

# Application framework for global sensitivity analysis in traffic simulation

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**Qiao Ge & Monica Menendez**

“Traffic Engineering” Group (SVT)  
Institute for Transport Planning and Systems (IVT)  
ETH Zurich, Switzerland

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Eidgenössische Technische Hochschule Zürich  
Swiss Federal Institute of Technology Zurich



Institut für Verkehrsplanung und Transportsysteme  
Institute for Transport Planning and Systems

# Introduction

- Sensitivity analysis (SA) studies the relationship between the model inputs and outputs



\*Model input = model parameter, input variable, factor, simulation scenario, etc.

- Global SA:
  - a Monte Carlo approach to analyze the model using random samples taken from the entire input space
  - ✓ SA in the entire input space, able to detect interaction effects, etc.
  - ✗ complicated, lack of guidelines in the context of traffic simulation

# Objective



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- Pragmatic guidance for practitioners
- Reduce the difficulties in implementing state-of-the-art global SA techniques in the context of traffic simulation
- Increase the efficiency and effectiveness of model calibration

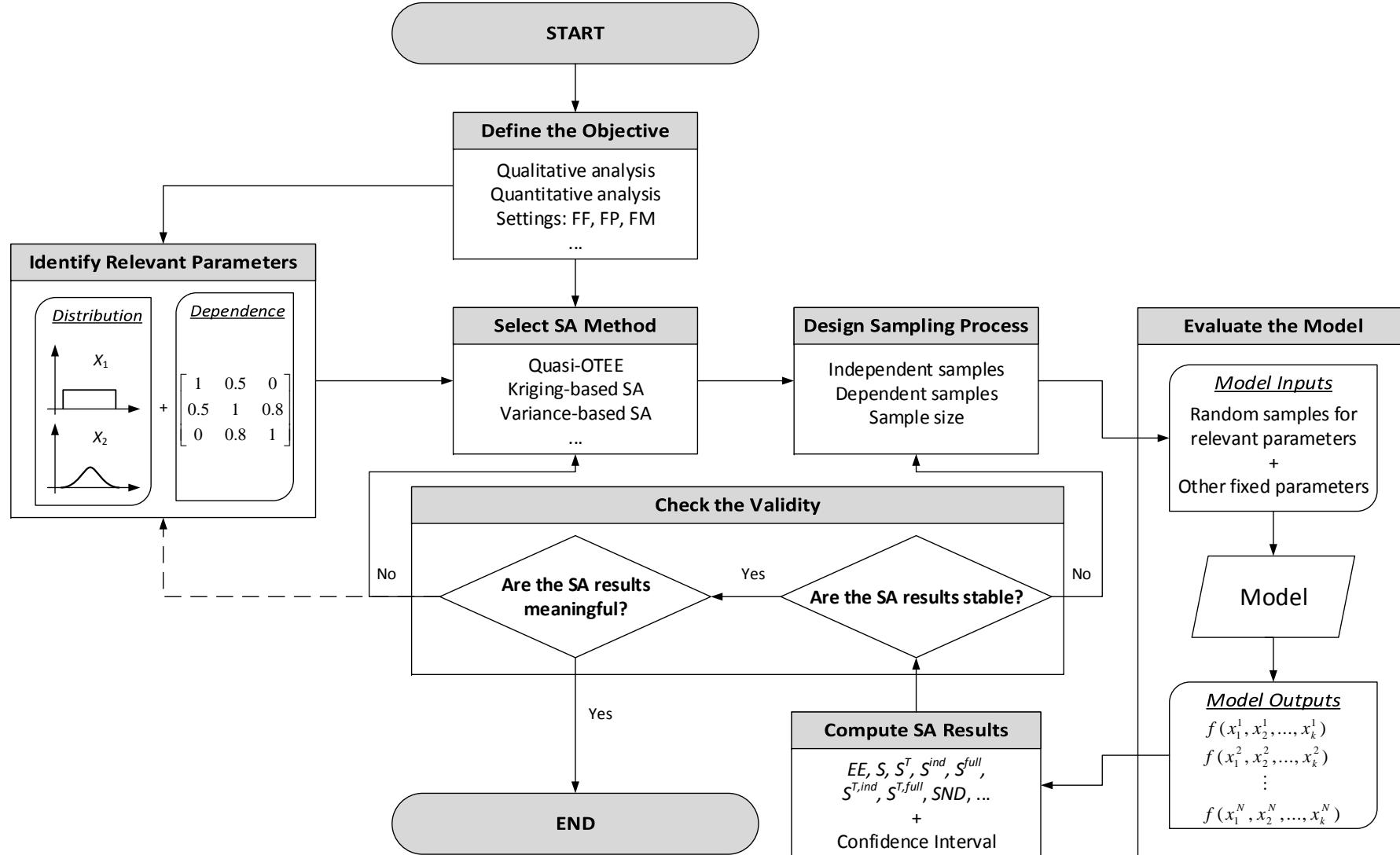
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# Working Steps

