MICROSIMULATION HIGHWAY DRIVER BEHAVIOUR CALIBRATION FROM REAL-WORLD TRAJECTORY OBSERVATIONS

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INTRODUCTION

The main barrier to widespread use of microsimulation for highway design studies, especially those particularly relevant to driver behavioural characteristics such as safety studies, is the challenge of implementing and validating realistic driver behaviour models. This research project aims to help increase the accuracy of simulated transportation models for highway design and analysis studies, particularly at the microscopic driver behaviour scale using real-world trajectory information.

The data collected for this study is part of a larger highway safety research project initiated by the Ministère des Transports du Québec to investigate driver behaviour on urban freeways, especially at entrances and exits and for under-designed urban highway segments. The data collection is performed with semi-automated video feature tracking and trajectory extrapolation (1). Some of the trajectory analysis is performed using the tools developed in a related highway driver behaviour study using the same dataset (2).

The behavioural data collected will typically be site specific, but not necessarily model specific; this is because it has been argued that no possible general model can exist for describing traffic flow in all or even a majority of traffic situations and environments (3). The focus of this study therefore is on the methodology of efficiently obtaining calibration data and fitting it into traffic flow models. A case analysis is then performed for a highway segment in the Montreal region involving an entrance ramp by attempting to calibrate the car-following model in the microsimulation software VISSIM, which uses the Wiedemann 74 and Wiedemann 99 car-following model (4). Of these two, parameters will be evaluated for the Wiedemann 99 model which is geared towards highway flows.

The software version of VISSIM used for this analysis is 5.20.

LITERATURE REVIEW

The major problem is that no information or pertinent guideline has been published to help users of the software choose appropriate CC values. The general policy is to modify these variables only if, and until, the overall macroscopic behaviour of the vehicles corresponds to real-world measures and situations. This approach works for certain aspects, particularly those that are not very specialized driver behaviour studies, but may be inadequate for more specialized studies which rely particularly on modeling microscopic driver behaviour inside and around lanes and with respect to other road users: for example, a highway surrogate safety study.

This isn’t to say that no papers have been published regarding driver behaviour calibration directly from the source. Fellendorf and Vortish discussed the simulation resolution and model types used in VISSIM and how they affect driver behaviour measures for microscopic and macroscopic measures (5), however the discussion remained very general and didn’t attempt to apply any techniques to match driver behaviour results with real world-conditions. (6) Dowling *et al.* provide general flow patterns comparison techniques and guidelines (e.g. bottlenecks, queues, flow thresholds, speeds and travel times) (7). Hourdakis *et al.*, presented, much like this paper, a general automated iteration-based trial-and error methodology with a goodness-of-fit test (8). Park *et al.* use a surface function to validate the travel time result from a simulation of route 50, in Fairfax, Virginia (9). Menneni *et al.* compared speed-flow diagrams for a real-world and an identical simulated highway (10). Again, all of these studies were primarily focused around macroscopic conditions and may have not taken microscopic behaviour into account.

Listed in **Tables 1 through 3** are some of the most important parameters related to driving behaviour in VISSIM. These parameterize car-following models, routing decisions/pre-emptive manoeuvre decision making, and lane-changing models respectively.

TABLE 1 Wiedmann 99 model parameters as declared in VISSIM

Variable	Description	Default	Units/Type
CC0	Standstill Distance	1.50	Metres
CC1	Headway Time	0.90	Seconds
CC2	'Following' Variation	4.00	Metres
CC3	Threshold of Entering 'Following'	-8.00	Threshold
CC4	Negative 'Following' Threshold	-0.35	Threshold
CC5	Positive 'Following' Threshold	0.35	Threshold
CC6	Speed Dependency of Oscillation	11.44	Arbitrary
CC7	Oscillation Acceleration	0.25	m/s^2
CC8	Standstill Acceleration	3.50	m/s^2
CC9	Acceleration at 80km/h	1.50	m/s^2

TABLE 2 Routing decisions and pre-emptive manoeuvre decision making parameters as declared in VISSIM

Description	Default	Units/Type
Min. Look-ahead distance	0.00	Metres
Max. Look-ahead distance	250.00m	Metres
Min. Look-back distance	0.00	Metres
Max. Look-back distance	150	Metres
Probability of Temporary lack of attention	0.00	%
Duration of Temporary lack of attention	0.00	Seconds

TABLE 3 Lane-change model parameters as declared in VISSIM

Description	Default	Units/Type
Maximum deceleration (self)	-4.00	m/s^2
-1 m/s^2 pwe distance (self)	100.00m	Metres
Accepted deceleration (self)	-1.00	m/s^2
Maximum deceleration (trailing vehicle)	-3.00	m/s^2
-1 m/s^2 pwe distance (trailing vehicle)	100.00m	Metres
Accepted deceleration (trailing vehicle)	-1.00	m/s^2
Waiting time before diffusion	60.00	Seconds
Min. headway (front/rear)	0.50	Metres
To slower lane if collision time above (right-side rule only)	0.00	Seconds
Safety distance reduction factor	60	%
Maximum deceleration for cooperative braking	-3.00	m/s^2
Overtake in reduced speed areas	False	Boolean

Other behavioural input of significant importance includes: desired (free-flow) speed, network-based routing decision locations (particularly relevant for pre-emptive lane change behaviour, i.e. location of traffic signs and behaviour of a certain percentage of irregular commuters), and conflict area visibility, gap, safety distance factor, etc. (less relevant for highways which do not make much use of conflict zones). While a desired speed distribution is relatively easy to measure, routing decision locations are hard to define precisely without elaborate signage visibility and commuter ratio data. Routing decisions and conflict areas were assumed to have little impact on microscopic car following behaviours.

