A systematic Sensitivity Analysis of Driving Behavior Models' Parameters of VISSIM from Macroscopic and Mesoscopic Perspectives

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Abstract: *This paper illustrates a systematic sensitivity analysis experiment of the driving behavior models' parameters in VISSIM. The aim is to explore their impact on selected macroscopic (average travel time and number of lane changes) and mesoscopic (distribution of lane change locations along the road) outputs. The experiment starts by a one-at-a-time screening technique to determine the initial key parameters set and their reliable ranges and effective variation steps. Next, the elementary effects screening technique uses the first round outputs for verification and to reveal the interaction between these parameters. Out of 22 parameters related to car-following and lane changing models in VISSIM, 15 parameters showed various degrees of impact on the proposed macroscopic sensitivity measures. At the mesoscopic level, Maximum Look Ahead Distance, Safety Distance Reduction Factor, CC0, CC1, CC3, and CC4, and Lane Changing Distance were significant for free and discretionary lane changing maneuvers respectively. Although the same set of 15 parameters affects all sensitivity measures, their relative importance differs among those measures and there was no specific trend or correlation between their values and the magnitude of their influence.*

Keywords*:* "VISSIM", "Sensitivity Analysis", "Mesoscopic Analysis", "Elementary Effects"

1. Introduction

Traffic flow simulators provide a flexible, safe, relatively cheap and simple research environment for scenario exploration in traffic engineering and transport planning. These simulators are composed of different operational models such as car-following, lane-changing, lateral motion, and emission models. Each model either individually or incorporated with other models has a specific role producing a certain traffic behavior. This behavior, i.e. the impact of the model parameters on the traffic conditions can be measured at different levels of aggregation namely: macroscopic, mesoscopic, and microscopic. Calibrating a micro-simulator such as VISSIM is a challenging task since there are more than 30 parameters of various driving behavior sub-models that need to be tuned. Recently, automatic optimization techniques are used to perform this task. Nevertheless, this large number of parameters may mislead the optimization algorithm, possibly yielding only locally optimal solutions. Moreover, it substantially increases computation time.

This work proposes a systematic Sensitivity Analysis (SA) experiment of the driving behavior models' parameters in VISSIM. The impact of each parameter on the simulator output is explored on the macroscopic level presented by the vehicle Average Travel Time (ATT) and number of lane changes, and on the mesoscopic as the distribution of lane-changing locations. The experiment has two main parts. It starts by a One-At-a-Time (OAT) SA where the key parameters, effective range and variation step are identified using a one-way ANOVA test. The

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outputs of the first screening is used as inputs for the second analysis, where the Elementary Effects (EEs) method (Morris, 1991) is applied to verify the explored key parameters set and investigate the interaction between these parameters. The following sections outline the motivation of this work, methodology, results, and conclusion.

2. Motivation

The literature provides a few examples on SA of VISSIM. Lownes and Machemehl (2006) addressed a multi-parameter SA study of the Wiedemann-99 car-following model parameters in VISSIM using a two-way ANOVA test where the average capacity of the US 75 NB and SH190 interchange is used as sensitivity measure of the model parameters. The results showed that the *standstill distance* (*CC0*) and *time headway* (*CC1*) are the most influential parameters, were their influence degree is affected by the interaction with *standstill acceleration* (CC8) and *negative/positive following thresholds* (*CC4* and *CC5*) respectively. Habtemichael and Santos (2013) investigated the key parameters of the Wiedemann-99 car-following and lane-changing models in VISSIM by quantifying their impact on traffic safety and dynamics. The impact on traffic safety was quantified as the change in vehicle conflicts whereas the change in travel time was used to illustrate the impact on traffic dynamics. Relying on the student’s t-test, the key parameters affecting vehicle conflicts are *CC1* to *CC5*, *safety distance reduction factor*, *maximum deceleration of trailing vehicles*, and *lane changing position*. The same parameter set showed various impacts on the travel time. Menendez and Ge (2012) applied an enhanced version of the elementary elements (EE) method to reduce the screening time for identifying the most influential parameters of the Wiedemann-74 and lane-changing models in VISSIM. The key parameters were considered for calibrating the inner network of Zurich city, Switzerland. They concluded that Wiedemann 74 parameters were all effectively coupled with only two parameters of the lane-changing model namely: *safety distance reduction factor* and *lane change distance*. An intuitive interpretation for this result is that the model network serves urban traffic so lane-changing maneuvers are relatively unimportant compared to freeways.
The calibration of VISSIM for freeway weaving sections is not an easy task, as because of the complex maneuvering all the driving behavior models are triggered. To measure the sensitivity of driving behavior models in VISSIM it is important to consider scenarios for SA that cover all possible traffic conditions that may occur on the freeway, both in congested and free flow states. However, previously mentioned studies relied on specific scenarios that may not produce all desired traffic conditions and that hence may not give the chance to some parameters to show their effect on the model output. Moreover, they did not specify the effective range and minimum perturbation step of each parameter, although this would be useful information to exploit in a calibration optimization algorithm (e.g. Genetic Algorithm) to provide a realistic optimal solution at less computation time. Finally, calibrating microscopic simulators to macroscopic output only may not be enough to reproduce realistic traffic flow characteristics on the mesoscopic and microscopic levels especially the distribution of lane changes locations. Therefore, besides the above mentioned points and as a key contribution of this work, we are aiming to find the driving behavior parameters that have a significant influence on the model output at the mesoscopic level in terms of lane changing distributions over the length of a freeway section.

3. Methodology

Since it is crucial to consider a scenario that triggers all the driving behavior models’ parameters, the modelled road section should be capable of producing all possible traffic conditions and maneuvers such as free and mandatory lane changing, a mixture of vehicles with different destinations, etc. One such scenario is a freeway section with an upstream on-ramp and a downstream off-ramp, see Figure 1, and this is actually where practitioners find it difficult to calibrate VISSIM specifically on the mesoscopic level.

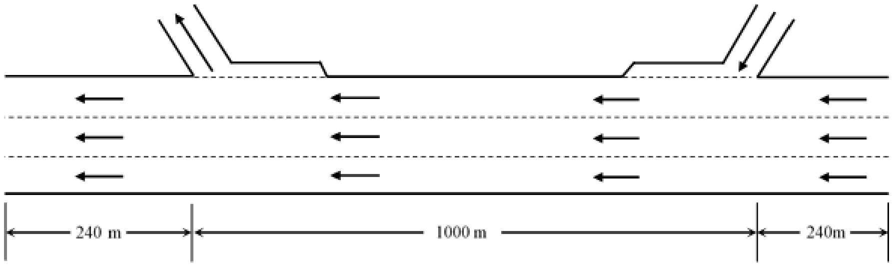

Figure 1: Scheme of the section layout

The One-At-a-Time (OAT) screening technique is applied to 22 selected parameters of the driving behavior models in VISSIM. Each parameter's input space x_i $(i = 1,..,22)$ is explored over its initial range $R = [x_i^{min}, x_i^{max}]$ by varying its default value x_i^d four times with a variation step α_i^k $(k = 1,..,4)$, where in each step α_i takes a different arbitrary value and direction, see Table 1. This is useful to identify the minimal effective variation step α_i^* that is needed to trigger an impact on the model output.

