Sensitivity Analysis for Calibrating VISSIM in Modeling the Zurich Network

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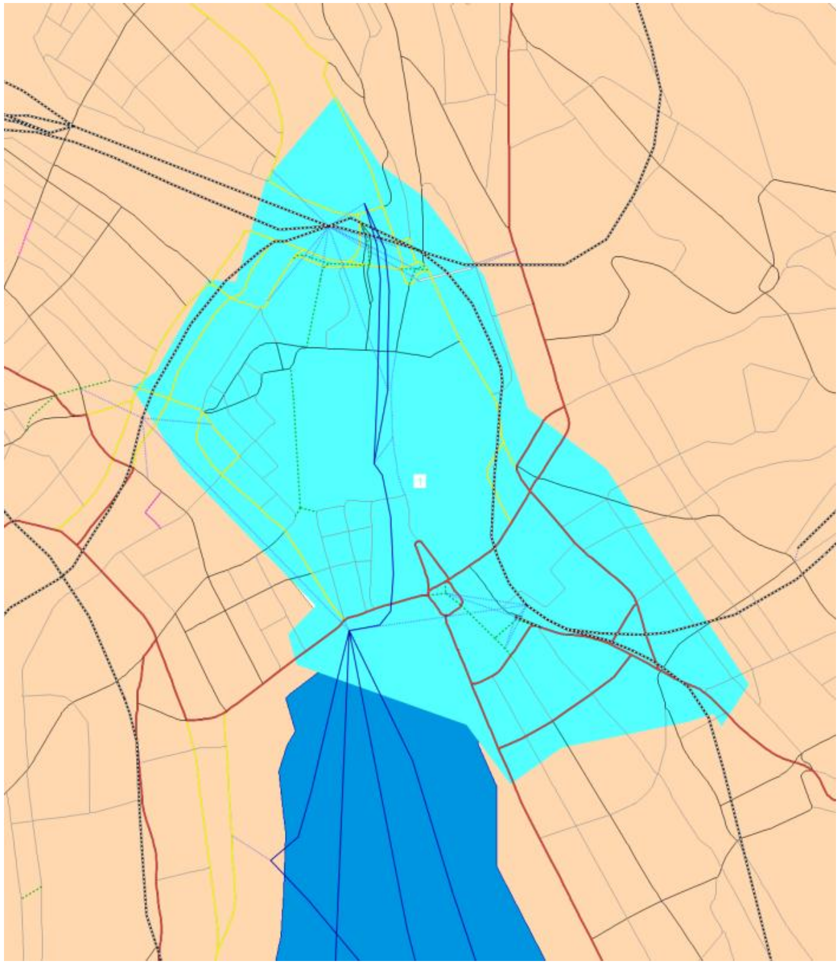
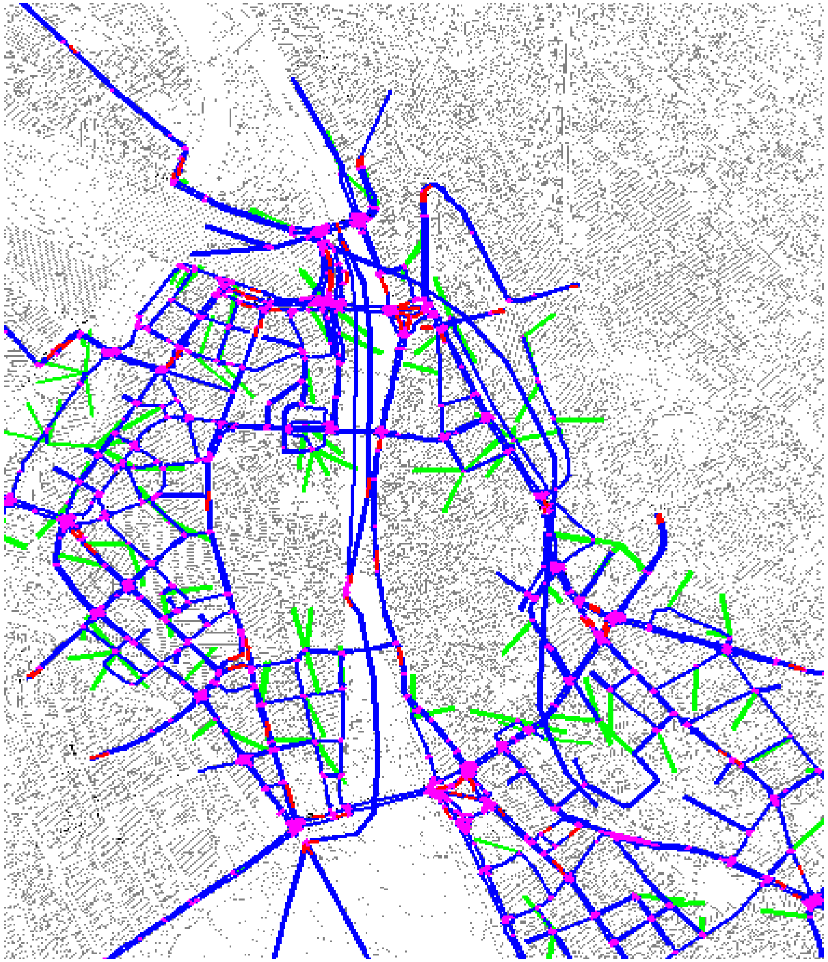
Background

