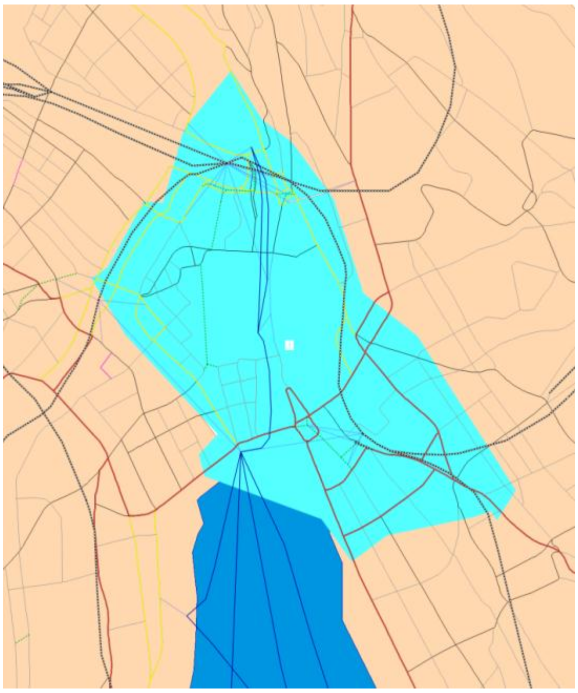 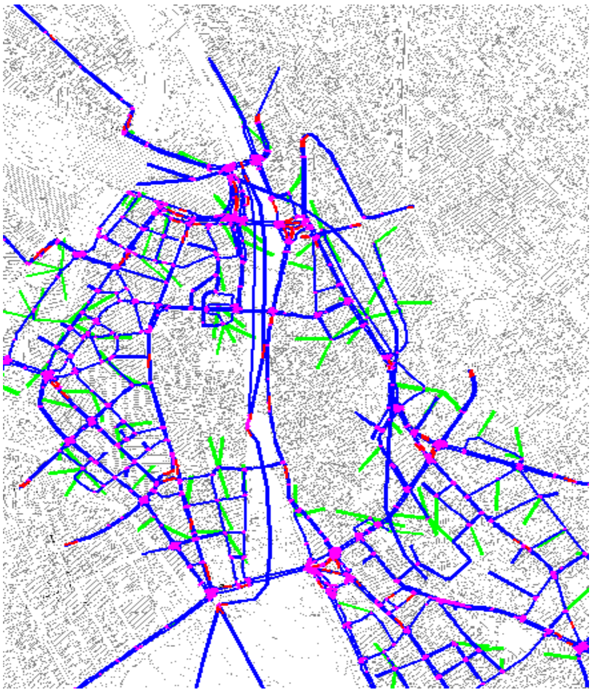

Sensitivity Analysis for Calibrating VISSIM in Modeling the Zurich Network

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Abstract

In the last few decades microscopic traffic simulation has grown into a major resource for the researchers and practitioners in the field of traffic engineering. The use of commercial traffic simulators (i.e., software) has become widespread, and these programs have indeed become necessary tools for planning and designing transportation networks. In order for a traffic simulator to accurately describe reality, it must be supported by a valid traffic model, and it must be properly calibrated.

VISSIM is one of the most widely used microscopic traffic simulators with many applications and high potential. However, like other commercial microscopic traffic simulators, VISSIM has a very large number of input parameters which makes the model calibration rather difficult. In addition, if the spatial scope of the modeled network is quite large, the calibration will usually be very time consuming. In order to overcome these difficulties, a Sensitivity Analysis (SA) is essentially required as a preliminary step for the model calibration. Through SA the modeler can obtain a better knowledge about the relationship between the model inputs and outputs, and hence focus on the most important parameters for further calibration.

This paper is based on a research project to calibrate the VISSIM network model for the inner city of Zurich. The complex network of the inner city makes the computational cost of running the simulation very expensive. Therefore it does not allow using a brute force approach to do the SA. An improved SA method, which is based on the Elementary Effects method, was proposed and applied in this project. This method reduced the computation time required for the SA from 77 days to 2 days for this specific case. The results are presented in this paper. They show that the proposed method is accurate and efficient, especially for dealing with the SA of complex VISSIM networks.

Keywords

Sensitivity Analysis, Elementary Effects Method, Microscopic Traffic Simulation, Network Model Calibration

1. Introduction

In the last few decades traffic simulation has grown into a major resource for the researchers and practitioners in the field of traffic engineering. The use of commercial traffic simulators (i.e., software) has become widespread, and these programs have indeed become necessary tools for planning and designing transportation networks. This, of course, assumes that the model can accurately and efficiently represent the interaction that occurs between drivers, vehicles and the environment, which is essential for both traffic planning and operation applications.

In order for a traffic simulator to accurately describe reality, it must be supported by a valid traffic model, and it must be properly calibrated. A traffic model is considered valid if it reflects the real world operations in a reasonable way (e.g., how vehicles move in a road, how they change lanes, etc.). In other words, the rules within the model must be coherent, and for most of the cases, make physical sense. Calibration, on the other hand, implies that the input parameters (e.g., driving behavior, desired speed, etc.) allow the model to recreate the specific network under certain circumstances (i.e., replicate observations, field measurements, and other empirical data). This step is vital, but can be rather complex. Such complexity is driven by the fact that not two networks are ever the same, and typical traffic simulators usually have many parameters to cover all those differences. Moreover, a large number of these parameters are often unobservable in the field and/or really hard to measure.