Table 1: The considered parameters for SA with their initial ranges and variation steps

Parameter	Range	x_i^d	α_1	α_2	α_3	α_4
Maximum look ahead distance	[200, 300]	250	-50.0	-20.0	10.0	40.0
Maximum look back distance	[100, 200]	150	-50.0	-20.0	10.0	40.0
Temporary lack of attention, duration	[0, 2.5]	0.00	0.50	1.00	1.50	2.00
Temporary lack of attention, Probability	[0, 10]	0.00	2.00	4.00	6.00	8.00
Standstill distance (CC0)	[0.5, 2.5]	1.50	-0.75	-0,25	0.25	0,75
Following variation (CC2)	[2, 8]	4.00	-2.00	-1.00	2.00	4.00
Threshold of entering following (CC3)	[-12, -4]	-8.00	4.00	2.00	-1.00	-4.00
Negative following threshold (CC4)	[-1.5, -0.01]	-0.35	-1.15	-0.65	-0.15	0.34
Positive following threshold (CC5)	[0.01, 1.5]	0.35	-0.34	0.15	0.65	1.15
Oscillation acceleration (CC7)	[0.1, 0.5]	0.25	-0.15	-0,05	0.05	0.25
waiting time before diffusion	[10, 120]	60.0	-40.0	-20.0	20	40.0
min. headway front/rare	[0.2, 1]	0.50	-0.30	-0,10	0.20	0.50
Meso-React-Time	[0.6, 2.5]	1.20	-0.60	-0,20	0.40	1.30
safety distance reduction factor	[0.1, 1]	0.60	-0,40	-0,10	0.20	0.40
Maximum cooperative deceleration	[-5, -1]	-3.00	-2.00	-1.00	1.00	2.00
Maximum deceleration Own	[-6, -2]	-4.00	-2.00	-1.00	1.00	2.00
Maximum deceleration Trailing	[-5, -1]	-3.00	-2.00	-1.00	1.00	2.00
Accepted deceleration Own	[-1.5, -0.5]	-1.00	-0.50	-0.25	0,25	0.50
Accepted deceleration Trailing	[-1, -0.5]	-0.50	-0.50	-0.25	0.00	0.25
Cooperative lane change – max. speed difference	[10.2, 11.4]	10.8	-0.40	-0.20	0.19	0.39
Mean of time headway distribution (CC1)	[0.5, 1.5]	0.90	-0.40	-0.20	0.30	0.60
lane changing distance	[100, 300]	200	-80.0	-40.0	40.0	80.0

For each parameter, we have 5 groups where the first group is common for all parameters because it is the output of default parameters values, so the total number of different groups is 89. The change in ATT along the proposed section in free flow and congested traffic conditions separately is the (macroscopic) sensitivity measure of parameters. This choice is motivated by observing that travel time is affected by other traffic flow variables such as density, speed, headway, etc. Due to the interaction and the dependency between all these variables any change in them would lead to a change in the travel time. A one-way ANOVA test is used to identify the key parameters. Since the ANOVA test only tells *if* the groups' means are significantly different or not, we need Tukey's Honest Significant Difference (HDS) test to determine *which* groups are different so we can identify the minimum effective variation step α^*_{min} and the reliable range R^* of each parameter[1]. Another consideration is the stochastic nature of VISSIM. The simulator has stochastic functions that take different values upon each function call, leading to random fluctuations in traffic flow, vehicle arrivals, etc. If the simulation time period is too short such that these fluctuations are not sufficiently averaged over time, this may bias our identification of the key parameters set. In order to determine an appropriate duration of the simulation, we systematically varied the time period and determined the key parameters after each simulation. In order to make sure that the traffic flow is still in the free flow conditions the initial ranges were corrected based on the average speed then R^* is identified. The influential parameters are labeled (*) if the number of different groups is only 2 and (**) if it is greater than 2. This qualitative assessment helps to select the most proper simulation duration (a higher repetitions of **). For some parameters such as CC0 there was no specific α^*_{min} so it can take any value within its range. Tables 2 and 3 summarize key parameters, R^*, and α^*_{min} of the different simulation runs by considering free flow and congested traffic conditions respectively. It is clear that simulation durations of 40 and 60 minutes are appropriate for free flow and congested conditions scenarios respectively as they give the highest number of parameters which have more than 2 different group, see Tables 2 and 3.

Table 2: Key parameters for free flow conditions

Key Parameter	Identified after simulation duration of				R^*	α^*_{min}
	10 min	20 min	40 min	120 min		
CC0	**	**	**	**	[0.75, 2.25]	-
CC1	**	**	**	**	[0.7, 1.5]	0.30
CC2	*	*	**	**	[2, 6]	1.00
CC3	**	**	**	**	[-12, -4]	1.00
CC4	*	*	**	**	[-1, -0.01]	0.10
CC5	*	**	**	*	[0. 35, 1.5]	0.10
CC7	**	**	**	**	[0.1, 0.5]	0.10
lane changing distance	*	*	**	**	[180, 280]	40.0
Max. cooperative deceleration	*	*	**	**	[-4, -2]	0.50
Max. deceleration Trailing	*	**	**	*	[-4, -2]	0.50
Max. look ahead distance	*	*	**	*	[200, 300]	20.0
Safety distance reduction factor	*	*	**	**	[0.2, 0.8]	0.10
Min. headway front/rare			*	*	[-0.5, -0.1]	0.20
Waiting time before diffusion			*	*	[0.5, 1]	0.20
Accepted deceleration Trailing			*	*	[20, 60]	20.0
Max. look back distance				*	[100, 150]	20.0
Coop. lane change – max. speed diff.				*	[10.6, 10.8]	0.20
Max. deceleration Own				*	[-3, -4]	0.20

Table 3: Key parameters for congested conditions

Key Parameter	Identified after simulation duration of		R^*	α^*_{min}
	40 min	60 min		
CC0	**	**	[0.75, 2.25]	1.00
Lane changing distance	**	**	[120, 280]	40.0
Safety distance reduction factor	**	**	[0.2, 0.6]	0.20
Waiting time before diffusion	**	**	[20, 60]	20.0
CC2		**	[2.0, 8.0]	1.00
CC4		*	[-1.5, -0.01]	0.50
Max. cooperative deceleration		*	[-5, -1]	1.00
Min. headway front/rare		*	[0.5, 1]	0.20

[1] α^*_{min} and $R^*$are not generic values, they present the minimum variation step and reliable range for the proposed experiment setup.

