of trajectories (OT) that covers the total input space as much as possible.





● = Sample Point

Optimized Trajectories (2/2)

1. Randomly generate m trajectories
2. Enumerate all possible sets containing n trajectories from the original m random trajectories ($n << m$)
3. Pick the set with the highest dispersion

Source: Campolongo et al., 2006

e.g. k = 14, n =10, 30 min/run
Total computation time for EE ≈ 3 days

Problem of the Original OT Sampling

However:

when *m* is large, the total number of combinations could be huge!

$$N = \frac{m!}{n! * (m-n)!}$$

e.g. *m* = 200, *n* = 10, *N* ≈ 2 x 10^{16}

Computation time for enumerating ≈ 50 days

Quasi-Optimized Trajectories

Step 1: Pick the optimized set (i.e., S_1) of m – 1 trajectories from the original set (i.e., S_0, containing m trajectories)

Step 2: Pick the optimized set (i.e., S_2) of m – 2 trajectories based on S_1

……

Step m-n: only n trajectories are left

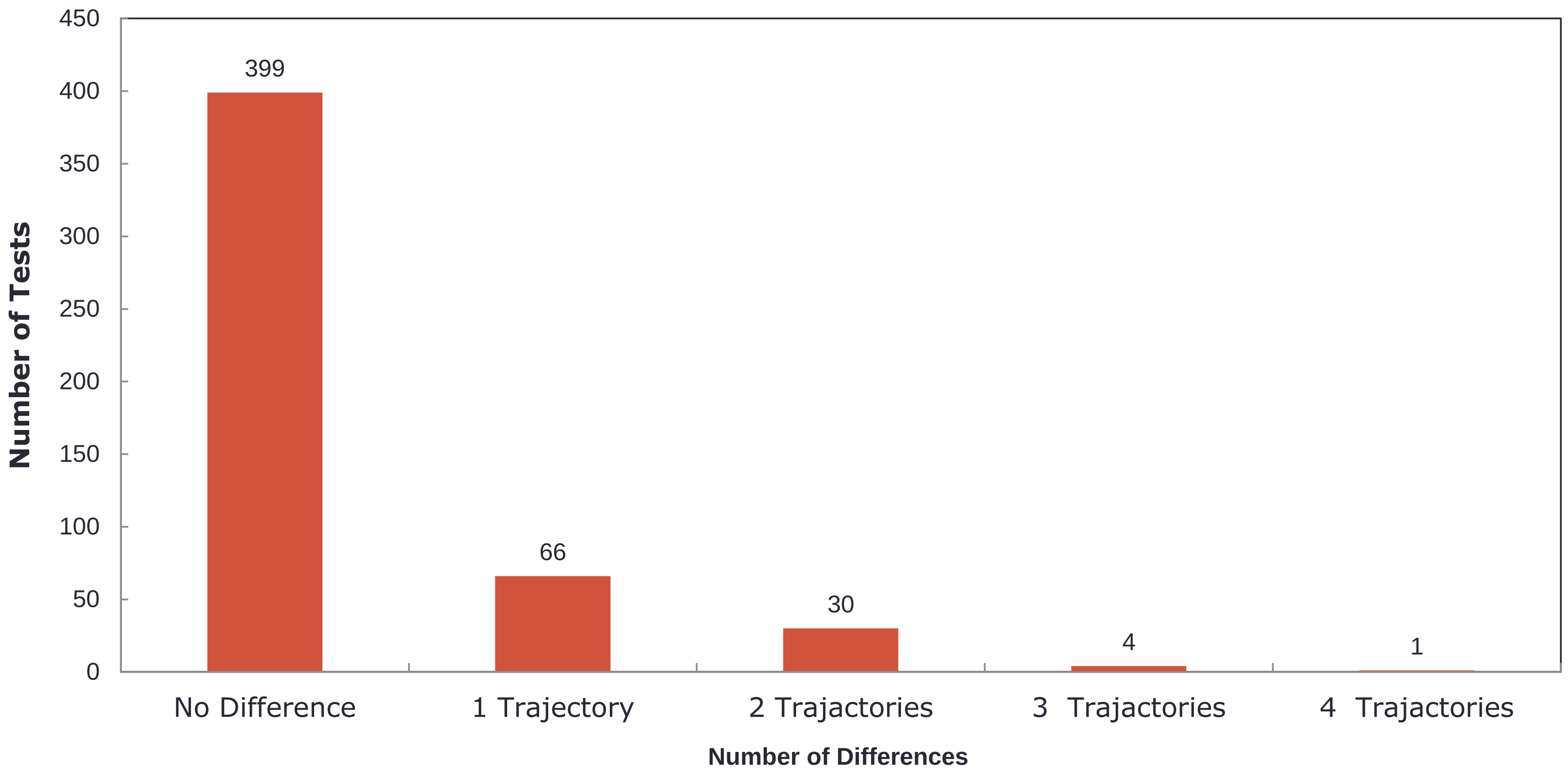
Total combinations $= m + (m-1) + \cdots + n = \frac{(m+n)(m-n+1)}{2} \ll \frac{m!}{n! * (m-n)!}$.