- Project: Calibration Study for VISSIM (CSV)
- Study area: inner city of Zurich (around 2.6 km^2)
- Simulation period: 1-hour in the evening peak (17:00 to 18:00)
- Scope of work: optimize the calibration process, so the City of Zurich could calibrate the VISSIM model in the most efficient way, tailored to its specific needs and requirements.

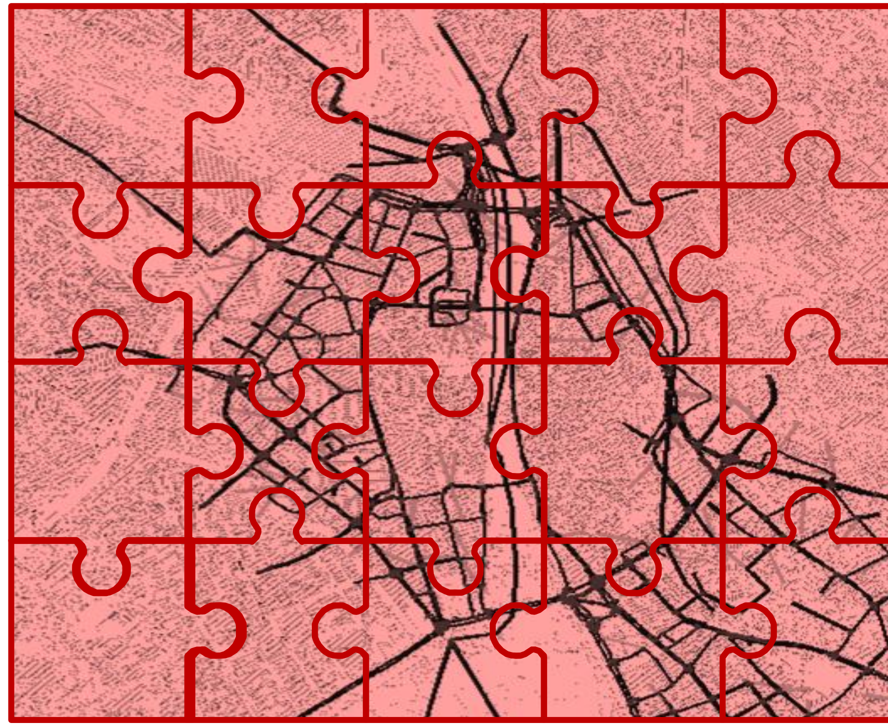
Study Area of CSV





Source: City of Zurich, 2011

Challenges of the Calibration Process



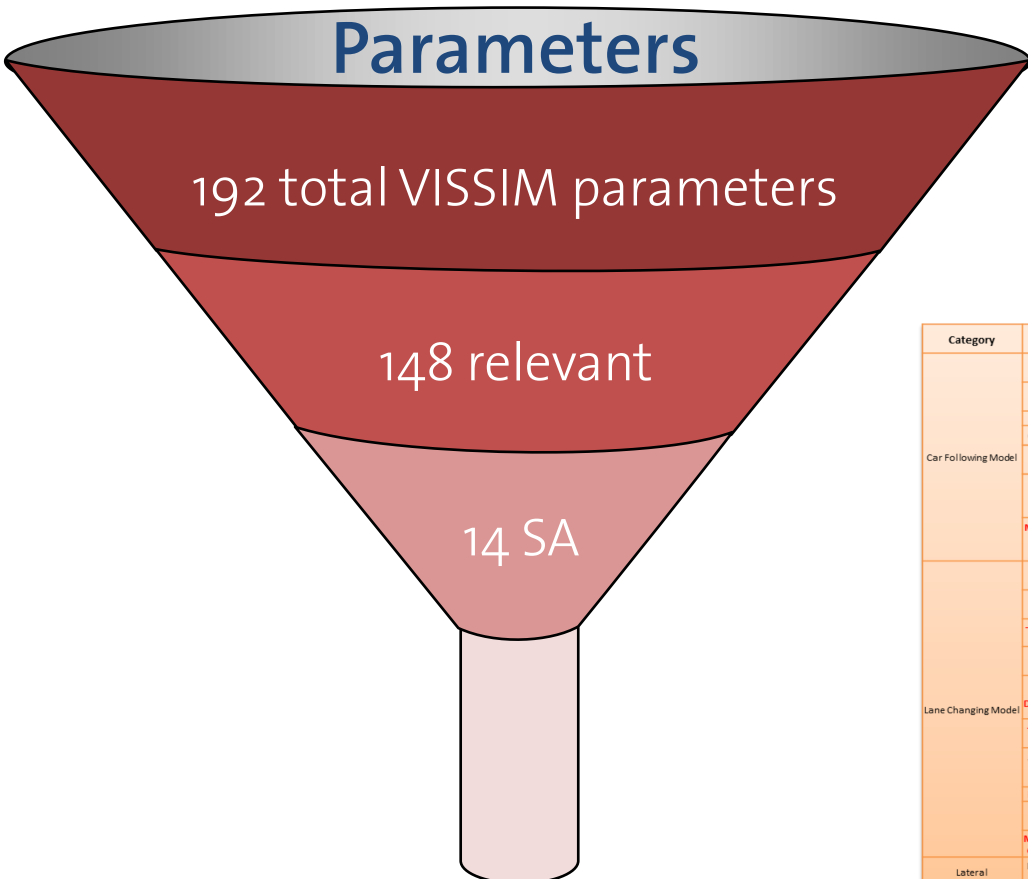
- Computational cost is very high (> 20 min per simulation run)
- The brute-force approach is not feasible for the calibration