The outputs of this first screening step are the initial key parameters set (first 15 parameters from Table 1 which also includes the key parameters of congested conditions scenario), R_i^*, and α_i^*. To verify this first screening and investigate the interaction between parameters, in a next step the EEs method is applied.

4. Elementary Effects Method (EEs)

Morris (1991) proposed a method to quantify the change in a model's output related to change in its parameters values. The effect of a single parameter on the model output can take three different levels: negligible, linear and additive, or non-linear and/or involved in interactions with other parameters. Let $X = (x_1, x_2, \dots, x_k)$ be a vector of normalized model parameters, hence x_i , $i = 1, \dots, k$, is uniformly distributed in [0,1] and it is divided into p levels forming the set $A_i = \left\{0, \frac{1}{p-1}, \frac{2}{p-1}, \dots \dots, 1\right\}$, and a matrix $\Omega \rightarrow \mathbb{R}^{p\times k}$ sampled from that set as the input space[2].

$$\Omega = \begin{bmatrix} x_1^1, x_1^2, \dots \dots \dots, x_1^k \\ x_2^1, x_2^2, \dots \dots \dots, x_2^k \\ . \\ . \\ . \\ x_p^1, x_p^2, \dots \dots \dots, x_p^k \end{bmatrix}$$

By using the OAT screening technique with differencing step Δ , the EEs of the ith parameter is computed by numerically approximating the derivative as a local sensitivity:

$$EEs_j^i = d_i(X_j) = \left(\frac{y\left(x_j^1, \dots, x_j^{i-1}, x_j^i + \Delta, x_j^{i+1}, \dots, x_j^k\right) - y(X_j)}{\Delta}\right) \tag{1}$$

Where: k is the number of parameters; and X_j, j=1,…, p, is the jth row in Ω.

The finite distribution of EEs (F_i) associated with the ith parameter is obtained by randomly sampling different X from Ω. The following illustration gives a clearer image about the process, where each parameter value, $x_j^i + \Delta$,at the level set X_j is coupled with the other fixed parameters over all levels.

$$\overrightarrow{EEs_i} = \begin{bmatrix} \left(\left(x_1^1, \dots, x_1^{i-1}, x_1^i + \Delta, x_1^{i+1}, \dots, x_1^k\right) - \left(x_1^1, \dots, x_1^{i-1}, x_1^i, x_1^{i+1}, \dots, x_1^k\right)\right) / \Delta \\ . \\ . \\ \left(\left(x_p^1, \dots, x_p^{i-1}, x_1^i + \Delta, x_p^{i+1}, \dots, x_p^k\right) - \left(x_p^1, \dots, x_p^{i-1}, x_1^i, x_p^{i+1}, \dots, x_p^k\right)\right) / \Delta \\ \left(\left(x_1^1, \dots, x_1^{i-1}, x_p^i + \Delta, x_1^{i+1}, \dots, x_1^k\right) - \left(x_1^1, \dots, x_1^{i-1}, x_p^i, x_1^{i+1}, \dots, x_1^k\right)\right) / \Delta \\ . \\ . \\ \left(\left(x_p^1, \dots, x_p^{i-1}, x_p^i + \Delta, x_p^{i+1}, \dots, x_p^k\right) - \left(x_p^1, \dots, x_p^{i-1}, x_p^i, x_p^{i+1}, \dots, x_p^k\right)\right) / \Delta \end{bmatrix} \tag{2}$$

[2] The experiment space Ω within its boundaries contains all the possible values of each continuous variable (parameter input space), and the levels (rows) in Ω present the initial parameters vectors for the subsequent analysis.

The computational cost of this basic method is $2mk$ where m is the number of EEs required for each parameter. Since m should be as large as possible to produce unbiased samples for performing the SA, this basic design is very costly especially if the number of parameters is large as in our case. Morris improved his approach with a better design to reduce the computational cost. The new design considers the initial values of parameters at the jth level, $X_j \to \mathbb{R}^k, X_j \in \Omega \to \mathbb{R}^{p\times k}$, and construct a trajectory $T_j, j = 1,..,p$, of $k+1$ points[3] where the parameters are consecutively perturbed by Δ. Consequently, each trajectory will give k elementary effects, one per parameter:

$$T_j = \begin{cases} (x_1, x_2, \dots., x_k) \to P_1 \\ (x_1 + \Delta, x_2, \dots., x_k) \to P_2 \\ (x_1 + \Delta, x_2 + \Delta, \dots., x_k) \to P_3 \\ . \\ . \\ . \\ (x_1 + \Delta, x_2 + \Delta, \dots., x_k + \Delta) \to P_{k+1} \end{cases}$$

$$EEs_i(X_j) = \frac{P_{i+1} - P_i}{\Delta} \quad (3)$$

The number of simulation runs required to construct one trajectory is k+1, therefore constructing r trajectories[4] will require $r(k$+1) runs which is much cheaper than the basic design where in the first step computing one EE requires two simulation runs. The Latin Hypercube design is used to sample Ω (input space which contains all levels) since it maximizes the distance between the sampled values for each parameter space (R^*). The perturbation step Δ is the same for all parameters so it is possible to rank them based on their influence. The idea behind determining α^*_{min} (positive direction) in this experiment is to make sure that Δ is effective for all parameters :

$$\Delta = max(\alpha^*_{i,min}/x_i^d \mid i \in H) \quad (4)$$

H: the set of key parameters

The resulting $F_i = (EEs_1^i, \dots.., EEs_p^i)$ provides three sensitivity measures: *1)* absolute mean of EEs (μ^*) which quantifies the average magnitude of the impact of the parameter; *2)* mean of EEs (μ) which differs more from the absolute mean as the direction of impact of the parameter has no consistent sign across the input space; *3)* standard deviation of EEs (σ) quantifies the parameter's interaction with others. If σ is larger than μ, then the parameter's effect is correlated with the values of other parameters. However, if σ is small or relatively equal to μ^*, it means that most of the EEs are around the same value, therefore the parameter's effect is not correlated with other parameters.