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1. Defining the objective of the SA
2. Identifying relevant parameters
3. Selecting the SA method
4. Designing the sampling process
5. Evaluating the model
6. Computing the SA results
7. Checking the validity of the SA results

# Step 1. Defining the objective of the SA

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- The objective decides which **parameters** to be included and which **SA method(s)** to be used
- Three common objectives:
  - Factor fixing: screen ***non-influential*** parameters  
→ high dimensional model (e.g., more than 30 parameters)
  - Factor prioritization: rank ***influential*** parameters  
→ low dimensional model (e.g., less than 10 parameters)
  - Factor mapping: identify ***critical regions*** of the parameters that make the outputs fall beyond certain thresholds

# Step 2. Identifying relevant parameters

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- Relevant parameters

- Based on e.g., features of the simulation model, empirical data, relevant research, common sense, and available experience.
  - Reasonable size: **20~50**

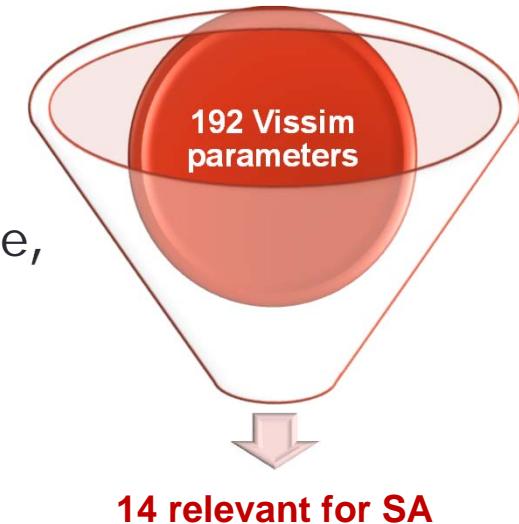
- Distributions

- Assume: ***uniform*** distribution when no a priori information available.  
← **VALIDATION**
  - Avoid: extremely wide or narrow range

- Dependence structure

- Assume: ***independent*** if no a priori information ← **VALIDATION**
  - “independent” parameters could be actually dependent

For example:  $v_{min} < v_{max} \rightarrow v_{max} = v_{min} + \Delta$  with  $\Delta > 0$



14 relevant for SA

# Step 3. Selecting the SA method

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- Factor fixing (qualitative approaches):
  - Quasi-OTEE for independent parameters
  - Extended EE for dependent parameters
  - Parameter grouping (over 50 parameters, 1h per run)
- Factor prioritization (quantitative approaches):
  - Classic variance-based SA
  - Extended variance-based SA for dependent parameters
  - Kriging-based SA (high dimensional model)
  - Sequential SA (screening + variance quantification)
- Factor mapping:
  - Monte-Carlo Filtering (MCF)
- Other methods:
  - Derivative-based SA, regression-based SA (linear model)
  - Scatter plot (< 10 independent parameters)