VISSIM (Verkehr In Städten – SIMulationsmodell in German) is one of the most widely used traffic simulators with many applications and high potential. It is a microscopic, time step and behavior-based simulation model developed by PTV AG from Germany (PTV, 2011). It is mostly used for modeling and analyzing urban and inter-unban traffic, although it is also capable of modeling other transport modes (e.g., public transportation, pedestrians, etc.). The widespread use of VISSIM has driven huge advances in the development of the software, and the complexity of the program has been simultaneously increased greatly. One drawback of such increase in complexity is, among others, the multiplicity of parameters contained within VISSIM. The huge number of parameters has made the model calibration rather difficult. In addition, when the spatial scope of the modeled network is quite large, the calibration will usually be very time consuming. Furthermore, the lack of standard calibration procedures and guidance for traffic models in general (MULTITUDE, 2011a) makes the calibration a very tedious process. As a matter of fact, a recent survey carried out within the European COST Action TU0903 (Punzo, 2011) indicates that many VISSIM users are not able to use guidelines or scientific publications (see Figure 1) when calibrating their models. Survey results also show that a great potion of VISSIM users have to adopt “manual trial and error” as the standard method for model calibration (see Figure 2) instead of an automatic optimization by computers, a far more efficient and accurate method.

Figure 1 Survey results: use of guidelines or scientific publications to guide the calibration of VISSIM (Source: Punzo, 2011)

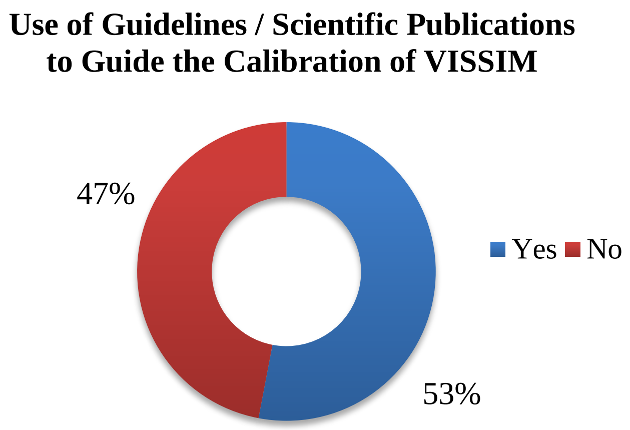
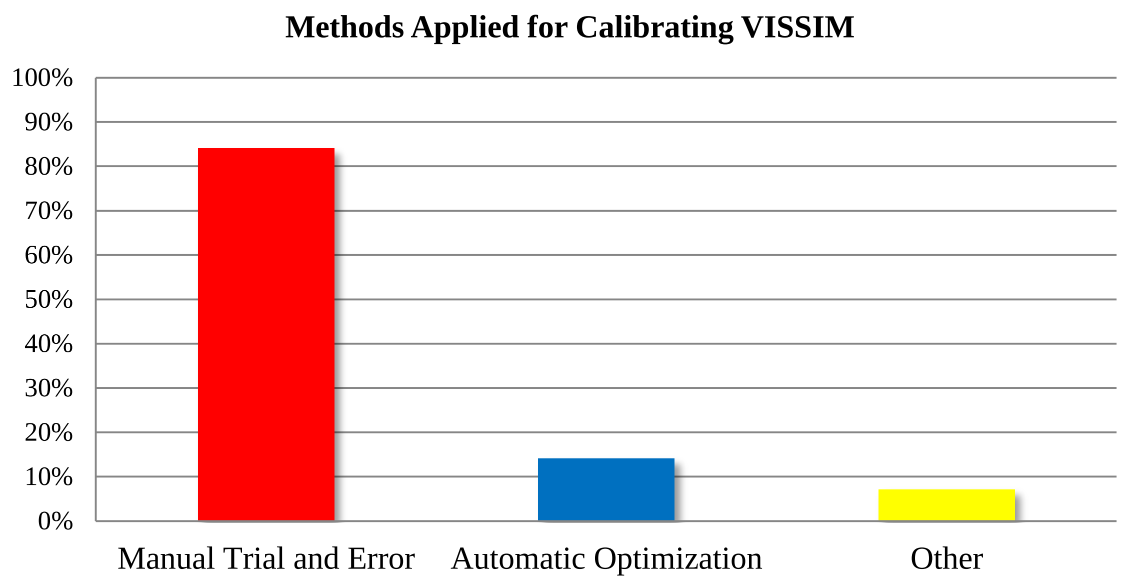


Figure 2 Survey results: methods applied for calibrating of VISSIM (Source: Punzo, 2011)



Fortunately, and due to the problems described above, the calibration of traffic simulation models such as VISSIM has been a topic of growing attention over the last few years. Many ideas from other fields where simulations are also common have been borrowed, and innovative calibrating methods are being tested nowadays (Ciuffo et al., 2011). One area of traffic model calibration in which meaningful contributions are still needed is the Sensitivity Analysis (SA) of the input parameters for the calibration itself.

The sensitivity analysis explores the relationship between the analysis outcome and the parameter assumptions (Cascetta, 2009). Due to the limitation of time and other resources, most calibration procedures cannot afford to calibrate all the parameters in the model. Thus, calibration is carried out only for a limited number of input parameters. However, there is usually no formal procedure for selecting these parameters, other than choosing the ones that appear to the model user as most likely to have a significant effect on the result (such criteria is often dictated by their former experiences). As one could imagine, the selection of an incomplete set of parameters for calibration may lead to multiple issues, including but not limited to, model imprecisions or unrealistic values for the calibrated parameters. These problems should not be a surprise, as in traffic models like VISSIM, there are usually many interactions between different parameters (e.g., many of the car-following parameters also impact the lane-changing model). Hence, focusing on the incorrect set might have a cascading effect.

Therefore, a proper sensitivity analysis, including the initial screening of the parameters, can be very valuable for the subsequent calibration process. Moreover, it may actually reduce the total efforts needed during the model calibration. A good sensitivity analysis could provide both quantitative and qualitative information regarding the effects of the different model parameters (and their variations) on the simulation results.