5. EEs with Optimized and Quasi-Optimized Trajectories

The previously mentioned design does not guarantee a maximum coverage of the input space in a way that trajectories may overlap at some points. Campolongo, et al. (2007) enhanced the sampling strategy of the EEs method to have a wider screening of the input space and it is

[3] In this paper a trajectory point defines a vector with variables correspond to the parameters' values.
[4] The number of trajectories is equal to the number of levels p, as the level is the starting point for building up the trajectory.

referred as Optimized Trajectories (OT) based EEs. The enhanced sampling strategy considers the most spread set of *n* Morris trajectories sampled from a larger set containing *m* trajectories where *n*<<*m*. The most spread set (most dispersed trajectories) is the set of trajectories with the maximum Euclidean distance between all trajectories in that set. The Euclidean distance between two trajectories T_a and T_b is computed by:

$$d_{ab} = \begin{cases} \sum_{l=1}^{k+1} \sum_{q=1}^{k+1} \sqrt{(P_l^a - P_q^b)^2} & a \neq b \\ 0 & otherwise \end{cases} \tag{5}$$

This gives:

$$d_{sn} = \begin{bmatrix} 0 & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & 0 \end{bmatrix}$$

The total distance:

$$D_{sn} = \sqrt{0.5 \times \left(\sum_{a=1}^{n} \sum_{b=1}^{n} d_{ab}^2\right)} \tag{6}$$

Where: P_l^a and P_q^b are the lth and qth points in the trajectories a and b respectively; d_{sn} the distance matrix of set *S* i.e., *S* ={ T_1, T_2,…., T_n}; and D_{sn} is the total distance of *S*.

Models with a large number of parameters e.g. driving behavior models in VISSIM require a higher number of trajectories *n* in order to get an unbiased distribution F_i since some parameters may have interaction between each other. In that case *m* should be as large as possible, however; this gives $m!/[n!\,(m-n)!]$ different sets which is unfeasible in our case.

Ge and Menendez (2014) developed a Quasi-Optimized Trajectories based EEs method to overcome the combinatorial optimization problem of the OT based EEs. The idea is to enumerate *m* sets where each set has *m-1* trajectories and written as $S_{m-1}(p)$, where *p=1,…,m* is the index of the eliminated trajectory T_p, e.g. $\{S_{m-1}(1)$, $S_{m-1}(2)$,….., $S_{m-1}(m)\}$. The set with the highest total distance $S_{m-1(p)}^*$ is selected as the optimal set in this step:

$$S_{m-1(p)}^* = \max\left\{D_{S_{m-1}(1)}, D_{S_{m-1}(2)}, \ldots\ldots, D_{S_{m-1}(p)}\right\} \tag{7}$$

Where:

$$D_{S_{m-1}(p)} = \sqrt{D_{sm}^2 - \sum_{z=1}^{m} d_{zp}^2} \tag{8}$$

Where: D_{sm} is the total distance of the set S_m computed by (6); and $\sum_{z=1}^{m} d_{zp}^2$ is the sum of all distances between the trajectories in S_m and the eliminated trajectory T_p.

For example in in this study we selected m=500 then we enumerated 500 sets, each set has 499 trajectories. In the next step, again we enumerated *m-1* sets from $S^*_{m-1(p)}$ (499 sets) each set has 498 trajectories and again choosing the one with the maximum distance. Thus, in each step the number of trajectories in the new optimal set is reduced by one trajectory until the optimal set with n trajectories is reached after *m-n* iterations. A comprehensive comparison study with other sensitivity analysis techniques revealed the effectiveness and reliability of Quasi-OT based EEs method. Ge and Menendez (2014) evaluated its performance against the original OT based EEs (Campolongo et al., 2007) and another optimized sampling strategy-based EEs (Ruano, et al., 2012). The three methods gave relatively similar results however; the Quasi-OT based EEs method outperformed them in terms of the total computation time of 500 cases. In addition Ge et al. (2014) compared the performance of the Quasi-OT based EEs and Kriging-based (variance-based) approach in finding the sensitivity indices (SIs)/rank of Aimsun and VISSIM models' parameters. They conclude that the Quasi-OT EEs method was robust in finding the noninfluencial parameters in the case of high-dimensional interactions. However, the Kriging-based approach was better in ranking the key parameters. This study focuses on finding the set of influencial parameters and cluster them into groups based on their SIs and interactions where finding their ranking is left for further work.

The literature does not mention any findings on the sufficient number of trajectories (EEs) n that would give an unbiased distribution of EEs. A practical way is to use a relatively high number of trajectories up to 100 especially when the model parameters interact with each other (Campolongo, et al., 2007; Ruano, et al., 2012). If the goal is to find the key parameters on the macroscopic output of VISSIM, by automating the process this will not be a difficult task e.g. we evaluated 1600 simulation runs (100 trajectories/EEs) of the proposed section in approximately 4 hours. However, if the goal is to find the impact on the mesoscopic output in which the data at the microscopic level should be also extracted and processed it is important to know the minimum number of EEs that will give an unbiased distribution. Recall that the approach by Morris provides two important measures: absolute mean (μ^*) and standard deviation (σ) of the EEs. Using σ and μ^* as the x-axis and y-axis respectively, the result plot represents the interaction-impact space and the location of the ith parameter in this space is defined by the coordinates (σ_i, ${\mu^*}_i$).

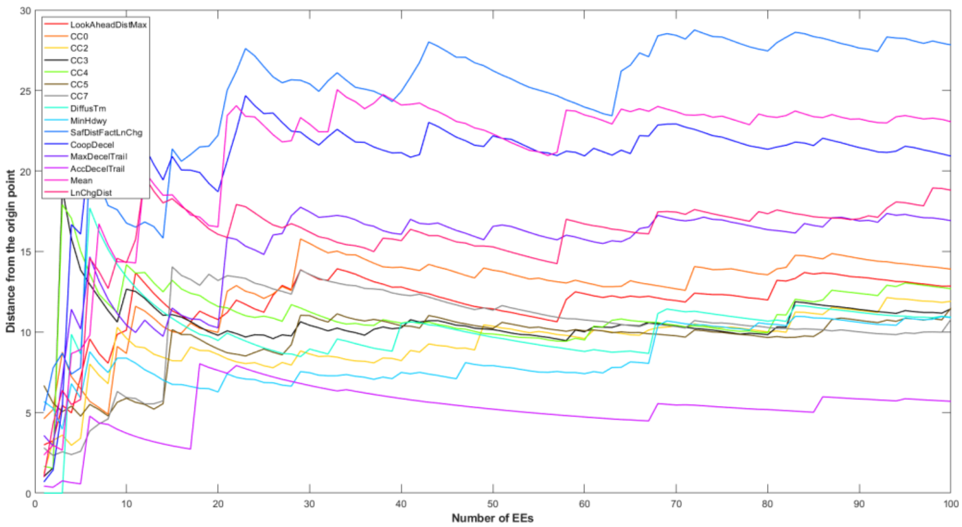

Figure 2: parameters dispersion evolution over the number of EEs

Figure 2 presents the evolution of Euclidean distance between the ith parameter's coordinates and the origin point of the interaction-impact space over the number of EEs, the sensitivity measure is ATT. At number of EEs n=30, the distance from the origin starts to stabilize, giving a reasonably stable absolute and relative position of the parameters in the impact-interaction space.