Note: the trajectories may not always be identical to the ones found by the original OT approach, so we call them the quasi-OT

e.g. *m*= 200, *n*=10, *N*=20,055
Computation time for enumerating ≈ 15 min

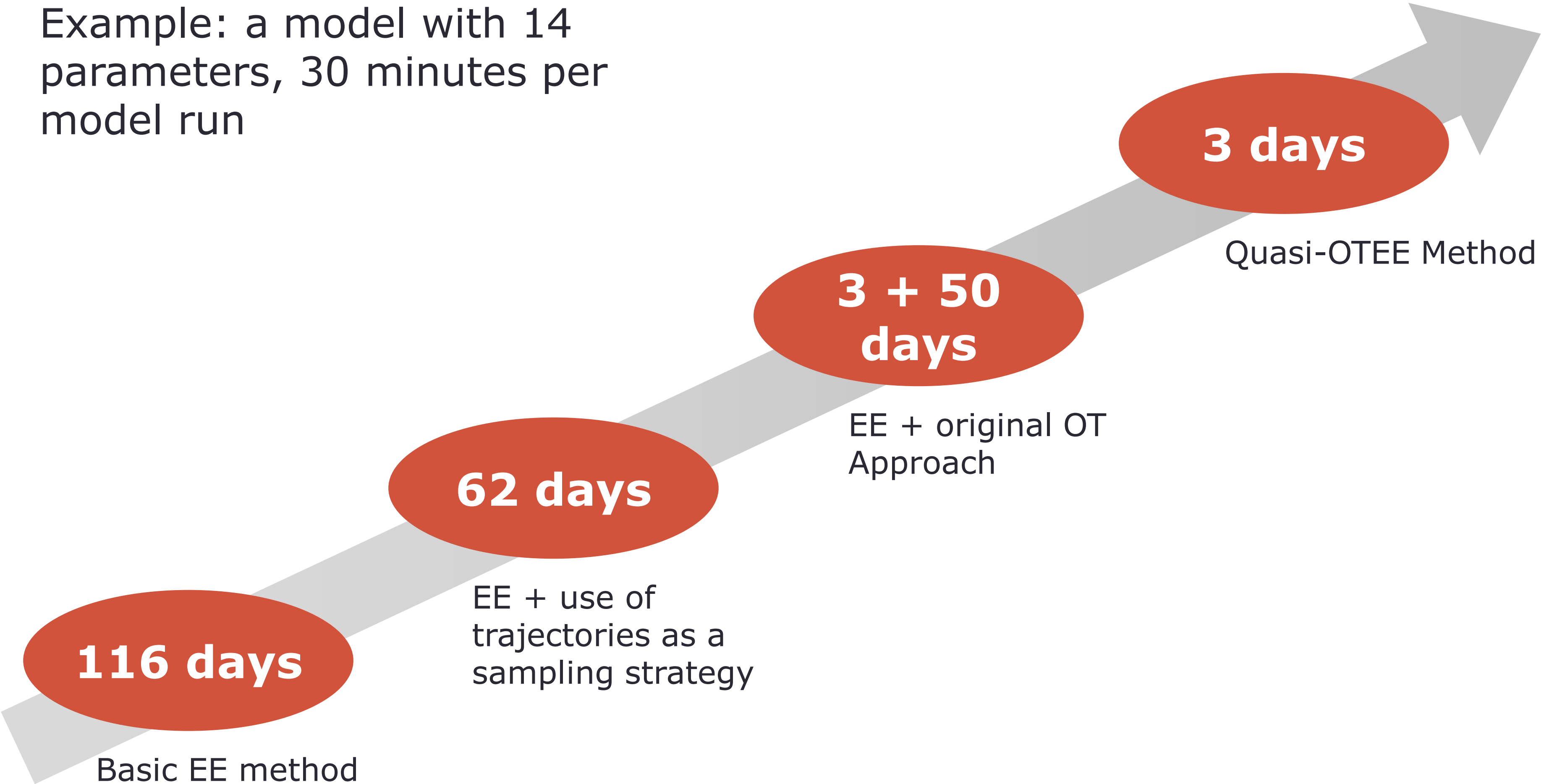
OT Sampling V.S. Quasi-OT Sampling

500 tests of selecting 10 OT / quasi-OT from 20 randomly generated trajectories



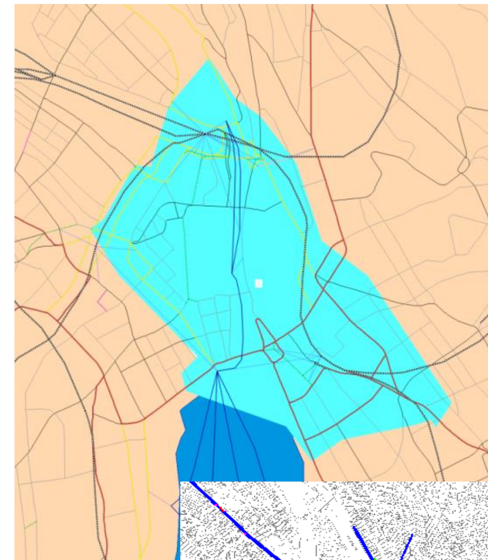
Review of Progress

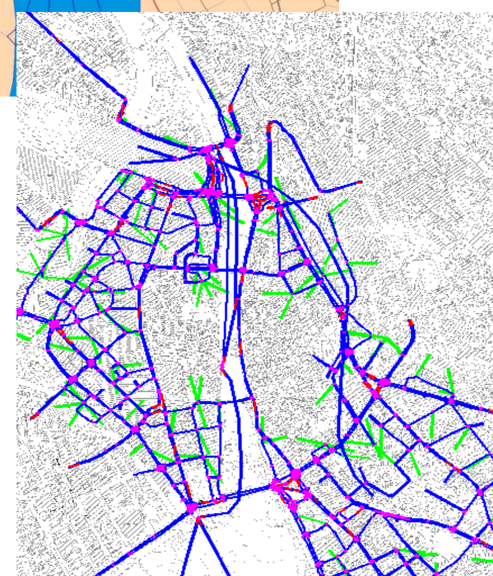
Example: a model with 14 parameters, 30 minutes per model run