Unfortunately, to the authors' knowledge, there are very few examples on the application of SA in VISSIM calibration: Lownes and Machemehl (2006) used the One-At-a-Time (OAT) method in the calibration of the VISSIM model to find the parameters influencing capacity in congested situations. Mathew and Radhakrishnan (2010), in a research involving the simulation of intersections using VISSIM, changed each parameter value by a fixed amount (e.g., 10%) while keeping the default value for other parameters, and evaluated the sensitivity of the output to each individual change. Kesting and Treiber (2008) employed the same OAT approach when calibrating the Intelligent Driver Model (IDM) and Velocity Difference Model (VDM). Cunto and Saccomanno (2008) applied a variance-based SA approach to screen the parameters during the calibration and validation of VISSIM in a safety performance study. However, there appears to be no previous research suggesting a standard sensitivity analysis method to be applied in the calibration of VISSIM. Thus, some critical questions still remain for the VISSIM users: Which sensitivity analysis method would be the best option in the model calibration, especially when the modeled network is rather complex? How does it compare to the other methods regarding both performance (e.g., accuracy) and computational requirements (e.g., complexity, time and man power required)? Our research is therefore motivated by these issues. It aims at answering the questions posted above as well as disseminating the best practices of applying SA for VISSIM calibration.

This paper represents our preliminary attempt to develop an efficient SA in a recent VISSIM calibration project for the City of Zurich. It is organized as follows: Section 2 describes the detailed information about this calibration project; Section 3 introduces the SA approach we developed for this project; Section 4 presents the results of the SA analysis; and Section 5 induces our conclusions and some recommendations for future research.

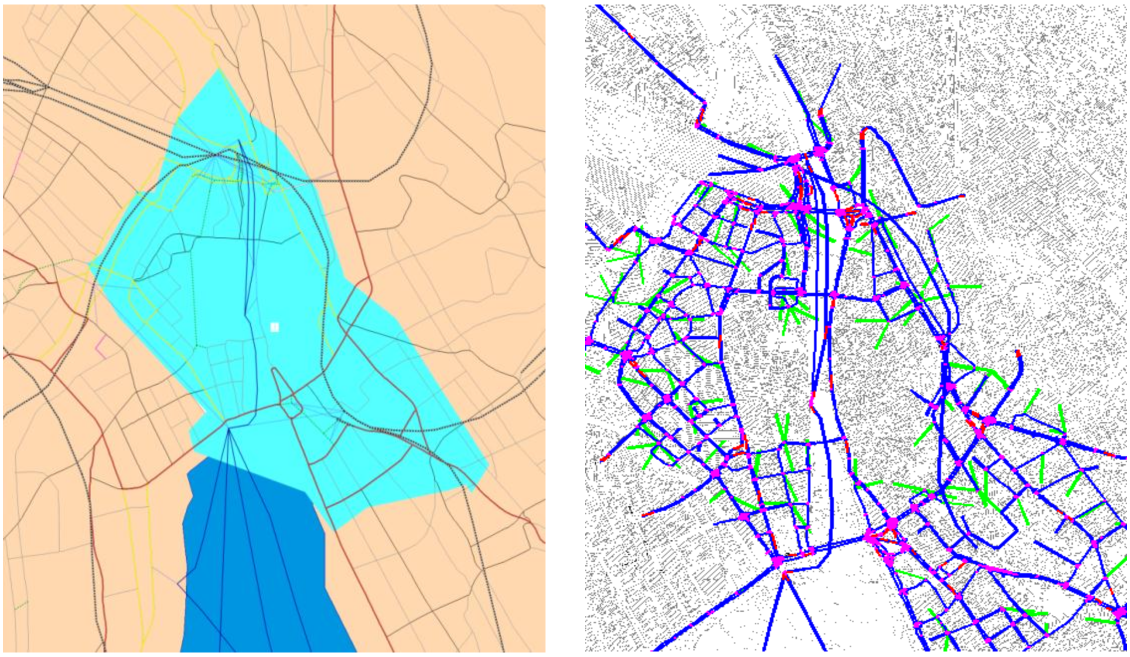
2. Sensitivity analysis in the CSV project

Since July 2011 we have been involved in a cooperative project named Calibration Study for VISSIM (CSV) with the Modeling and Simulation group within the Traffic Division of Transport for the City of Zurich. As part of this project, the City of Zurich is using VISSIM to effectively model the traffic, first within the inner city, and later in the future throughout the whole city.

However, as mentioned in the last section, VISSIM has a very large number of input parameters: in the most recent version 5.40 it has around 192 parameters (PTV, 2011), and this figure will most likely continue to increase as PTV launches new updated versions. In addition, the non-open source nature of this commercial simulator makes the model a black-box to the model users. The users may know the physical meaning of every single parameter in VISSIM, but they will not be able to understand how the simulator calculates the results according to their inputs. Hence it is rather difficult to perform a proper calibration. Furthermore, the spatial scope of the network being modeled is rather large (see Figure 3), as even the initial network encompasses the inner city of Zurich (a complex urban layout with narrow streets, hills, mixed transportation modes, a large amount of pedestrians, etc.).

All these characteristics have dramatically increased the complexity of calibration when compared to other VISSIM calibration studies (Park and Schneeberger, 2003; Gomes et al., 2004; Ahmed, 2005; Wu et al., 2005; Park and Qi, 2005; Yu et al., 2006; Miller, 2009) which focus only on single links, single intersections or at most, a few intersections along a single road. As a result, the computational cost for the CSV project is very expensive (about 20 minutes for a 1-hour simulation), therefore, it is not feasible to use a brute-force approach for the calibration work.

Figure 3 Study area (light blue area in the left figure) of the CSV project and the modeled network of Zurich inner city in VISSIM (right figure)