Presenting the output of the Morris method in the interaction-impact space may detract the importance of some parameters especially the ones with higher interactions. For a clearer explanation let (σ_1, μ_1^*) and (σ_2, μ_2^*) the coordinates of *CC1* and the *Maximum Look Ahead Distance* respectively. If $\sigma_2 > \sigma_1$ (485>467), and $\mu_2^* > \mu_1^*$ (504>374) then *CC1* has a higher impact and interaction compare to the *Maximum Look Ahead Distance*. However, the ratios σ_1/μ_1^* =1.24 and σ_2/μ_2^*= 0.96 show that the interaction of the second parameter is higher. Consequently, measure (3) is rewritten so it computes the relative derivative in the way that both the impact and interaction relative weights are preserved:

$$EEs_i(X_j) = \left(\frac{P_{i+1} - P_i}{\Delta}\right)/P_i \quad (9)$$

Figures 3, 4, and 5 depict the relationship between the investigated parameters in terms of μ^* and σ related to different outputs: the vehicle ATT, the number of free lane changes, and number of discretionary lane changes respectively. Regarding ATT all parameters (the 15 parameters identified in the first round) are influential except *AccDecelTrail*. The degree of influence varies between these key parameters, for example, *Safety Distance Reduction Factor* is the most influential parameter on the ATT and its effect involves higher interaction with other parameters. The same set of parameters holds for the total number of free lane changes except *AccDecelTrail* and *Waiting Time before Diffusing*; however, their impact level varies where *CC1* is the most influential while *Maximum Look Ahead Distance* has the highest interaction, see Figure 4. The number of discretionary lane changes is mainly affected by CC1 the impact of which is much higher than others', see Figure 5.