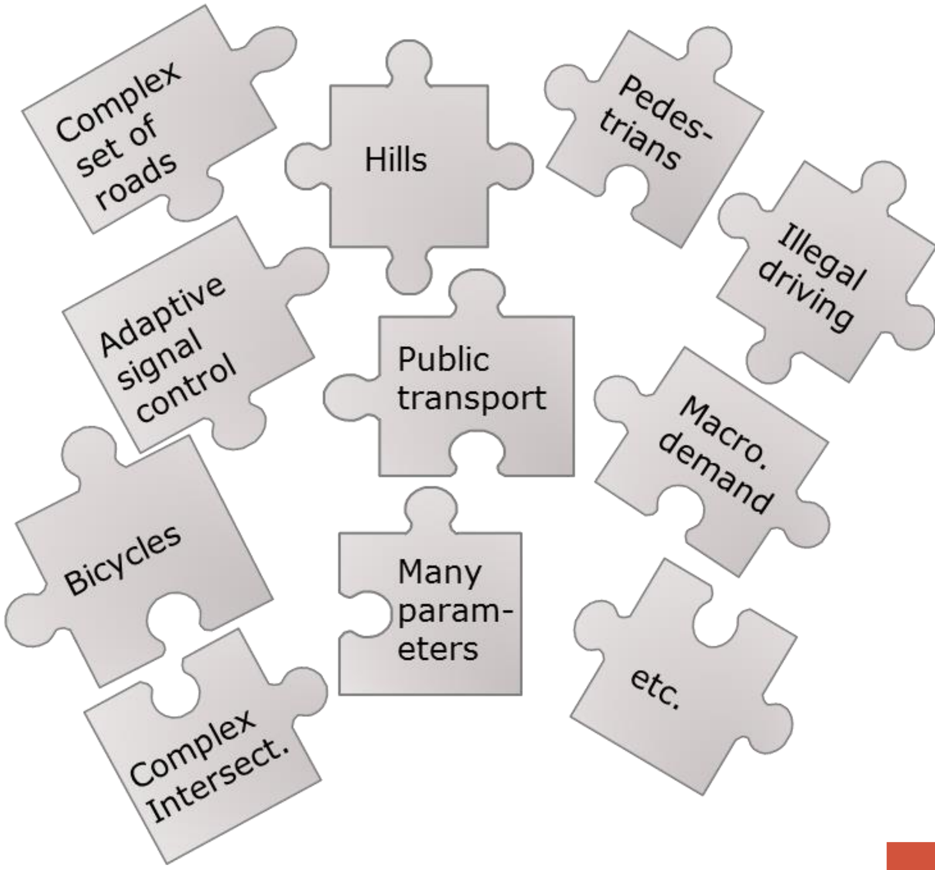
Case Background

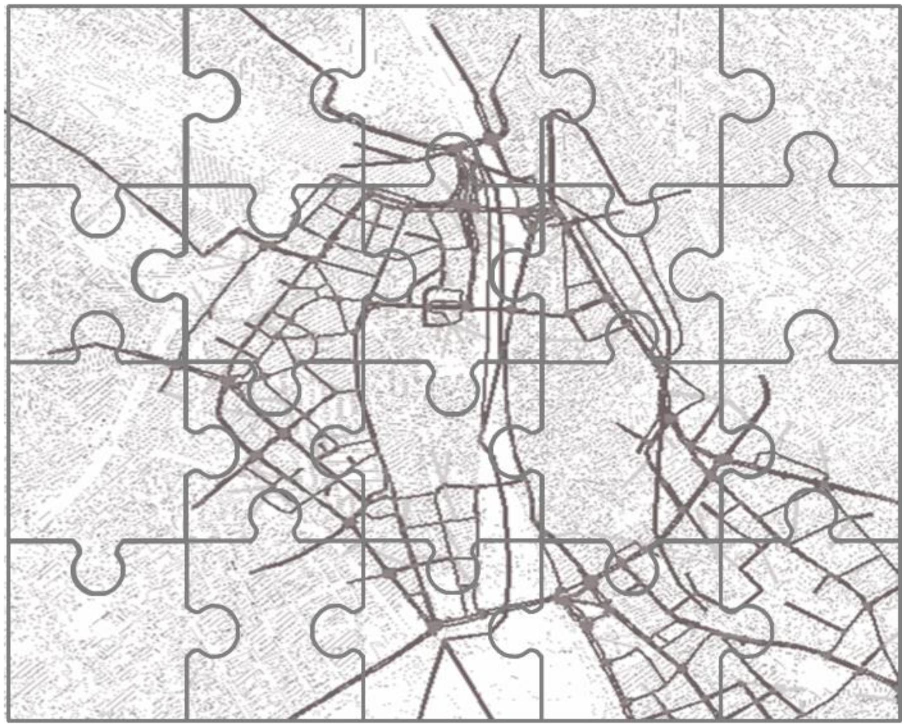
- Study area in VISSIM: inner city of Zurich (around 2.6 km^2)
- Simulation period: 5pm to 6pm
- Warm up period: 900 simulation seconds