# Step 4. Designing the sampling process

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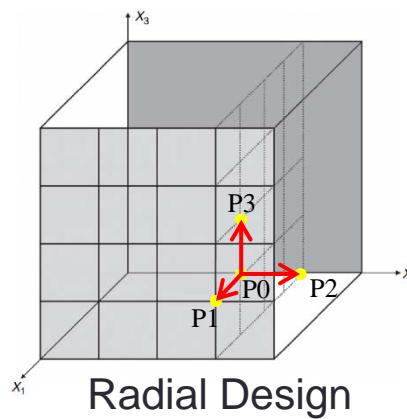
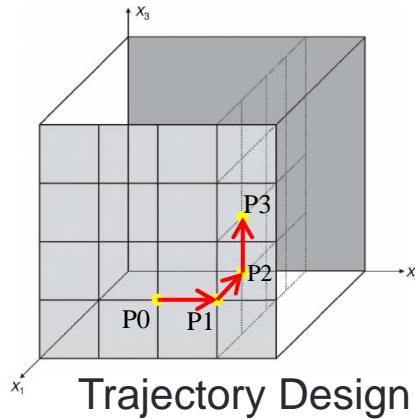
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$$\tilde{\mathbf{X}} = \begin{bmatrix} x_{1,1} & x_{2,1} & \cdots & x_{k,1} \\ x_{1,2} & x_{2,2} & \cdots & x_{k,2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1,N} & x_{2,N} & \cdots & x_{k,N} \end{bmatrix} \rightarrow \text{Model} \rightarrow \tilde{\mathbf{Y}} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} f(x_{1,1}, x_{2,1}, \dots, x_{k,1}) \\ f(x_{1,2}, x_{2,2}, \dots, x_{k,2}) \\ \vdots \\ f(x_{1,N}, x_{2,N}, \dots, x_{k,N}) \end{bmatrix}$$

Independent random samples:



Other Designs:

- Latin Hypercube Sampling (LHS)
- Full factorial (FF) design
- etc.

Dependent random samples:

- Sampling based on copula with known marginal distributions and dependence structure
- etc.

# Step 5. Evaluating the model

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- Model inputs:
  - random samples for the relevant parameters
  - fixed values for the non-relevant parameters
- Computer program to run the model automatically
- Model outputs:
  - in accordance with the ***Measure of Performance*** (MoP)  
in calibration: time series of speeds and counts, headways, queue length and turning flows at intersections, network travel time, and vehicle trajectories
  - single output / multiple outputs

# Step 6. Computing the SA results

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- SA results:
  - Elementary effects
  - Sensitivity index for independent parameters
  - Sensitivity index for dependent parameters
  - Sigma-Normalized Derivatives (SND)
  - Regression coefficients
  - etc.
- Confidence interval of the SA results:  
e.g., 90% Bootstrap Confidence Interval (BCI)

# Step 7. Checking the validity of the SA results



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- 1) Check if the results are stable:
  - wide BCI = results are not stable  
→ use a larger sample size
  - rule-of-thumb: BCIs of the most sensitive parameters should be less than **10%** of the corresponding sensitivity indexes
- 2) Check if the results are meaningful and making sense for the traffic model:
  - adjust the set of relevant parameters
  - adjust the assumption of distribution / dependence structure
  - use other SA method
  - etc.