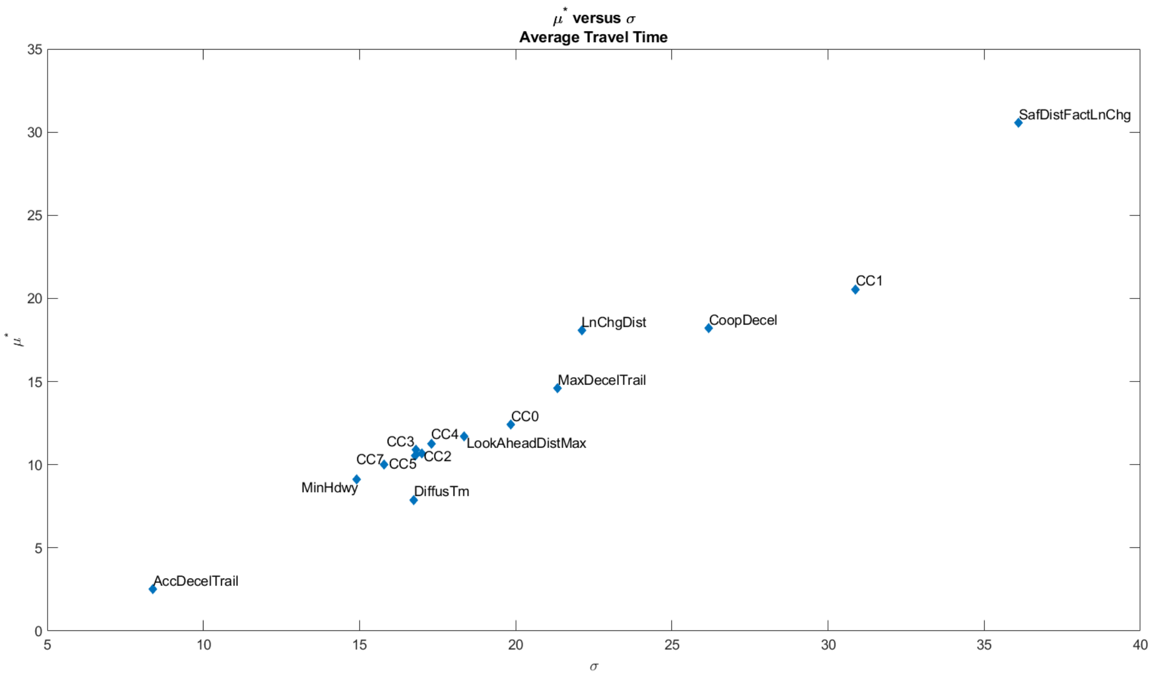

Figure 3: interaction-impact plot with respect to the ATT

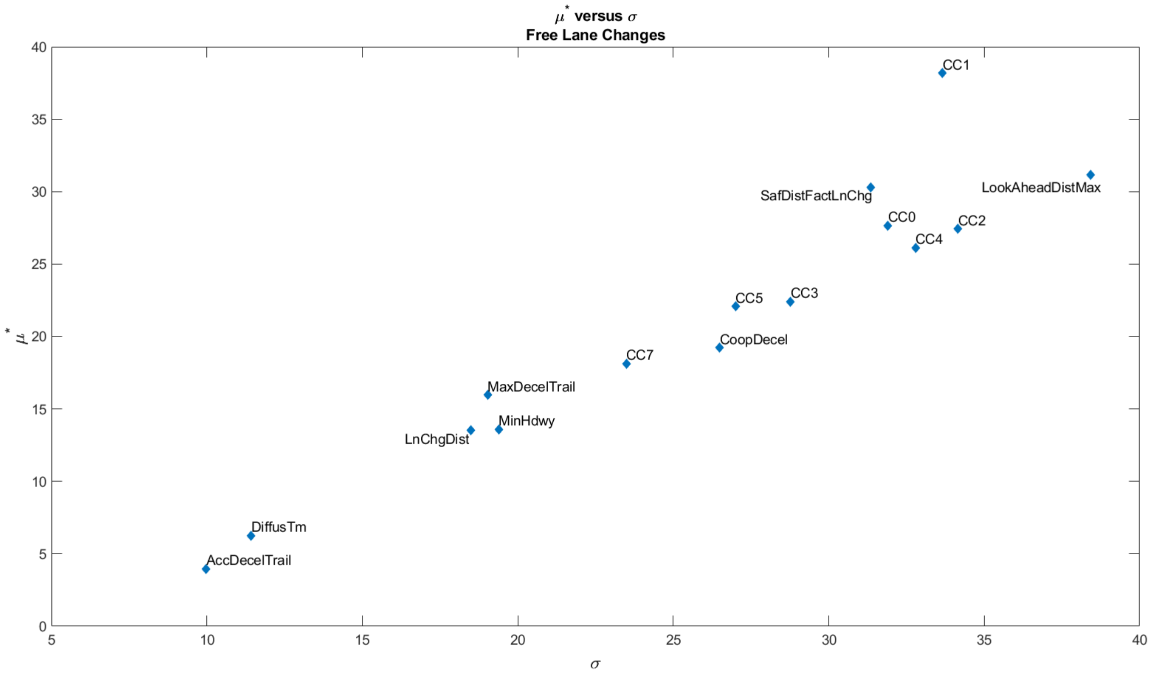

Figure 4: interaction-impact plot with respect to the number of free lane changes

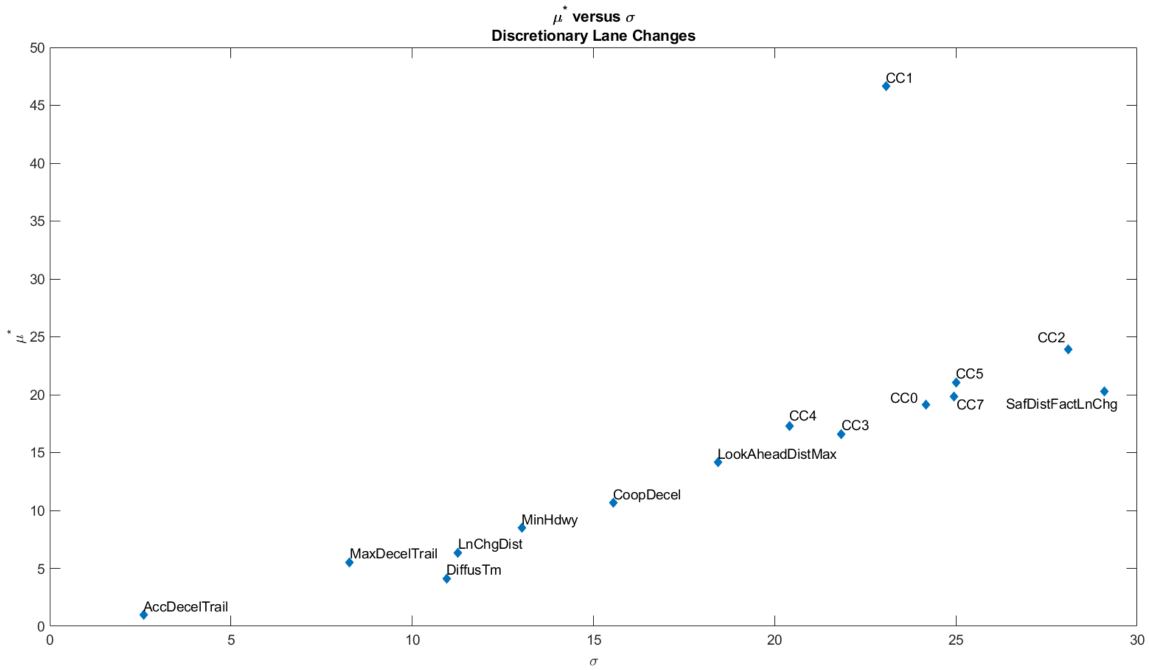

Figure 5: interaction-impact plot with respect to the number of discretionary lane changes

6. Mesoscopic Analysis

As mentioned previously, this work aims to explore the influence of these parameters on traffic conditions at the mesoscopic level in terms of distribution of lane changing positions along the road length. We developed a MATLAB tool for identifying from VISSIM default detailed outputs the locations of lane changing maneuvers over the length of the section. Thus, for each parameter there are 60 different lane changing maneuvers locations data sets, i.e. each trajectory gives two sets (as a result of P_i and P_{i+1})for each parameter [5]. This data were extracted from trajectories of vehicles as an output of the EEs method experiment simulation runs. A two-

[5] For the mesoscopic analysis we considered only 30 trajectories (which is sufficient as shown in Figure 2) rather than 100 in order to save computation time.

sample Kolmogorov-Smirnov test is used to check whether those two data sets have different distributions or not.

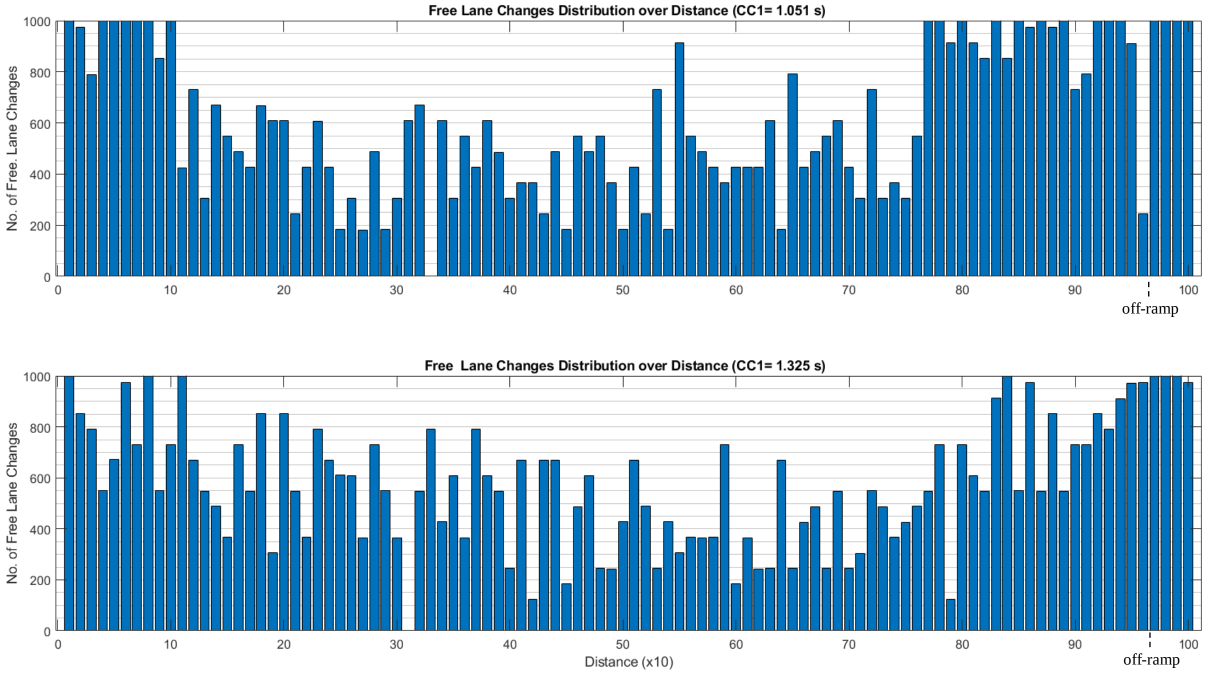

Figure 6: spatial distribution of free lane changes corresponding to *CC1*= 1.051 and 1.325 s