- Aim of SA: to identify the parameters with the highest influence on travel time





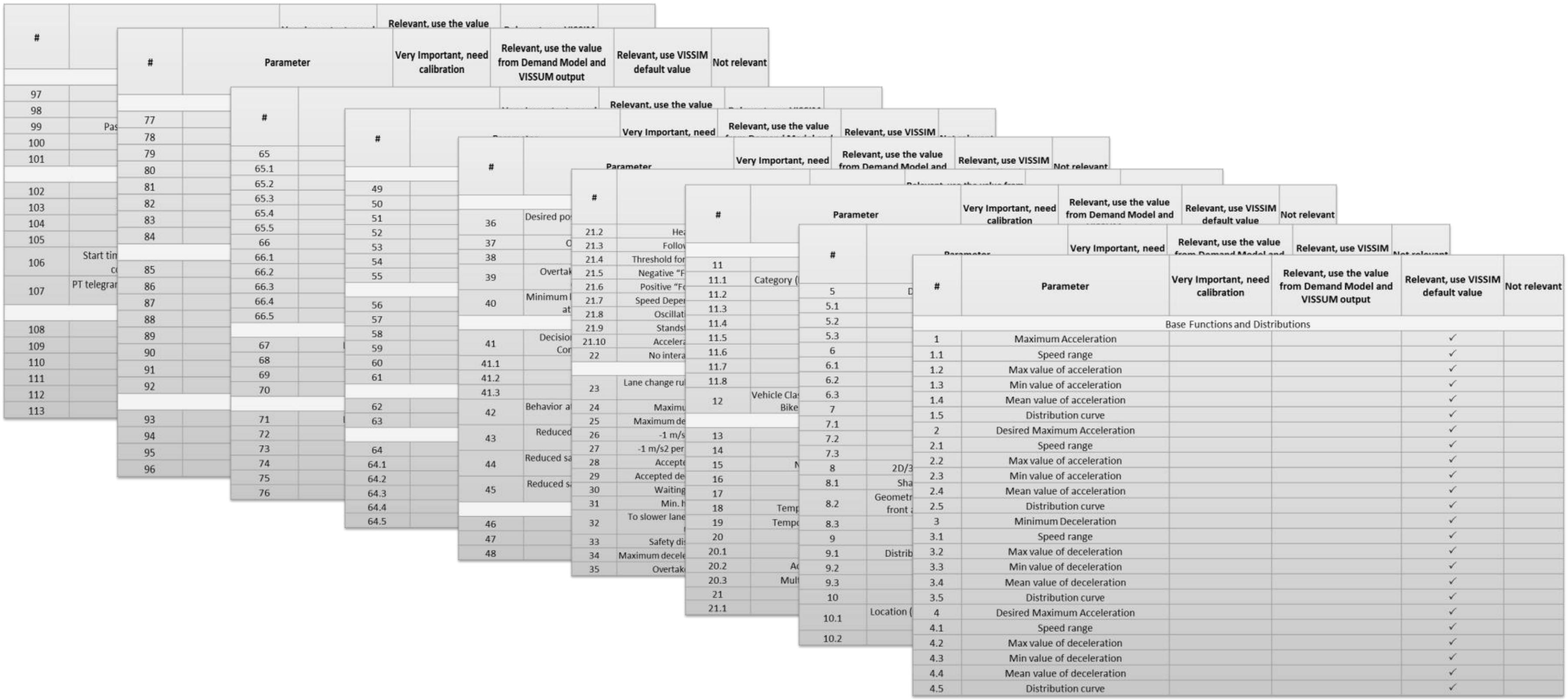
Challenges of the SA





- **192 VISSIM parameters**
- **VISSIM model is complicated and behaves like a black box**
- **Computational cost is very high (> 30 min per simulation run)**