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)



Category	Parameters	PTV	TfL	Ahmed	Gomes et al.	Yu et al.	Wu et al.	Park and Schneeberger	Park and Qi	Miller
Car Following Model	Min. Look Ahead Distance	20 to 30 m	30m	ND	ND	ND	ND	ND	ND	N
	Max. Look Ahead Distance	250	ND	ND	ND	273.7	ND	ND	I	ND
	Observed Vehicles	4	ND	4	ND	ND	ND	1 to 4	I	N
	Car Following Model	Wiedemann 74	Wiedemann 74	Wiedemann 74	Wiedemann 99	Wiedemann 74	Wiedemann 99	Wiedemann 74	Wiedemann 74	Wiedemann 74
	Average Standstill Distance (m)	2	1.2	ND	ND	1.6	ND	1 to 3	I	I
	Additive Part of Desired Safety Distance	2	ND	2.25	ND	4.4	ND	ND	I	I
	Multiplicative Part of Desired Safety Distance	3	ND	3.25	ND	3.72	ND	ND	I	I
Lane Changing Model	Max Deceleration (Own)	-4	ND	ND	ND	-4.4	ND	ND	I	I
	Accepted Deceleration (Own)	-1	ND	ND	ND	-0.3	ND	ND	I	N
	-1 m/s^2 per Distance (Own)	100	ND	ND	ND	78.8	ND	ND	I	N
	Max Deceleration (Trailing)	-3	ND	ND	ND	-4.4	ND	ND	I	I
	Accepted Deceleration (Trailing)	-1	ND	ND	ND	-0.3	ND	ND	I	N
	-1 m/s^2 per Distance (Trailing)	100	ND	ND	ND	78.8	ND	ND	I	N
	Waiting Time Before Diffusion	60	ND	ND	60s or 1s	64.2	90s for peak and 45s for none-peak	20, 40, 60	I	N
	Minimum Headway	0.5	ND	ND	ND	1	ND	0.5 to 7	I	I
	Safety Distance Reduction Factor	0.6	ND	ND	ND	ND	ND	ND	ND	I
	Max. Deceleration for Cooperative Braking	-3	ND	ND	ND	ND	ND	ND	ND	I
Lateral	Distance of Standing at 50 km/h	1	ND	ND	ND	1.9	ND	ND	ND	ND
Signal	Amber Signal Decision Model	Continuous Check	ND	Continuous Check	ND	ND	ND	ND	ND	Continuous Check
Connector	Lane Change Distance	200	ND	200	Calibrated separately	ND	300	150-300m	ND	I
	Emergency Stop Distance	5	ND	ND	Calibrated separately	ND	ND	2-7 m	ND	N
Distribution	Desired Speed Distribution	ND	ND	ND	Calibrated separately	ND	ND	ND	ND	I

Introduction of EE Method

The method we developed is based on the *Elementary Effects* (EE) method:

- Qualitative and stochastic approach
- Efficient approach to analyze complex models
- It has been applied with e.g. chemistry and environmental engineering models, but never with a microscopic traffic model

Definition of Elementary Effect

Suppose a model Y has k parameters $[X_1, X_2, ..., X_k]$, the output is:

$$Y(X_1, ..., X_{i-1}, X_i, ... X_k)$$

If X_i changed with Δ, then the EE is defined as:

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

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

By calculating a certain number of EEs for any parameter based on randomly generated inputs, 3 sensitivity indexes can be derived: mean, absolute mean, and standard deviation

Source: Morris, 1991; Campolongo et al., 2006

Sampling Strategy (1/2)

- To calculate the EE for any parameter, the model must be run *twice*, i.e., with the basic point $[X_1, X_2, ..., X_{i-1}, X_i, X_{i+1},..., X_k]$ and the transformed point $[X_1, X_2, ..., X_{i-1}, X_i + \Delta, X_{i+1},..., X_k]$.