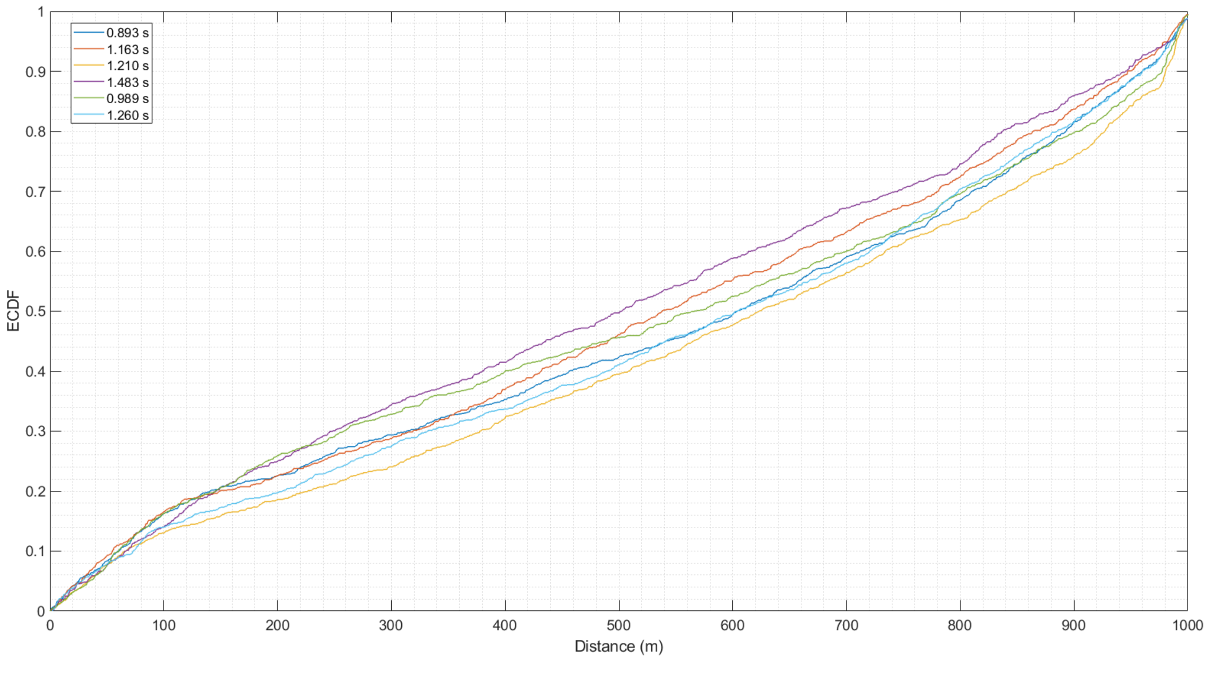

Figure 7: ECDF of free lane changes corresponding to different *CC1* values

On one hand, the results reveal that *CC0*, *CC1*, *CC3*, *CC4*, *Safety Distance Reduction Factor*, and *Maximum Look Ahead Distance* are the most influential parameters in terms of free lane changes position distribution. Figures 6 and 7 are spatial distribution and Empirical Cumulative Distribution Function (ECDF) of free lane changing positions respectively. By observing both figures, it is clear that the spatial distribution of free lane changing maneuvers responds to the change in *CC1*. On the other hand, *Lane Changing Distance*[6] parameter is the only influential

[6] The distance is measured from the starting point of the connector to the off-ramp.

factor on the distribution of discretionary lane changing maneuvers.. Figures 8 and 9 show that the smaller the lane changing distance the more discretionary lane changing maneuvers are postponed to positions more downstream.

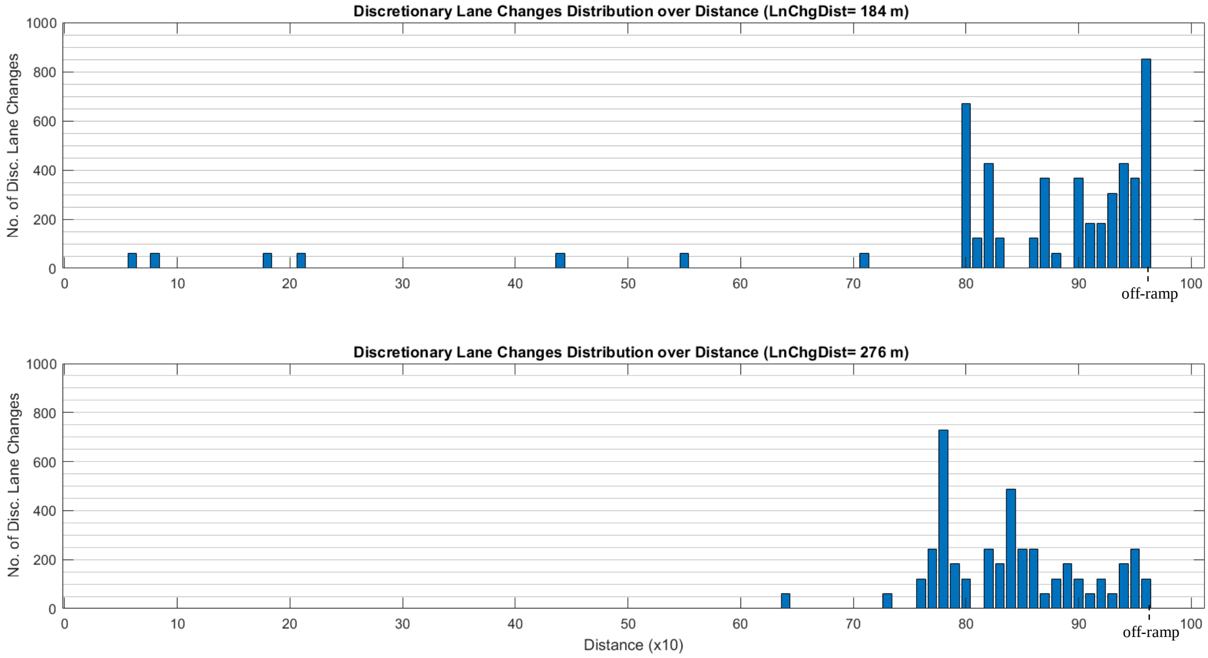

Figure 8: spatial distribution of discretionary lane changes of *lane changing distance* = 184 and 276 m