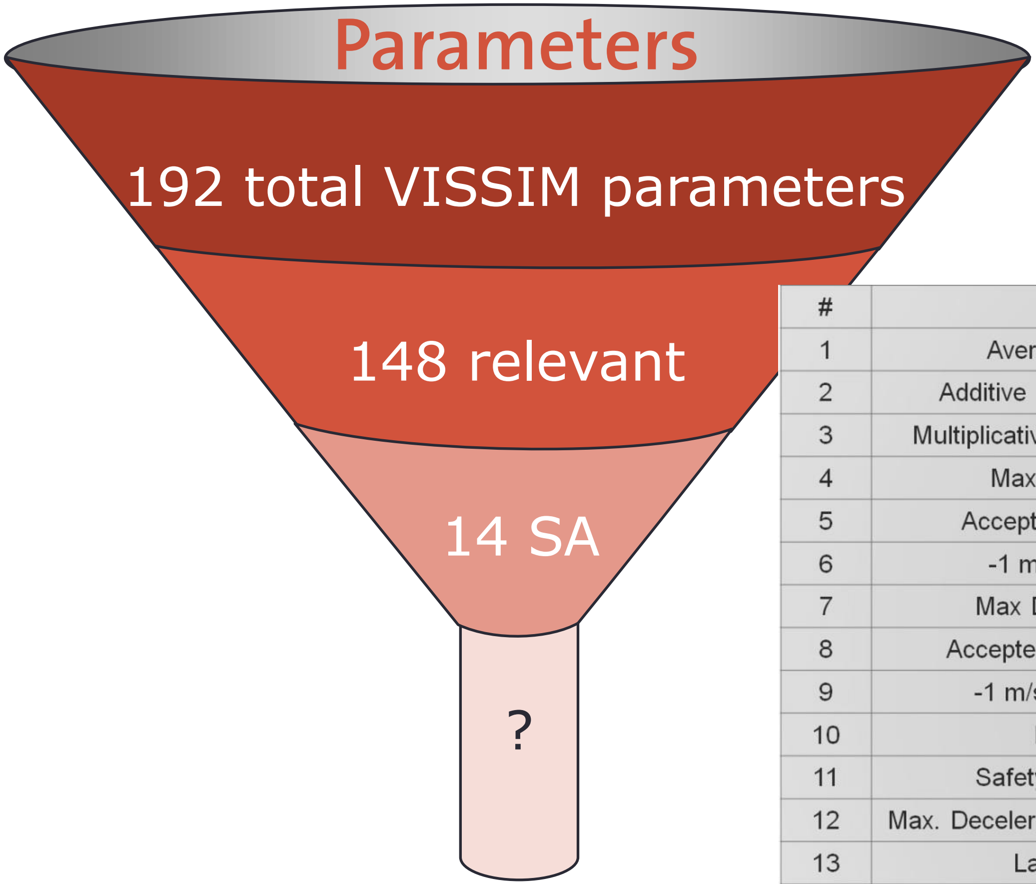
Pre-selection of Parameters (1/2)



#	Parameter	Very Important, need calibration	Relevant, use the value from Demand Model and VISSUM output	Relevant, use VISSIM default value	Not relevant
	Base Functions and Distributions				
1	Maximum Acceleration			✓	
1.1	Speed range			✓	
1.2	Max value of acceleration			✓	
1.3	Min value of acceleration			✓	
1.4	Mean value of acceleration			✓	
1.5	Distribution curve			✓	
2	Desired Maximum Acceleration			✓	
2.1	Speed range			✓	
2.2	Max value of acceleration			✓	
2.3	Min value of acceleration			✓	
2.4	Mean value of acceleration			✓	
2.5	Distribution curve			✓	
3	Minimum Deceleration			✓	
3.1	Speed range			✓	
3.2	Max value of deceleration			✓	
3.3	Min value of deceleration			✓	
3.4	Mean value of deceleration			✓	
3.5	Distribution curve			✓	
4	Desired Maximum Acceleration			✓	
4.1	Speed range			✓	
4.2	Max value of deceleration			✓	
4.3	Min value of deceleration			✓	
4.4	Mean value of deceleration			✓	
4.5	Distribution curve			✓	