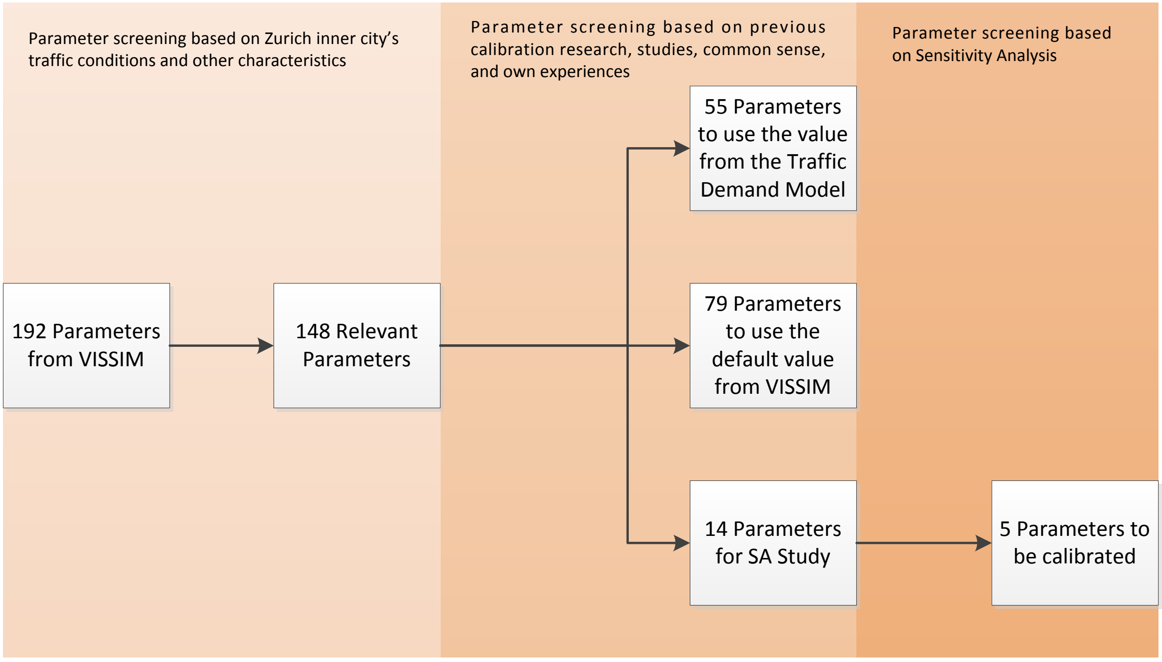


In order to find the most efficient calibration strategy to fit the specific needs and characteristics of this project, a preliminary SA was carried out. By reducing the number of calibration parameters and investigating their effects in a quantitative manner, the calibration process could then be optimized. Figure 4 shows a schematic representation of the approach used in this project in order to effectively reduce the number of parameters to a manageable level.

The first cut (from 192 parameters in the original model down to 148) was based on the study of Zurich inner city's traffic patterns and characteristics. Among those 148 parameters, 14 parameters from the car-following model, lane changing model and lane properties were regarded as the most important ones. Such selection was made based on previous calibration research, studies, common sense, and our own experience.

Unfortunately, given the time demands of running the model, calibrating all these 14 parameters with traditional methods (e.g. the brute-force approach) could take some months. This has forced us to carry out a more efficient SA to further reduce the number of parameters. The quasi-Optimized Trajectory approach based Elementary Effects (quasi-OTEE) method was developed for such task, and it will be introduced in the next section.

Figure 4 Set up process for calibrating VISSIM for the City of Zurich



3. Quasi-OTEE method for sensitivity analysis

3.1 Elementary Effects method

The Elementary Effects (EE) method was developed by Morris in 1991 (Morris, 1991). It is a qualitative and stochastic approach for screening the most important parameters from a complex model (Saltelli et al., 2008). It is especially useful in computationally costly mathematical models or in models with a large number of inputs, where the cost of applying other sensitivity measures is not affordable (or sometimes even feasible). This approach has been successfully applied for the sensitivity analysis of some complex models, e.g. in chemistry (Campolongo et al., 2007) and environmental engineering (Campolongo and Saltelli, 1997). However to the authors' knowledge, it has never been used in traffic engineering.

The idea of EE method is based on the One-At-a-Time (OAT) approach: in each step of the analysis, only one input parameter of the model is increased or decreased with a certain value, while all the other parameters remain fixed for that step. Suppose there is a model Y with k independent parameters [X_1, X_2, …, X_k], then the output of the model should be $Y(X_1, X_2, …,$

X_k). If the i-th parameter X_i is changed by a certain value Δ while the other k-1 parameters remain the same, the output of the model is consequently changed to $Y(X_1, X_2, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k)$. The Elementary Effect of the parameter X_i, which is written as EE_i, is then defined as:

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

Through randomly generating a certain number (i.e., m) of combinations of X_1 to X_k from the input space, and each time only varying X_i with Δ, consequently m EEs of X_i will be derived according to the equation above. The mean μ, the standard deviation σ, as well as the absolute mean μ^* of those m EEs for X_i can be calculated respectively. These three indicators are regarded as the sensitivity indexes of the parameters. They can be used afterwards to rank the parameters according to their influences to the model output. For instance, low values of both μ and σ indicate a non-influential parameter.

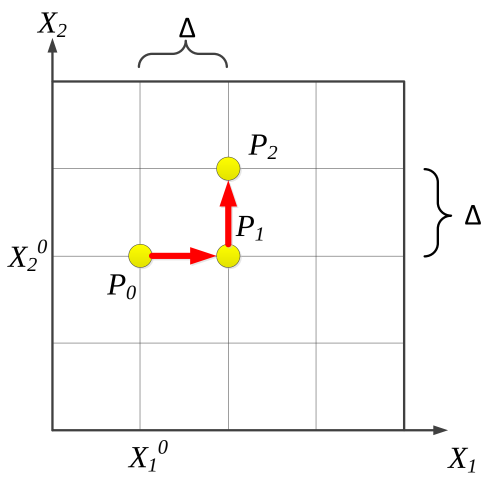
According to the definition of EE, two runs of the model are required in order to calculate one EE for one parameter: the first time with the initial inputs $[X_1, X_2, \ldots, X_{i-1}, X_i, X_{i+1}, \ldots, X_k]$, and the second time with varied inputs $[X_1, X_2, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k]$. For any single parameter of a k-parameter model, suppose that m EEs are required for calculating the sensitivity indexes of this parameter, obviously the total runs of the model should be $2mk$. This is the computational cost of the basic EE method.

When considering the fact that in this CSV project there are 14 different parameters for the SA, and normally m should be as large as possible (e.g. m = 200) in order to make unbiased sampling in the input space, the total number of simulations needed would be at least 5600 runs. As mentioned in the last section, it takes around 20 minutes to run each simulation, therefore the total computation time for the SA would be almost 77 days. Due to the high computational cost, the basic EE method is not feasible for this project as a stand-alone approach.