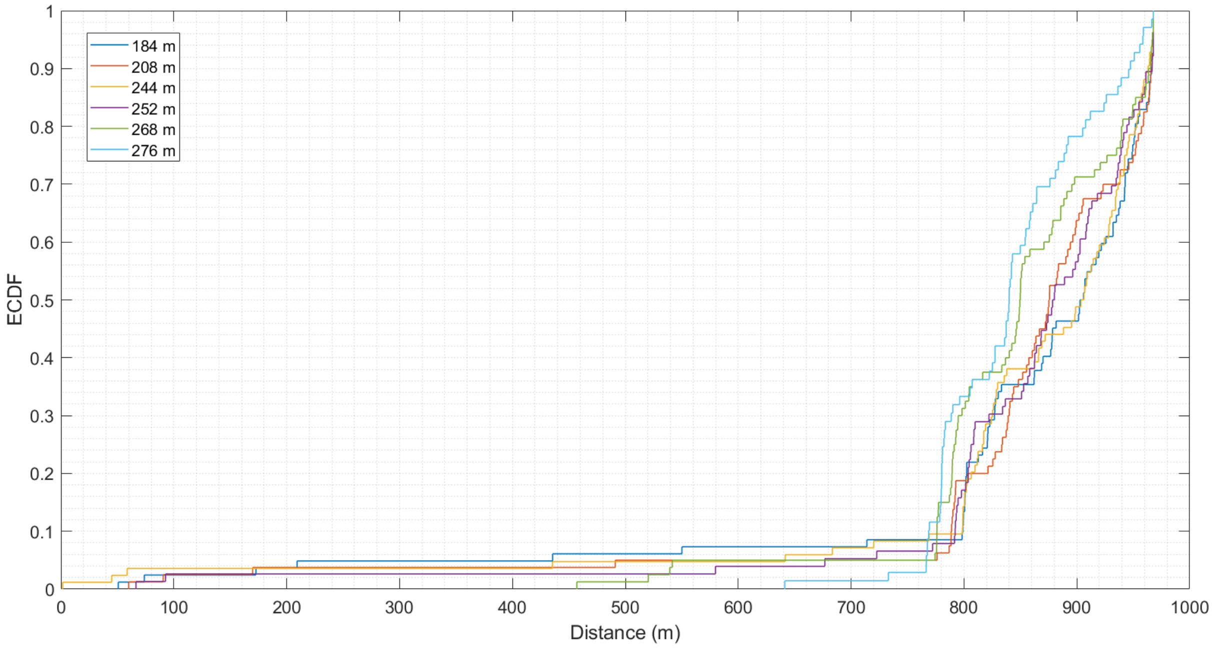

Figure 9: ECDF of discretionary lane changes of different *lane changing distance* values

7. Conclusion

This paper conduces a systematic sensitivity analysis experiment on the parameters of the microscopic traffic simulator VISSIM considering macroscopic and mesoscopic outputs. The analysis starts by identifying the key parameters which affect the macroscopic outputs of VISSIM such as the ATT and the total number of lane changing maneuvers in free flow and congested traffic conditions. This produces a set of 15 key parameters that affect significantly both outputs; however, the order and magnitude of their impact varies depending on the considered sensitivity measure. For example, *Maximum Look Ahead Distance* has a more significant impact on the number of free lane changes compared to ATT. The EEs method tells how much each parameter is important in terms of its impact and interaction which cannot be observed in the first screening output. For example, The *Safety Distance Reduction Factor* has the highest impact and interaction with other parameters when the ATT is taken as a sensitivity measure. The second step was to identify the key parameters that have impact on mesoscopic outputs like the distribution over the length of the road of free and discretionary lane changing maneuvers locations. *Maximum Look Ahead Distance, Safety Distance Reduction Factor*, *CC0*, *CC1*, *CC3*, and *CC4* are the most significant for free lane changes, while the *Lane Changing Distance* is the only parameter that influences the spatial distribution of discretionary lane changes. Finally, there was no clear correlation to link the parameter's value with its impact degree since this impact is involved with interactions with other parameters.

Acknowledgements

The authors herewith acknowledge the support of EU-CEF-project CONCORDA (Action 2016-EU-TM-0327-S) and FWO project G051118N "Ontwerp, analyse en optimalisatie van kruispunten van de toekomst" for financial support of this research.

Bibliography

Campolongo, F., Cariboni, J., & Saltelli, A. (2007, October). An effective screening design for sensitivity. *Environmental Modelling & Software, 22*(10), 1509-1518.

Ge , Q., & Menendez, M. (2014). An Efficient Sensitivity Analysis Approach for Computationally Expensive Microscopic Traffic Simulation Models. *International Journal of Transportation, 2*(2), 49-64.

Ge, Q., Ciuffo, B., & Menendez, M. (2014, June). An Exploratory Study of Two Efficient Approaches for the Sensitivity Analysis of Computationally Expensive Traffic Simulation Models. *IEEE Transactions on Intelligent Transportation Systems, 15*(3), 1288 - 1297.

Habtemichael, F. G., & Santos, L. d. (2013). Sensitivity Analysis of VISSIM Driver Behavior Parameters on Safety of Simulated Vehicles and Their Interaction with Operations of Simulated Traffic. *Transportation Research Board 92nd Annual Meeting.* Washington DC, United States.

Lownes, N. E., & Machemehl, R. B. (2006). Vissim: A Multi-Parameter Sensitivity Analysis. *Proceedings of the 2006 Winter Simulation Conference* (pp. 1406-1413). Monterey, CA, USA: IEEE.

Menendez, M., & Ge, Q. (2012). Sensitivity analysis for calibrating VISSIM in Modeling the Zurich Network. *12th Swiss Transport Research Conference (STRC 2012).* Ascona, Switzerland: 12th Swiss Transport Research Conference (STRC 2012).

Morris, M. D. (1991). Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics, Vol. 33, No. 2*, 161-174.

Ruano, M. V., Ribes, J., Seco, A., & Ferrer, J. (2012, November). An improved sampling strategy based on trajectory design for application of the Morris method to systems with many input factors. *Environmental Modelling & Software, 37*, 103-109.