- Suppose m EEs are required to calculate the sensitivity indexes for one parameter , we need to run the model ***2m*** times

- The model has k parameters, then in total we need ***2mk*** runs

m=200, k= 14,20 min/run
Total computation time is almost 77 days

Sampling Strategy (2/2)

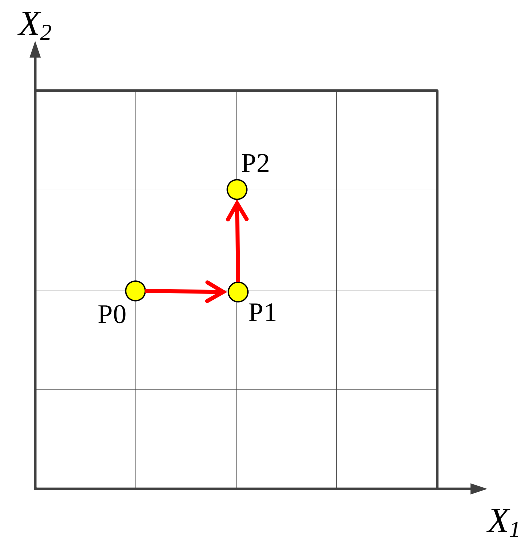
A model with 2 parameters $[X_1, X_2]$

	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, we will get the same amount of EE, but only need ***m(k+1)*** runs.

***m*=200, *k*= 14, 20 min/run**
Total computation time is almost 41 days

Optimized Trajectories (1/2)

Solution:

Reduce the total number of trajectories, but keep as many sample points as possible.

Find an optimized set of trajectories that covers as much as possible the total input space

Source: Campolongo et al., 2006

Optimized Trajectories (2/2)

1. Randomly generate m (e.g. m = 200) trajectories
2. Calculate the Euclidean distance between any 2 trajectories
3. Enumerate all possible sets containing n trajectories from those m random trajectories ($n \ll m$)
4. Compute the total distance D for each trajectory set
5. The set with the longest D is the OT set

n =10, k = 14, 20 min/run
Total computation time for EE is about 2 days

Source: Campolongo et al., 2006

Problem of the Original OT Approach

However:

When m is a large number, the total number of possible trajectory sets N $(= \frac{m!}{n! * (m-n)!})$ could be enormous:

m = 200, n = 10, $N \approx 2 \times 10^{16}$
Total computation time for enumerating is around 50 days

Quasi-Optimized Trajectories

Step 1: Pick the set (named S_1) of $m-1$ trajectories that have the longest Euclidean distance from the original set of m trajectories (named S_0)

Step 2: Pick the set (named S_2) of $m-2$ trajectories which have the maximum dispersion based on S_1