3.2 Sampling with trajectories

In order to improve the efficiency of the basic EE method, we can sample the parameter input space by using trajectories (Morris, 1991). Figure 5 gives an example of how to generate one trajectory for a model with 2 parameters (named X_1 and X_2). In Figure 5, the first point P_0 is randomly generated in the input space with the coordinates $[X_1^0, X_2^0]$. The second point P_1 is generated by changing[1] one parameter (e.g. the first parameter) with a certain value Δ based on P_0, and hence the coordinates of P_1 in this case, for example, are $[X_1^0 + \Delta, X_2^0]$. The third point P_2 is generated in the same way but by changing the other parameter based on P_1. As a result, the coordinates of P_2 are $[X_1^0 + \Delta, X_2^0 + \Delta]$. According to the definition of EE, two elementary effects can be derived based the sampling points along this trajectory: $EE(X_1) = [Y(P_1) - Y(P_0)] / \Delta$ and $EE(X_2) = [Y(P_2) - Y(P_1)] / \Delta$.

Figure 5 Illustration of one trajectory of two input parameters



The example above indicates that for a k-parameter model, a trajectory with $k + 1$ points can provide k EEs (one per parameter). Therefore, by randomly sampling m trajectories in the input space, each parameter can get m EEs. The same sensitivity indexes can be calculated but only $m(k + 1)$ runs of the model are required. Accordingly, the total computation time for the SA of the 14 parameters in VISSIM would be decreased to around 41 days. Although the efficiency of the EE method has been greatly increased by sampling with trajectories, the computation time is still too long, and thus a more efficient sampling approach must be applied to further reduce the computation time.

[1] Changing means randomly increasing or decreasing the value with equal probability. For illustration purposes, the example trajectory in Figure 5 only increases the value for each point along the trajectory.

3.3 Sampling with Optimized Trajectories

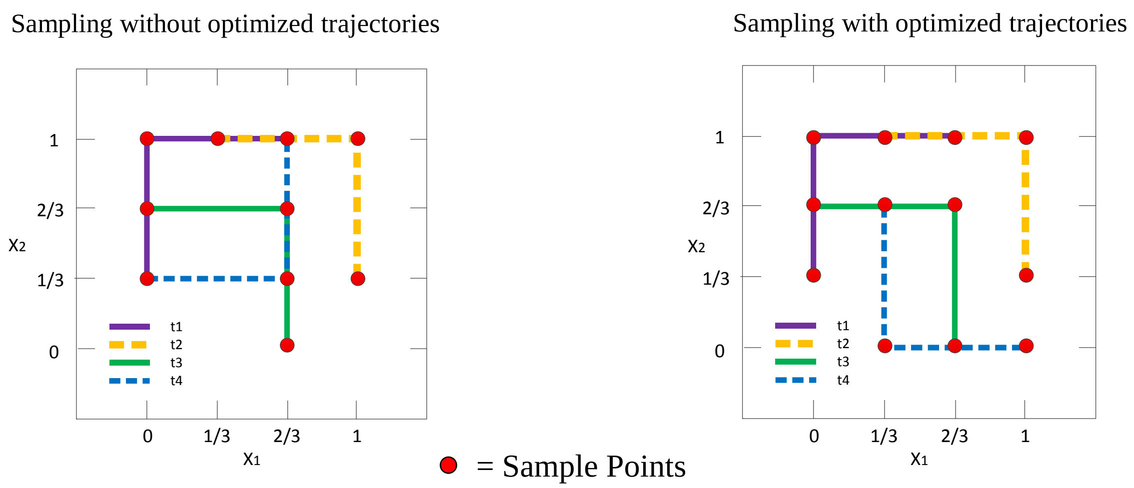
An improved sampling approach was proposed by Campolongo et al. in 2007. Instead of taking all m randomly generated trajectories as mentioned in the last section for deriving the elementary effects, they only consider a limited number (i.e., n being $n << m$) of trajectories. The selected n trajectories would have the maximum "spread" in the input space, hence they should be representative of all other random trajectories. The concept "spread" is defined based on the Euclidean distance d_{ij} between any two trajectories T_i and T_j:

$$d_{ij} = \begin{cases} \sum_{p=1}^{k+1} \sum_{q=1}^{k+1} \sqrt{\sum_{r=1}^{k} \left[X_p^{(i)}(r) - X_q^{(j)}(r) \right]^2} & i \neq j \\ 0 & \text{otherwise} \end{cases}$$

where k is the number of parameters in the model, $X_p^{(i)}(r)$ is the r-th coordinate of the p-th point in T_i. Then for any specific set (i.e., S) of n trajectories T_1, T_2, …, T_N, the total distance D_S of set S is defined as $D_S = \sqrt{0.5 * (\sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}^2)}$. By enumerating all possible sets which contains n trajectories from the initially generated m random trajectories, the set with the largest D_S can be picked out, and the trajectories within this set are regarded as the Optimized Trajectories (OT).

The advantage of using OT for sampling is that they have the maximum dispersion in the input space: the OT set can cover more sampling points than any other non-optimized trajectory set. Figure 6 gives a simple example of the non-optimized and optimized trajectories: with the same number of trajectories, the OTs can cover 12 sampling points while the non-OTs only cover 10 points.

Figure 6 Example of non-optimized and optimized trajectories



$$\sqrt{0.5 * (\sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}^2)}$$

Sampling with OT can facilitate a better scanning of the input space without increasing the number of model runs needed (Saltelli et al., 2008). Based on the OT sampling, almost the same sensitivity indexes can be derived but the total computation time will be greatly reduced. In the CSV projects if 10 OTs are used for the sampling, there would be only 2 days needed for running the model.

However, a new problem arises with this methodology: suppose initially 200 trajectories are randomly generated in the input space, and only 10 trajectories are finally taken out for deriving the sensitivity indexes, there would be around 2.2×10^{16} possible sets of 10 trajectories. In this case although running the model only takes 2 days, it could take the computer another 50 days to check all possible sets for finding the OTs. Therefore a more efficient approach is required to solve this combination optimisation problem and generate the optimal set of trajectories. This new approach is introduced in the next section.