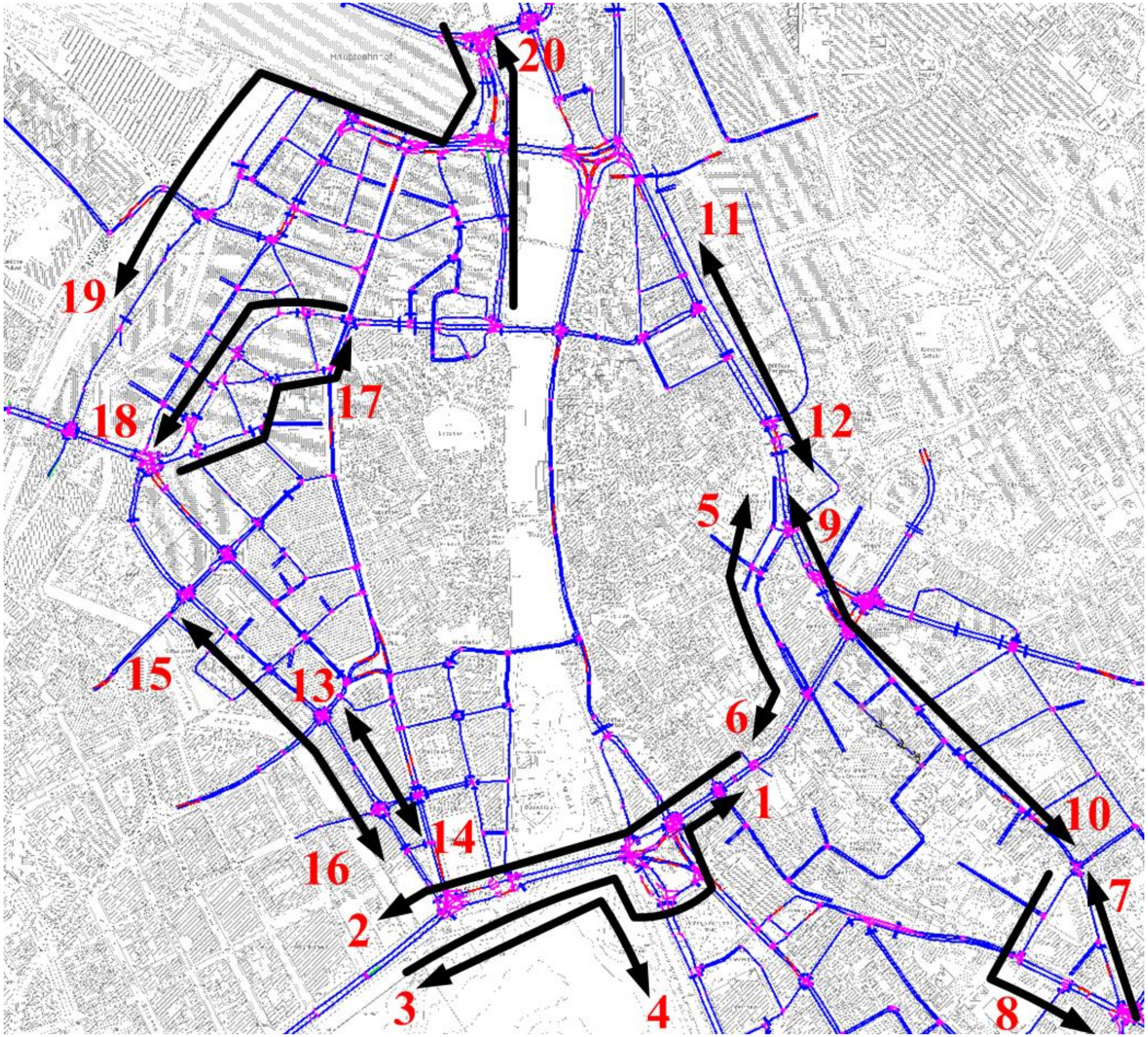
Each parameter was analyzed individually, and categorized according to its relevance within the Zurich model

Pre-selection of Parameters (2/2)