……

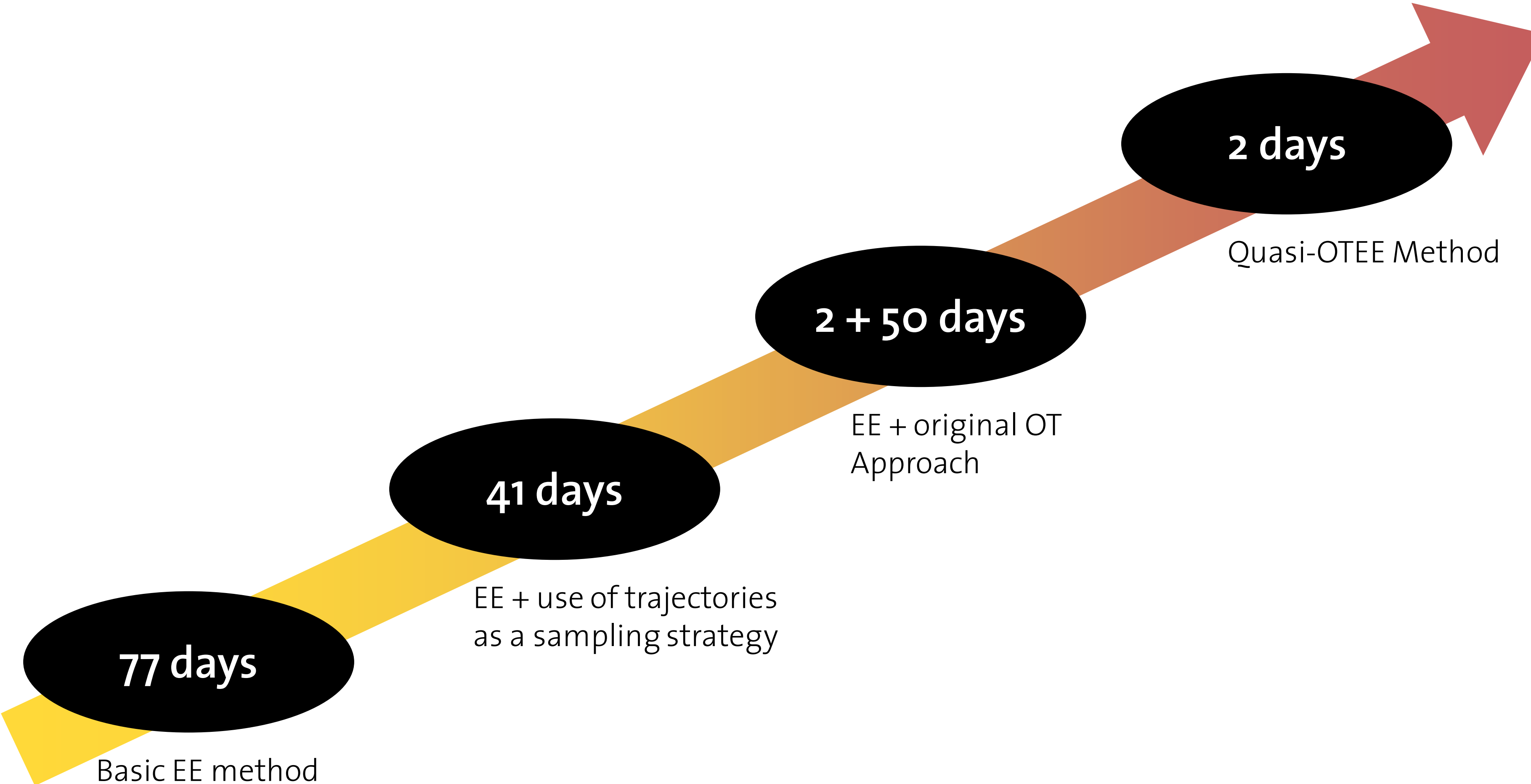
Step m-n: only n trajectories have been left

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

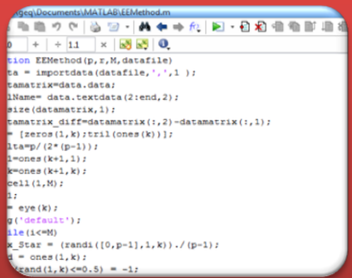
Although the result may not always be identical to the one obtained with the original OT approach, it is a good compromise between accuracy and efficiency.

n=10, m= 200, N=20055
Total computation time is about 15 minutes

Review of Process

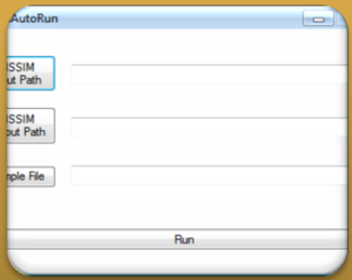


Software Development for SA



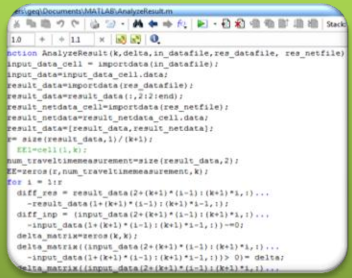
Trajectory Generator (MATLAB)

- Input: range of each parameter (min, max)
- Process: generate trajectories according to quasi-OTEE approach
- Output: sampling trajectories



Automatic VISSIM Simulator (C#.NET)

- Process: change the relevant parameter values in VISSIM input file according to the trajectories; automatically run the simulations
- Output: simulation results for each trajectory