3.4 Sampling with quasi-Optimized Trajectories (quasi-OT)

As mentioned in the last section, the OT sampling approach relies on finding the set of n trajectories out of the initial m trajectories with the longest Euclidean distance. The total number of possible combinations in such case is $m! / [n!*(m - n)!]$. However, under some circumstances this combination number could be huge (e.g. when $n = 10$, $m = 300$, there are over 1.3×10^{18} combinations). As a result it will take the computer quite long time to enumerate all combinations.

In order to solve this problem, we developed a so called quasi-Optimized Trajectories (quasi-OT) approach: instead of picking the n OTs directly from the original set (named S_0) of m trajectories, we first pick the set (named S_1) of $m - 1$ trajectories that have the longest Euclidean distance within S_0, and eliminate the remaining one trajectory; in the second step, we pick the set (named S_2) of $m - 2$ trajectories which have the maximum dispersion based on S_1; in the third step we do the same but based on S_2, etc. The size of the chosen trajectory set is decreased by one in each step, and finally there will be a set (named S_{m-n}) with only n trajectories. These n trajectories are defined as the quasi-Optimized Trajectories[2].

With the quasi-OT approach, there are only $m - 1$ possible combinations when picking S_1 out of S_0, and $m - 2$ possible combinations when picking S_2 out of S_1, etc. The total combinations

[2] These n trajectories are not necessary the same ones founded by the OT approach in Section 3.3, hence we call them the quasi-Optimized Trajectories.

considered in this approach in order to find the optimized set $S_{m\text{-}n}$ will be $(m - n+1)*(m + n)/2$. This number is much smaller than the number of combinations enumerated by the OT approach (e.g. when $n = 10$, $m = 300$ there are only 45105 combinations).

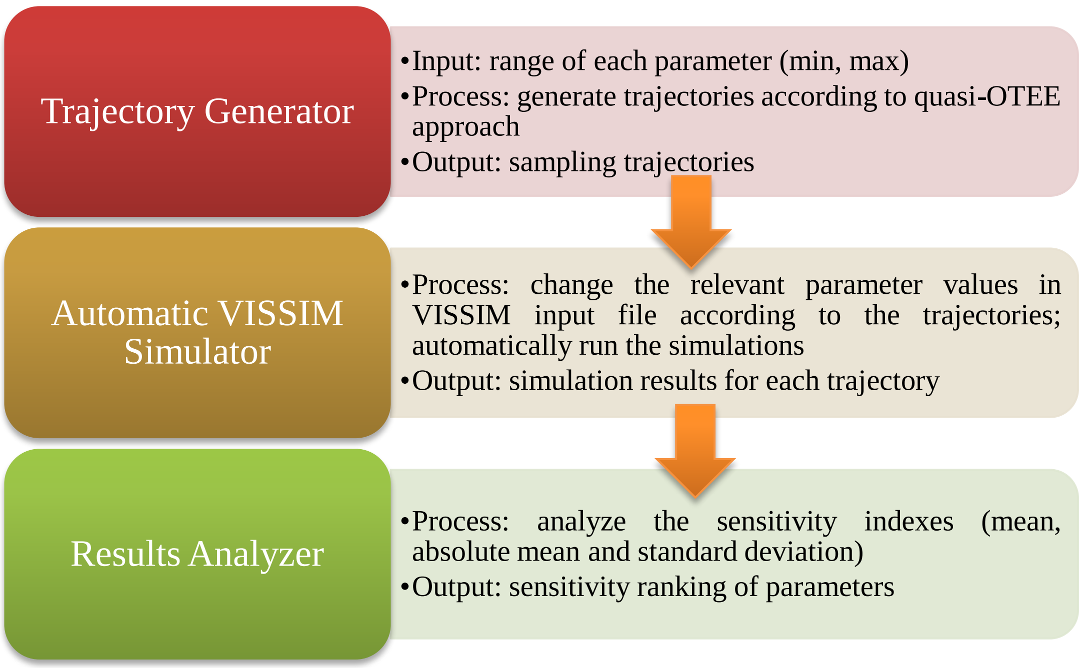
In the CSV project, the total number of combinations needed for selecting the 10 quasi-OTs from 200 random trajectories is 20055. The total computation time is accordingly reduced to 15 minutes. Although the trajectories generated by the quasi-OT approach might not always be identical to those obtained by the OT approach, if considering that the total computation time has been reduced from 50 days to 15 minutes, it is quite obvious that this approach is still more feasible due to the higher efficiency. Our study indicated that with the quasi-OTEE method, it just took the computer around 2 days to finish the whole SA for all 14 VISSIM parameters. The program and the SA results of this study are described in the next section.

4. Application and result

4.1 Sensitivity analysis program

In the CSV project, a sensitivity analysis program was developed in order to find the most important parameters based on the quasi-OTEE method introduced in Section 3. This program has three sequential function modules (see Figure 7).

Figure 7 Function modules of the SA program



1) Trajectory Generator

The first function module of the program is the trajectory generator. This module is used to randomly generate a certain number of trajectories in the input space. The input data for this module is the range (i.e., minimum possible value and maximum possible value) of each parameter. Table 1 shows the possible data ranges of the 14 parameters which are taken out from the total 192 VISSIM parameters. Based on the quasi-OT approach mentioned in Section 3.4, the program automatically generates the quasi-OTs according to the range of each parameter.

Table 1 The 14 parameters for the sensitivity analysis

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

2) Automatic VISSIM Simulator

The second module is called Automatic VISSIM Simulator. The inputs of this module are the trajectories generated from the last function module. The program reads the data of every sampling point from the quasi-OTs first and changes the value of corresponding parameters in the VISSIM input file. Then it runs the simulations with different parameters value sets. Finally it stores results (e.g., travel time, average speed, etc.) from each simulation in separate data files.