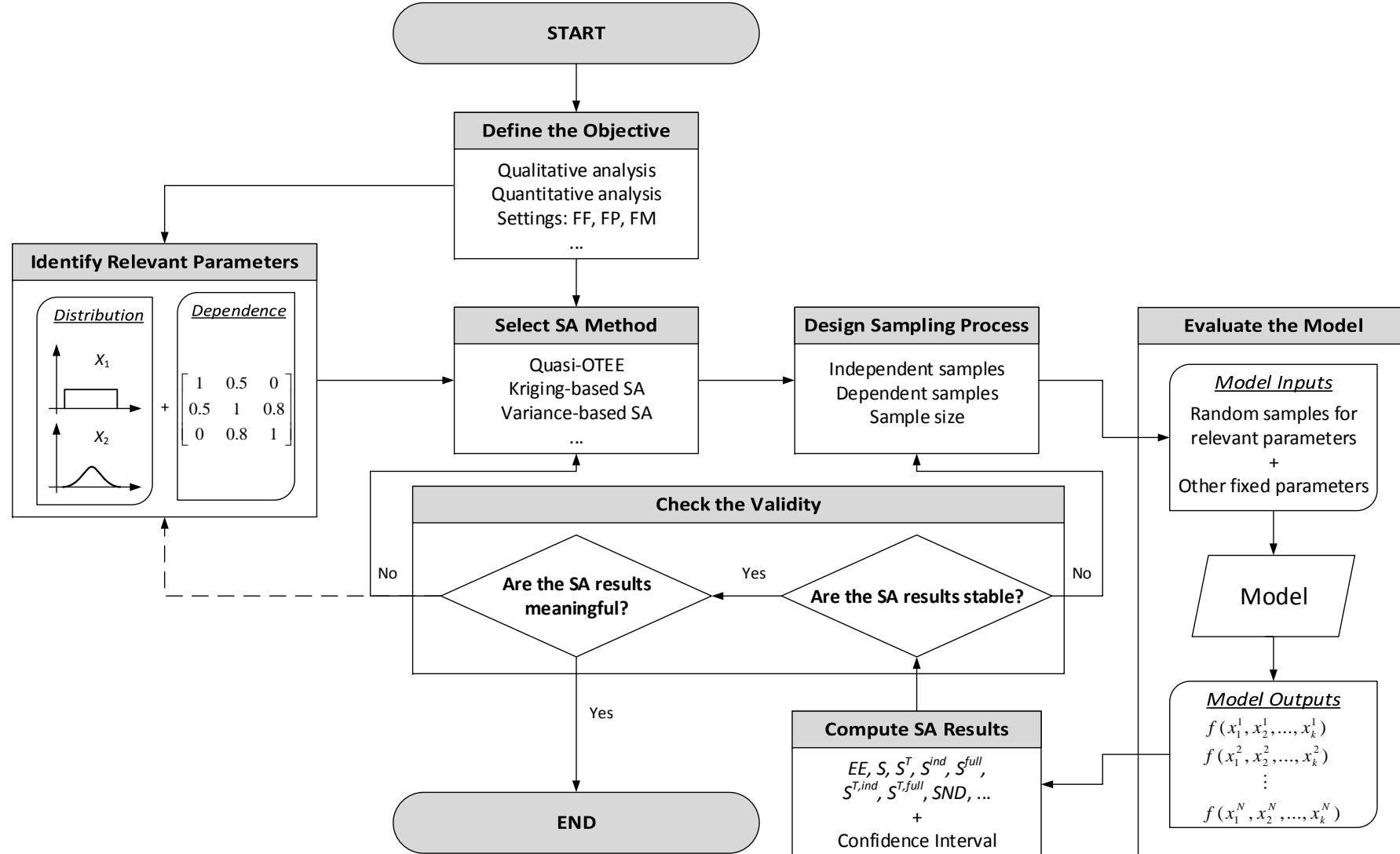
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# Wiedemann-74 car-following model



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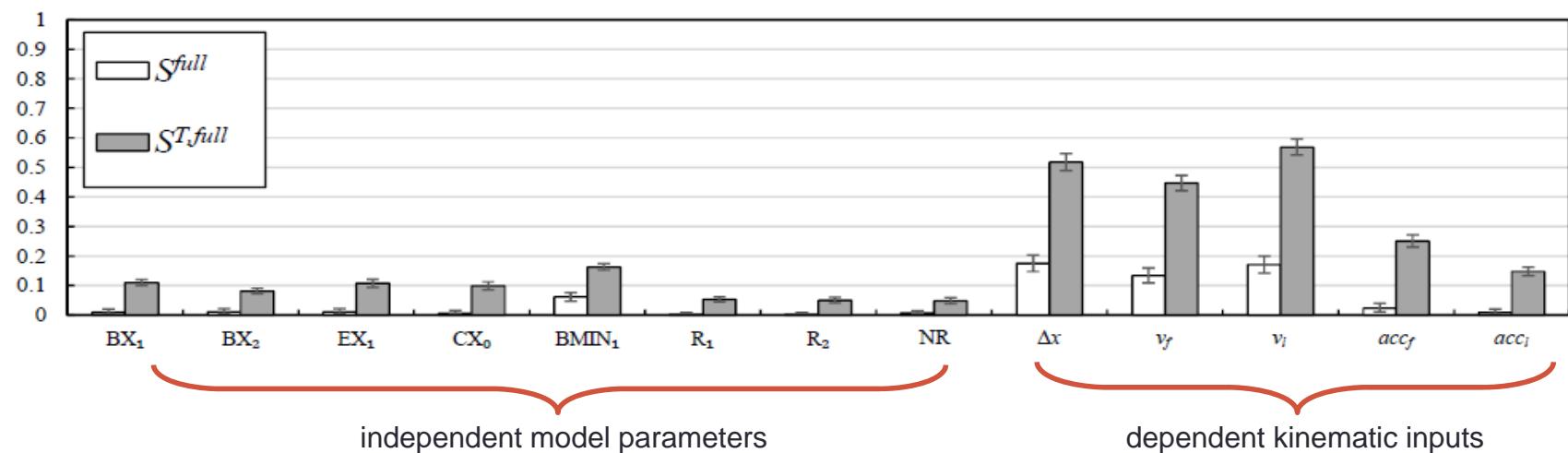
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24 independent model parameters + 5 dependent kinematic inputs