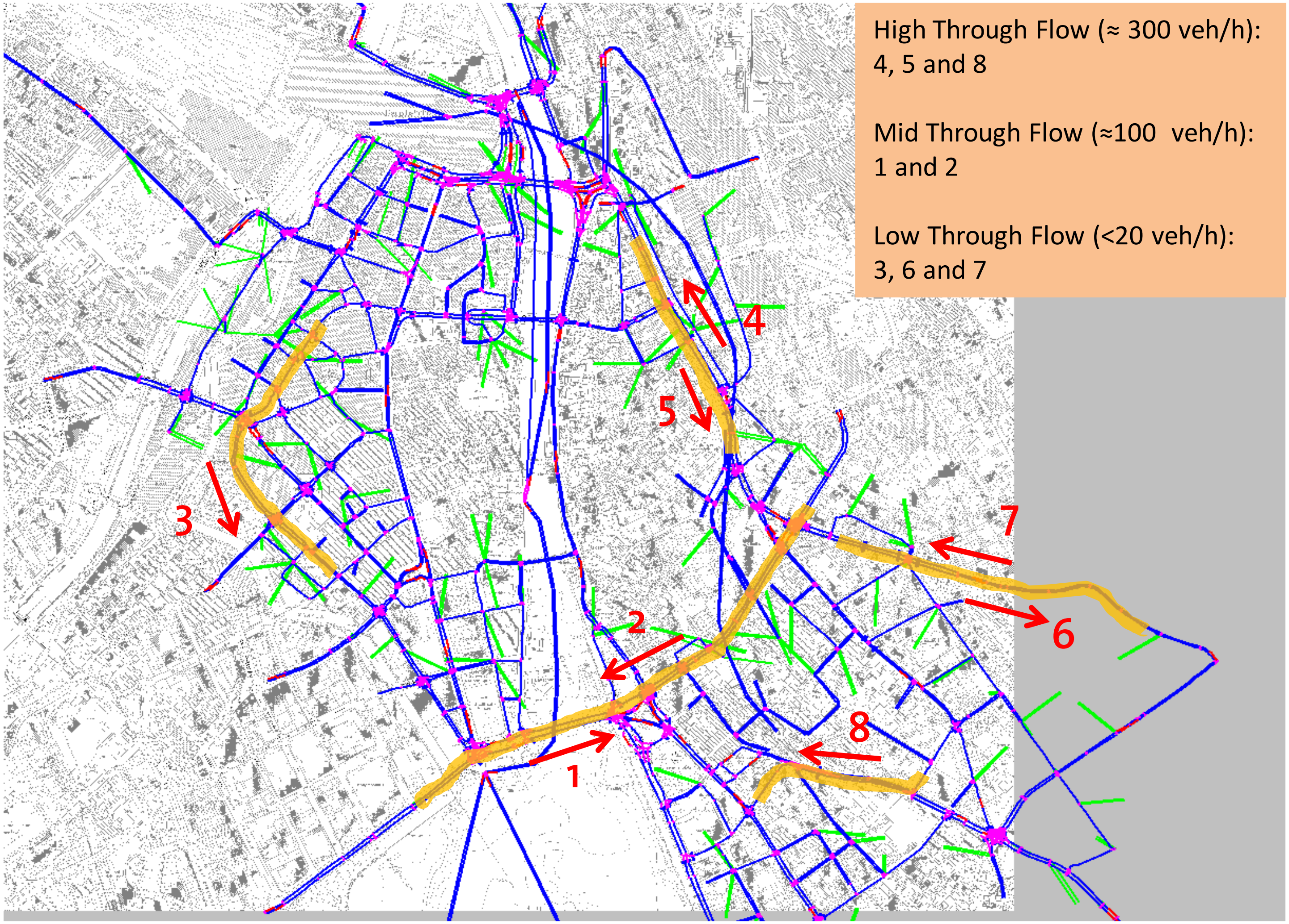


Results Analyzer (MATLAB)

- Process: analyze the sensitivity indexes (mean, absolute mean and standard deviation)
- Output: sensitivity ranking of parameters