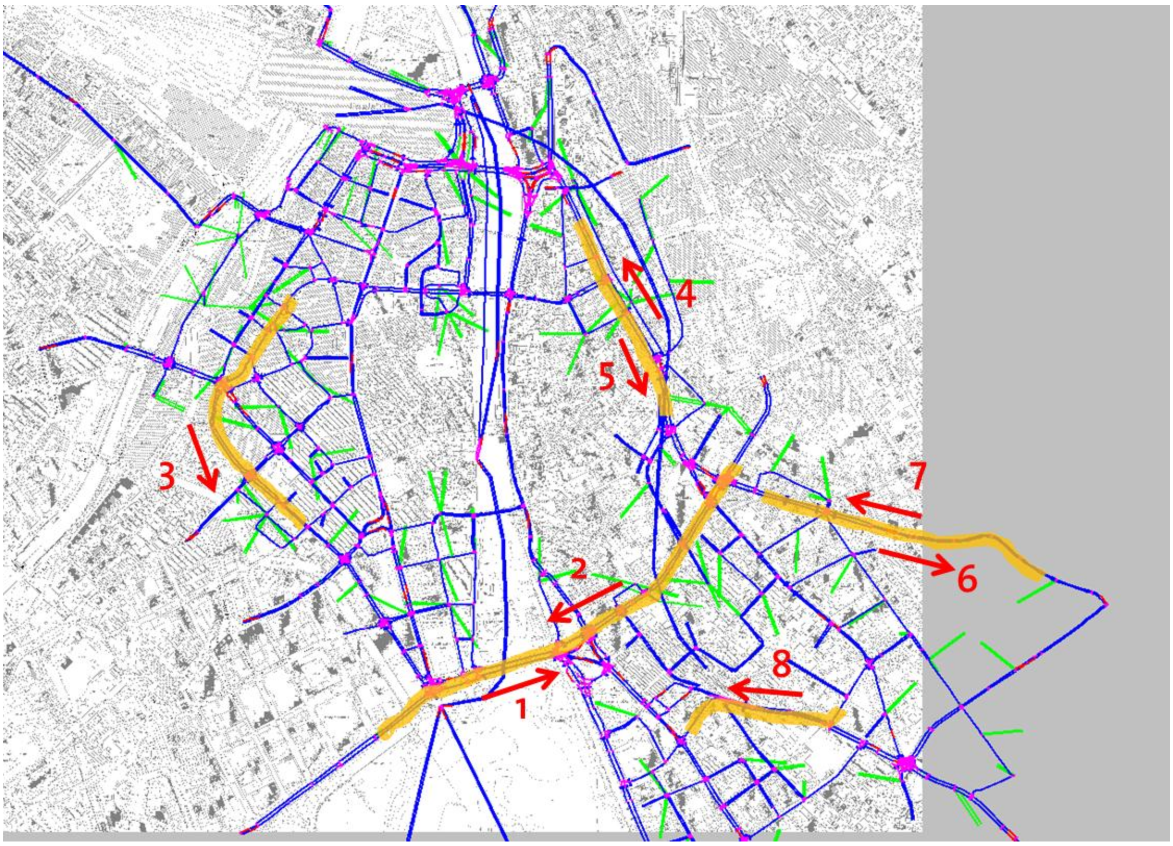
3) Results Analyzer

The last function module of the sensitivity analysis program is the Results Analyzer. This program reads the simulation results from the last module first and calculates the elementary effects for each parameter. Then it calculates the sensitivity indexes (i.e., mean, absolute mean and standard deviation) based on the EEs. Finally it gives the sensitivity ranking of the parameters according to their sensitivity indexes.

4.2 Design of the simulation

In order to get adequate data from the simulation for the sensitivity analysis, 8 road sections in the inner city of Zurich (see the road sections marked in orange in Figure 8) were chosen as the travel time measurement sections. During the simulation, the vehicles' travel time for passing through each road section was recorded for a period of one hour. The recorded values were then stored in different data files when the simulation was finished.

Figure 8 Travel time measurement sections in the VISSIM network



Additionally, we designed four different scenarios (see Table 2) in order to check the robustness of the SA results. The goal was to account for different values for the number of sampling trajectories, the random seed for generating the trajectories[3], and the resolution of the simulation (i.e., the number of times the vehicle's position is calculated within one simulated second).

Table 2 The four simulation scenarios

Scenario	Number of Trajectories	Random Seed for EE	Simulation Resolution
1	10	1	1
2	20	1	1
3	10	1	5
4	10	2	1

Scenario 1**:** this scenario is the basic scenario. It takes 10 trajectories from the input space. Those trajectories are generated from the random seed 1. The simulation resolution is set to 1.

Scenario 2: this scenario uses 10 more trajectories than Scenario 1 (i.e., including the 10 trajectories from Scenario 1 and 10 additional trajectories), as a result it takes almost twice the computation time. It uses the same random seed to generate the trajectories as Scenario 1, and the simulation resolution is also the same.

Scenario 3: this scenario adopts higher resolution than the first scenario. The other two settings are the same.

Scenario 4: it uses the random seed 2 to generate the EE trajectories. This scenario has the same number of trajectories and the simulation resolution as Scenario 1, therefore the computation time is almost the same.

4.3 Sensitivity analysis result

The simulations were run by the SA program as mentioned in Section 4.1 under different scenarios. Then the sensitivity indexes were aggregated across all scenarios and hence the so called Total Sensitivity Index (TSI) was derived. The TSI represents the sensitivity of the

[3] Since the computer is not able to provide true random numbers, it is essential to use different random seeds to generate the EE trajectories, otherwise the sampling process will not be stochastic.

model output to variations in the parameters: the model is considered to be more sensitive to one parameter if this parameter has a higher TSI than the others. The parameters were then sorted by the program. The results are shown in Figure 9 and Figure 10.