#	Objective	SA Method	Result	Cost
1	Screening non-influential independent parameters	Quasi-OTEE + parameter grouping	12 indep. parameters + 1 group (5 dep. parameters)	2,600
2	Screening non-influential independent & dependent parameters	Extended EE method for dependent parameters	8 indep. + 5 dep. parameters	13,000
3	Parameter ranking	Extended variance-based SA	see below	26,624



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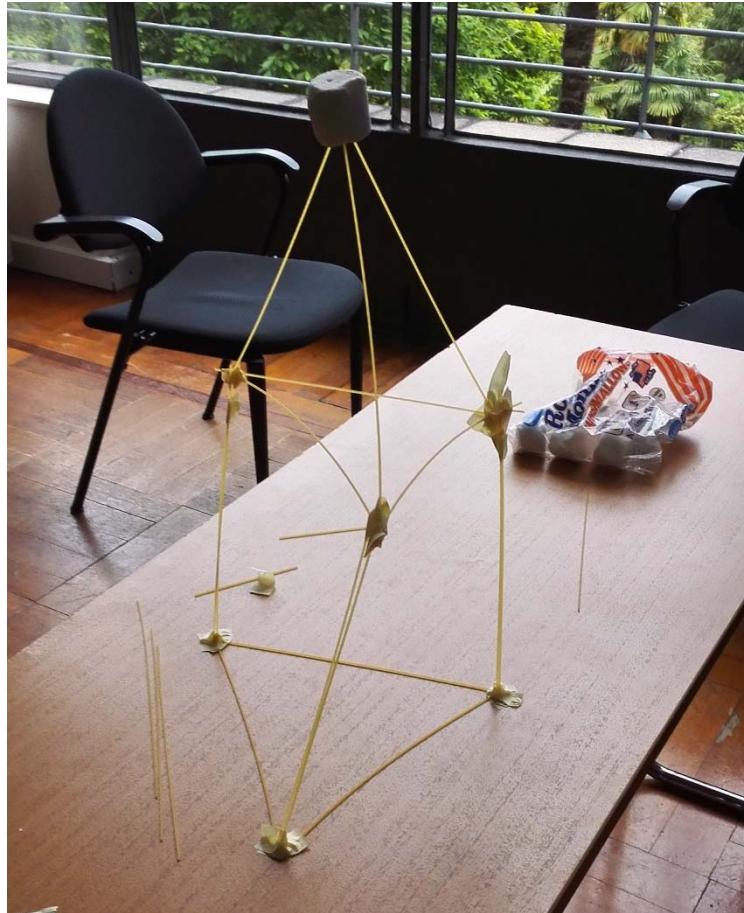
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- A general application framework to support the use of global SA in the calibration of traffic simulation models.

7 working steps that cover multiple important issues in the SA practice.

- Future work:  
combining other techniques such as simulation-based optimization in the traffic model calibration



*Thank you for  
your attention!  
Questions?*

[qiao.ge@ivt.baug.ethz.ch](mailto:qiao.ge@ivt.baug.ethz.ch)