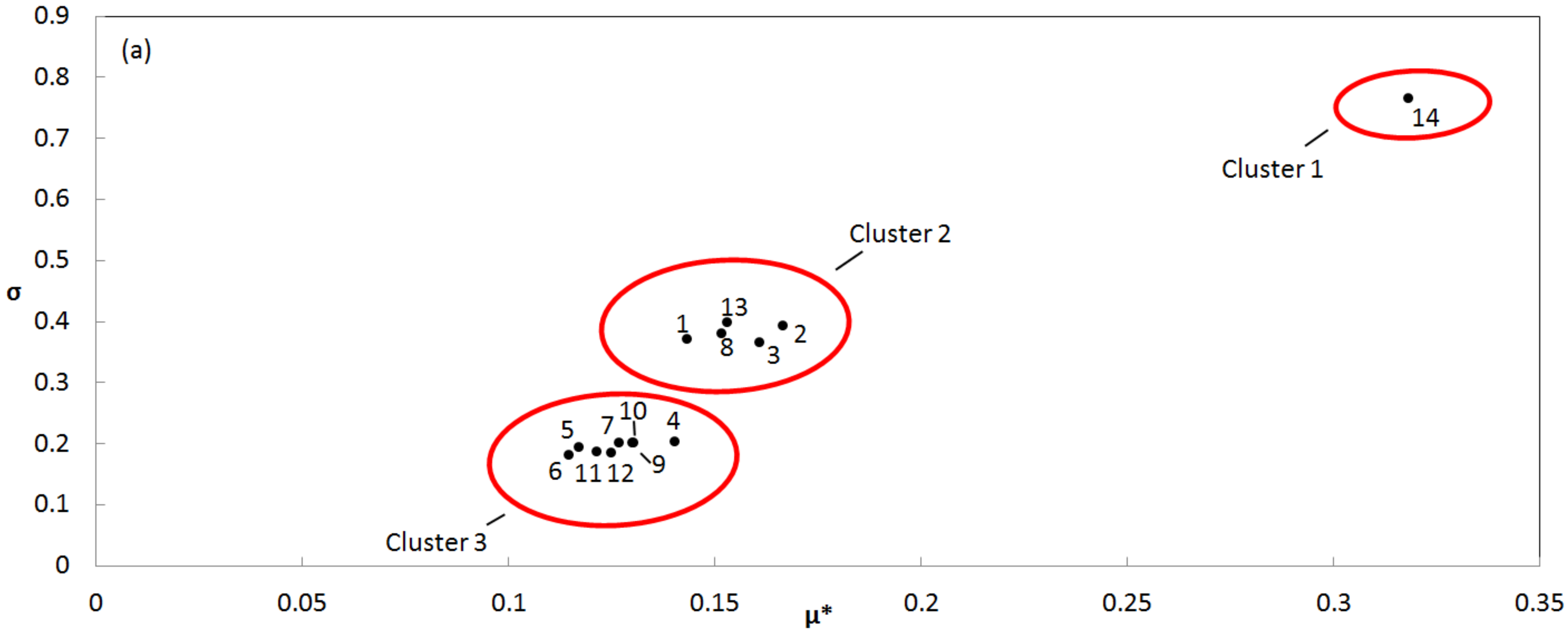
#	Parameters	VISSIM Default	Proposed Range
1	Average Standstill Distance (m)	2	[1, 3]
2	Additive Part of Desired Safety Distance	2	[0, 4]
3	Multiplicative Part of Desired Safety Distance	3	[1, 5]
4	Max Deceleration (Own) (m/s^2)	-4	[-6, -2]
5	Accepted Deceleration (Own) (m/s^2)	-1	[-1.5, -0.5]
6	-1 m/s^2 per Distance (Own) (m)	100	[50, 150]
7	Max Deceleration (Trailing) (m/s^2)	-3	[-5, -1]
8	Accepted Deceleration (Trailing) (m/s^2)	-1	[-1.5, -0.5]
9	-1 m/s^2 per Distance (Trailing) (m)	100	[50, 150]
10	Minimum Headway (m)	0.5	[0.3, 1]
11	Safety Distance Reduction Factor	0.6	[0, 1]
12	Max. Deceleration for Cooperative Braking (m/s^2)	-3	[-5, -1]
13	Lane Change Distance (m)	200	[150, 250]
14	Emergency Stop Distance (m)	5	[3, 7]

Travel Time Measurement in VISSIM



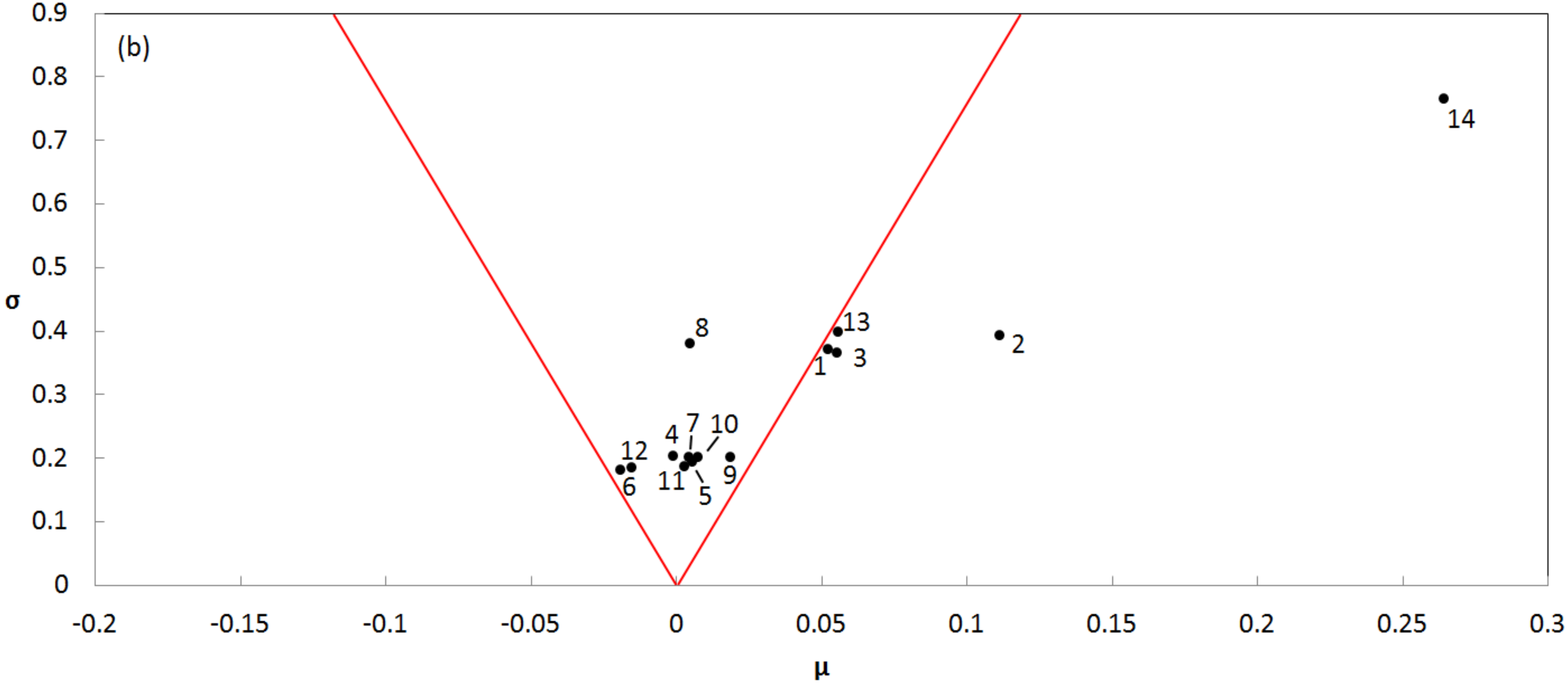
SA Results (1/2)