Figure 9 Sensitivity ranking of parameters with data from all 8 measurement sections

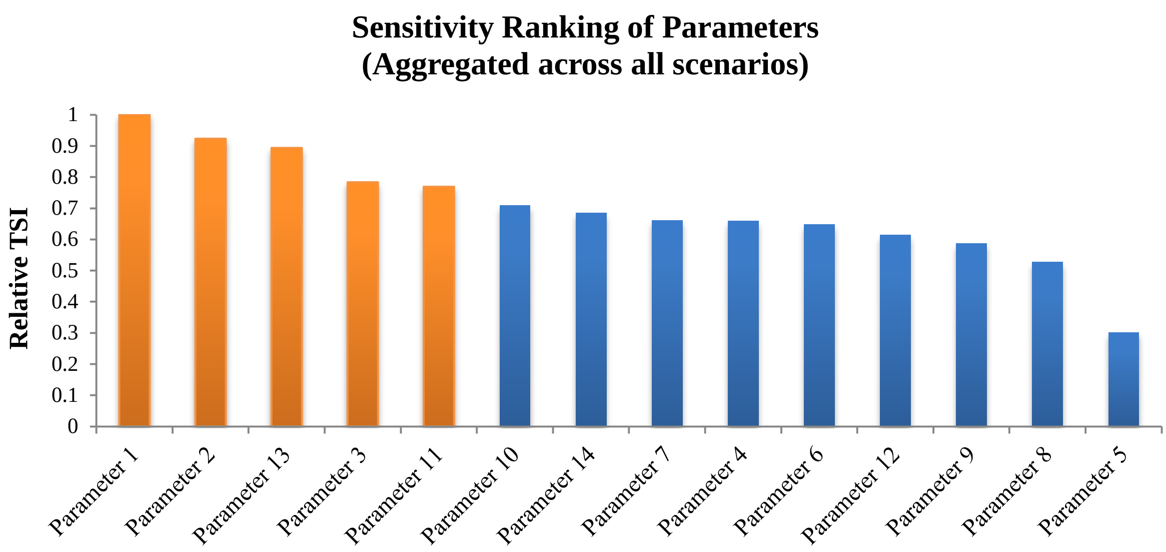
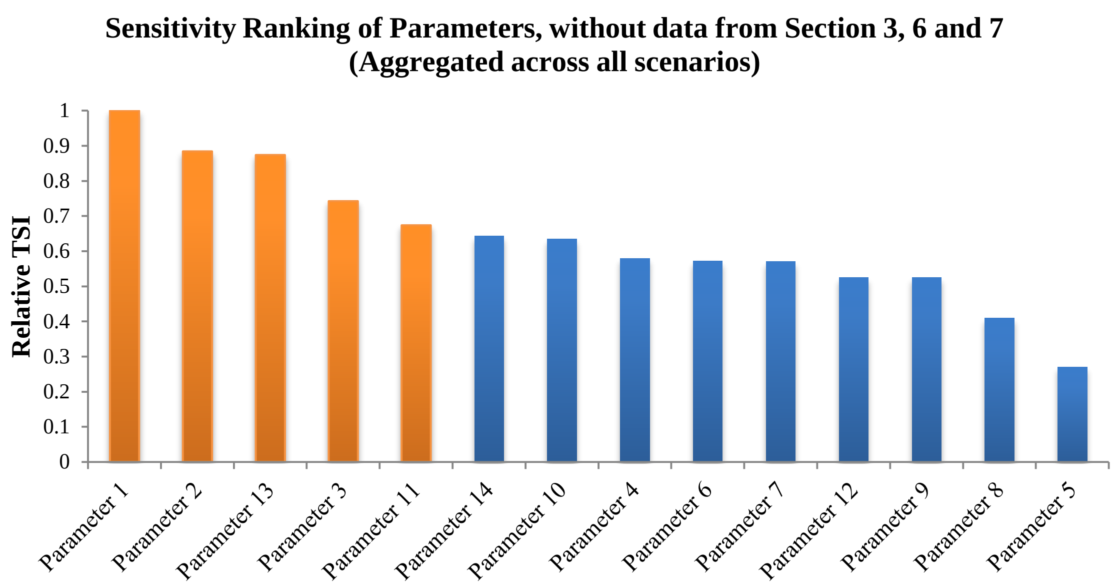


Figure 10 Sensitivity ranking of parameters without data from Section 3, 6 and 7



In Figures 9 and 10, the parameters were sorted according to their relative TSI from the highest to lowest. It is reasonable to use the relative TSI to compare the results under different circumstances: the highest TSI is manually set to 1 while the others are assigned with the relative values. Figure 9 took the data from all 8 measurement sections, while in Figure 10 the data from the sections which had very low traffic volume (i.e., less than 20 veh/h) were eliminated from the final result.

The results from Figure 9 and 10 showed that Parameters 1, 2, 13, 3 and 11 always had higher TSI than the other parameters. Moreover, if comparing to Parameters 10 and 14, the sequence of those 5 parameters was always the same in these two figures. This indicates that under any circumstances, the model was always more sensitive to Parameters 1, 2 and 3 (car-following model), Parameter 11 (lane-changing model) and Parameter 13 (lane model). On the contrary, the model was not sensitive to the variations from Parameter 5. Based on this analysis, those five parameters (see Table 3) were selected for the calibration.

Table 3 The five parameters for further calibration

Parameter number	Parameters
1	Average Standstill Distance (m)
2	Additive Part of Desired Safety Distance
3	Multiplicative Part of Desired Safety Distance
11	Safety Distance Reduction Factor
13	Lane Change Distance (m)

5. Conclusions

The quasi-OTEE method proposed by us is an improvement to the Elementary Effects method, providing higher performance in terms of less computation time. The sensitivity analysis performed for calibrating VISSIM, a microscopic traffic model with many parameters, highlights the advantage of this method when the modeled network is complex and hence it takes a long time for each simulation. By applying this method, the computation time for SA in the CSV project has been greatly reduced from 77 days to 2 days. The results from SA also show that this method is able to identify the most important parameters of a complex model in an accurate way.

When sampling the trajectories, this method differs from the Optimized Trajectories approach proposed by Campolongo et al. (2007), and as a result it only gets the so called quasi-

Optimized Trajectories. However if considering the great time saving, this method is still rather advanced with respect to accuracy and efficiency, especially for dealing with the SA of complex VISSIM networks. The future research could be devoted to further optimizing the sampling process and validating the quasi-OTEE approach under many different scenarios.

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