Travel Time Measurement in VISSIM

8 travel time measurement sections

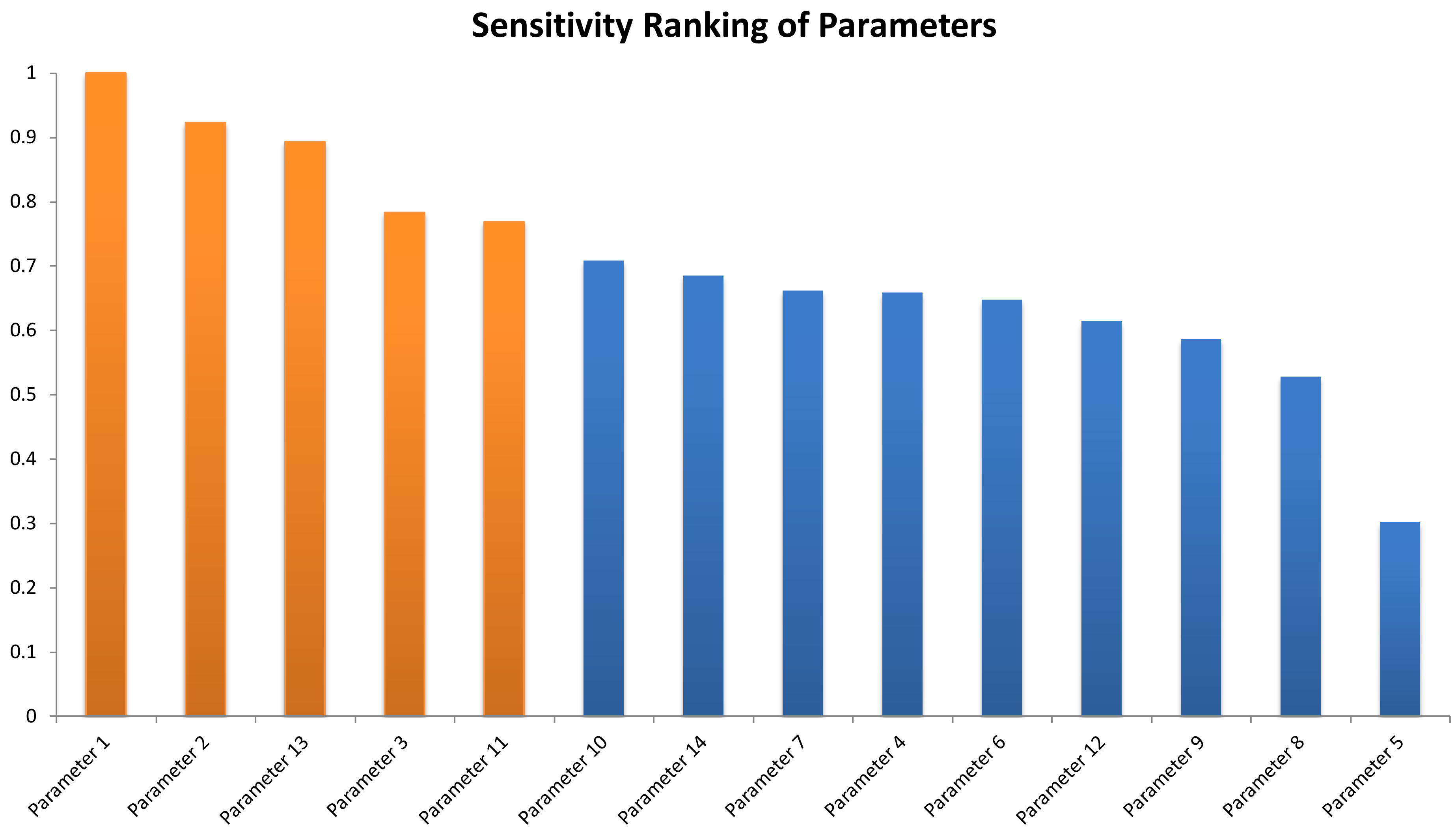


High Through Flow (≈ 300 veh/h):
4, 5 and 8

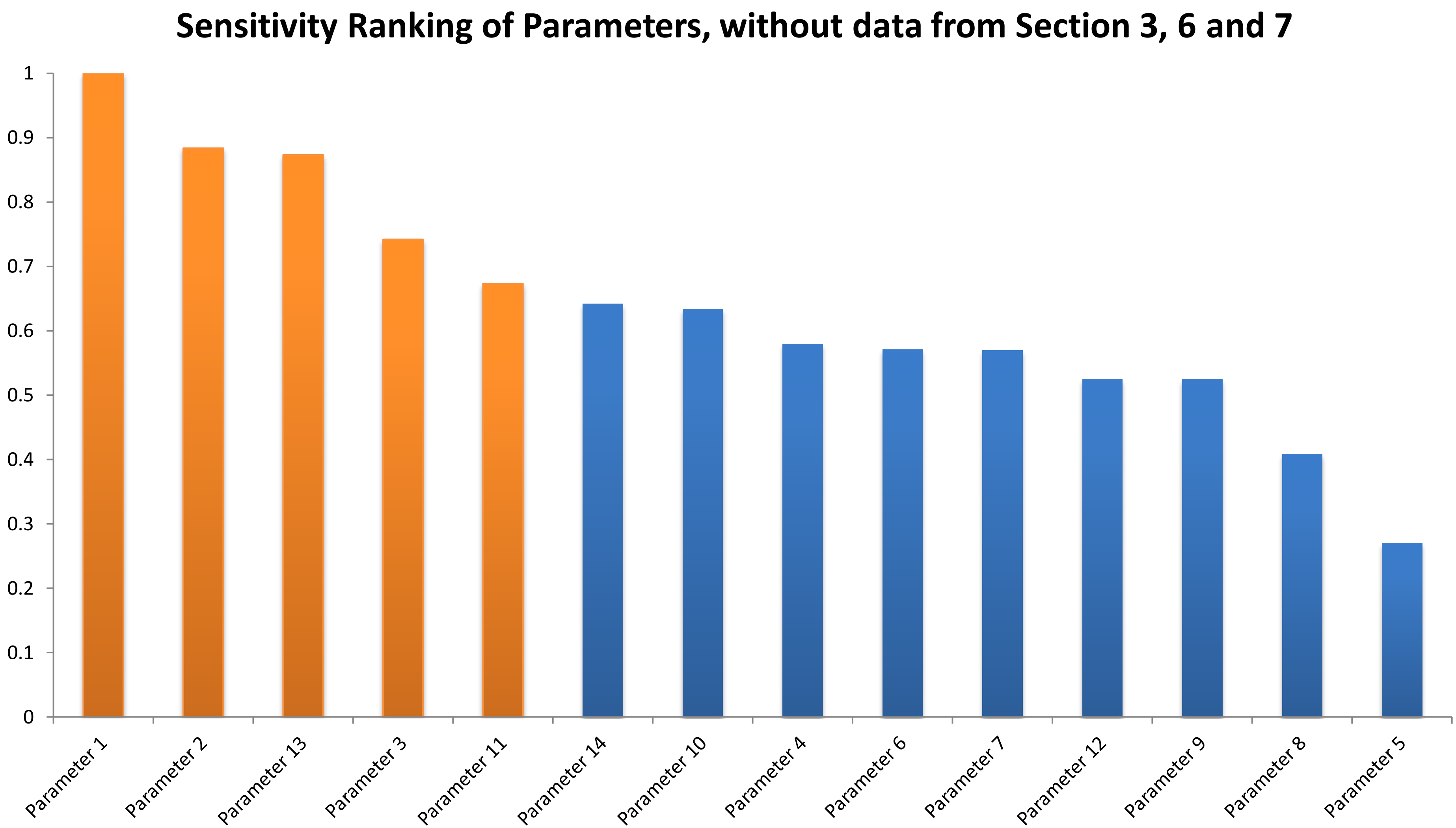
Mid Through Flow (≈100 veh/h):
1 and 2

Low Through Flow (<20 veh/h):
3, 6 and 7

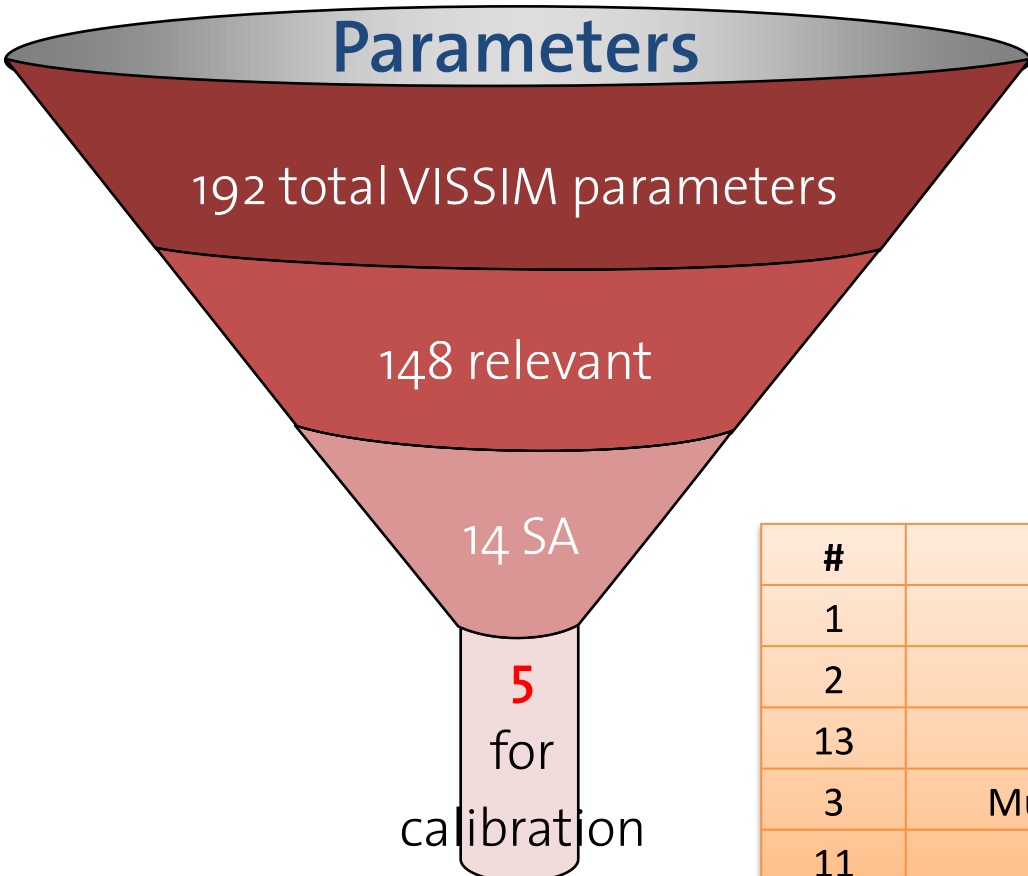
SA Results (1/2)



SA Results (2/2)



Parameters for Calibration



#	Parameters
1	Average Standstill Distance
2	Additive Part of Desired Safety Distance
13	Lane Change Distance
3	Multiplicative Part of Desired Safety Distance
11	Safety Distance Reduction Factor

Conclusions

- The quasi-OTEE method is an improvement to the EE method
- It is efficient to deal with the SA for VISSIM: e.g., the time cost of SA in the CSV project was reduced from 77 days to 2 days
- It is able to identify the most important parameters of a complex model in an accurate way

Potential extensions:

- Optimize the sampling process
- Validate the method under many different scenarios