Plots of μ^* versus σ of the EE for the 14 parameters. The plots are separated into 3 clusters based on the K-Means Clustering.



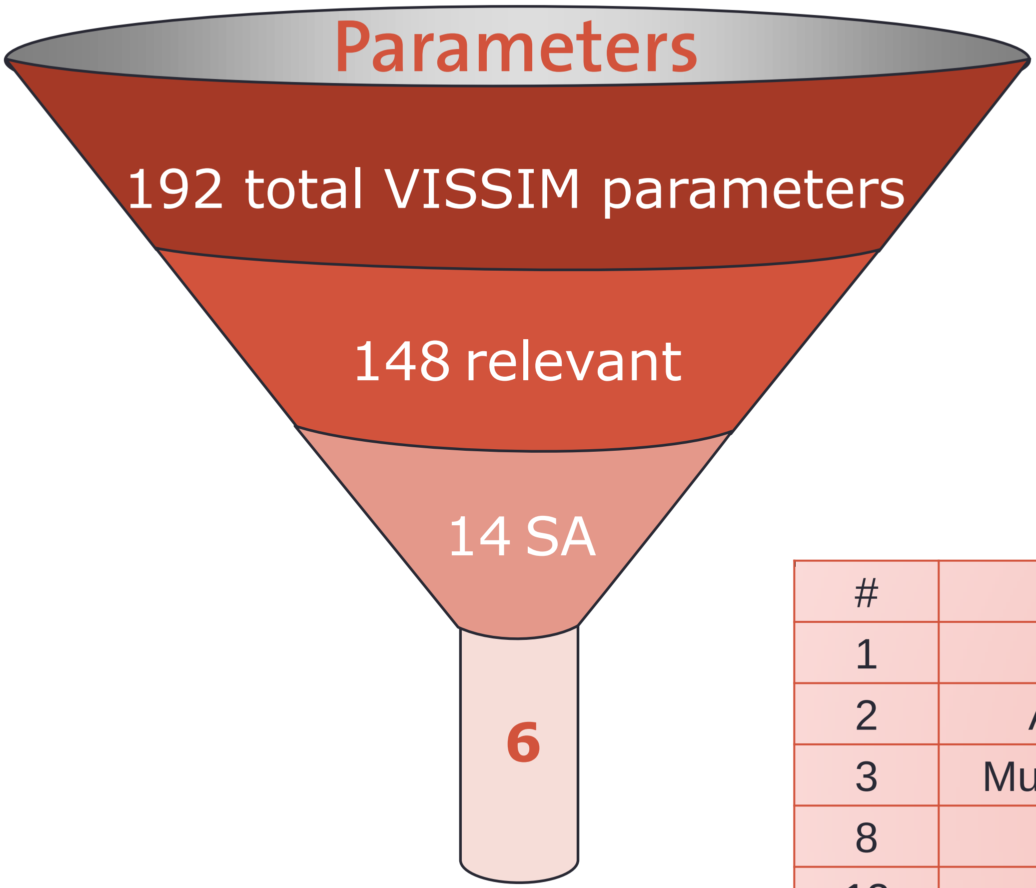
SA Results (2/2)

Plots of μ versus σ of the EE for the 14 parameters. Lines in the figure correspond to $\mu = \pm 2\text{SEM}^*$



*SEM = Standard Error of the Mean = $\sigma/\sqrt{\text{sample size}}$

Parameters for Further Analysis



#	Parameters
1	Average Standstill Distance (m)
2	Additive Part of Desired Safety Distance
3	Multiplicative Part of Desired Safety Distance
8	Accepted Deceleration (Trailing) (m/s^2)
13	Lane Change Distance (m)
14	Emergency Stop Distance (m)

Conclusions

- Quasi-OTEE is an improvement to the EE method with much higher efficiency. In the case study, the time cost was reduced from 116 days to 3 days.
- Quasi-OTEE is a practical and efficient screening tool for computationally expensive microscopic traffic models, as well as other complex models in the wider scientific community.

Potential extensions:

- Converting this approach into a quantitative SA approach based on the same design and sampling process.

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Thank you!