DATA COLLECTION AND METHODOLOGY

Methodology overview

As proposed in (9) a 5-step calibration procedure is roughly followed, with some provisions made for adapting to microscopic calibration:

i. Determination of Measures of Effectiveness (literature review and discussion of objectives, options)
ii. Data Collection
iii. Identification of Calibration Parameters
iv. Statistical Analysis
v. Validation

Unfortunately, PTV does not publish its Wiedemann 99 car-following model used in VISSIM. Therefore, solving for car-following parameters numerically is not possible. Instead, multiple tests are run on the simulator in order to guess which parameters to use and to gain some insight into what types of input are involved in the microscopic behaviour of vehicles, as well as testing the ability of the microsimulator to generate data consistent with real-world traffic observations.

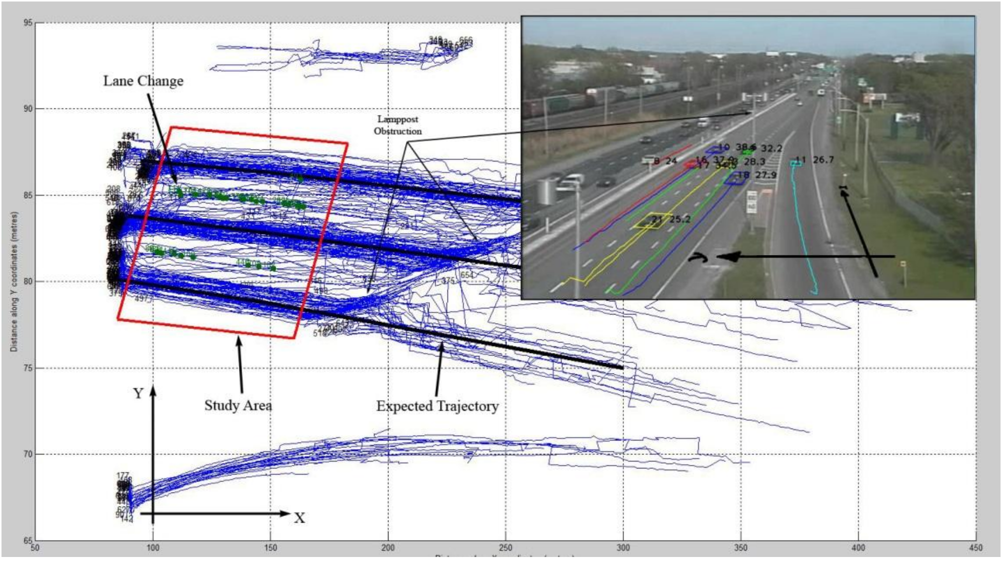


FIGURE 1 Sample data collection. Only the most reliable trajectories are kept. These trajectories are bound by a Study Area, shown here in red.

Data Collection

A semi-automated video feature-tracking program has been previously developed (1) and is now used in this research to assist in the video data collection. Trajectories are formed from datapoints with spatial (X, Y) and time (t) coordinates. These datapoints can be differentiated for velocity and acceleration parameters. Together with object size tracking (validation work in progress), information regarding driver behaviour for specific environments and conditions can be obtained. See **Figure 1** for a sample output of the data collection process.

For this research, video data collected for entrance 56 (Bouchard), Autoroute 20 eastbound, Dorval, Montreal, was used, in part because it was already available and analyzed using the trajectory extraction technique, and in part because the data was known to be acceptable. This is our control data and will be compared with the trajectory data generated by VISSIM 5.2.

Identification of Calibration Parameters

For this research paper, we will concentrate on the car-following model exclusively. While a comparison of macroscopic measures satisfies many microsimulation calibration efforts, we set as an objective to compare microscopic behaviour. To this end, we estimate that measuring the gap time between every two vehicles is possibly the easiest and most pertinent method of validating a car-following model. Since the gap time is a continuous measurement, it may be easiest to compare frequency distributions. The simulated gap time will be measured using data collection points (DCP) built into the simulator. When a vehicle drives over a DCP, the DCP changes its state from time *t* to -1 and when the vehicle exits the DCP its state changes back to time *t*. These events are output to a .mer file. The gap time can simply be calculated as the time $t_{on\ i}$ - $t_{off\ i-1,}$ and a probability distribution function can be calculated after many observations. Up to 3 DCPs are placed at approximately 30 metres distance per lane to allow for variations in the gap time from one end of the analysis zone to the next, all the while keeping data sizes respectively small.

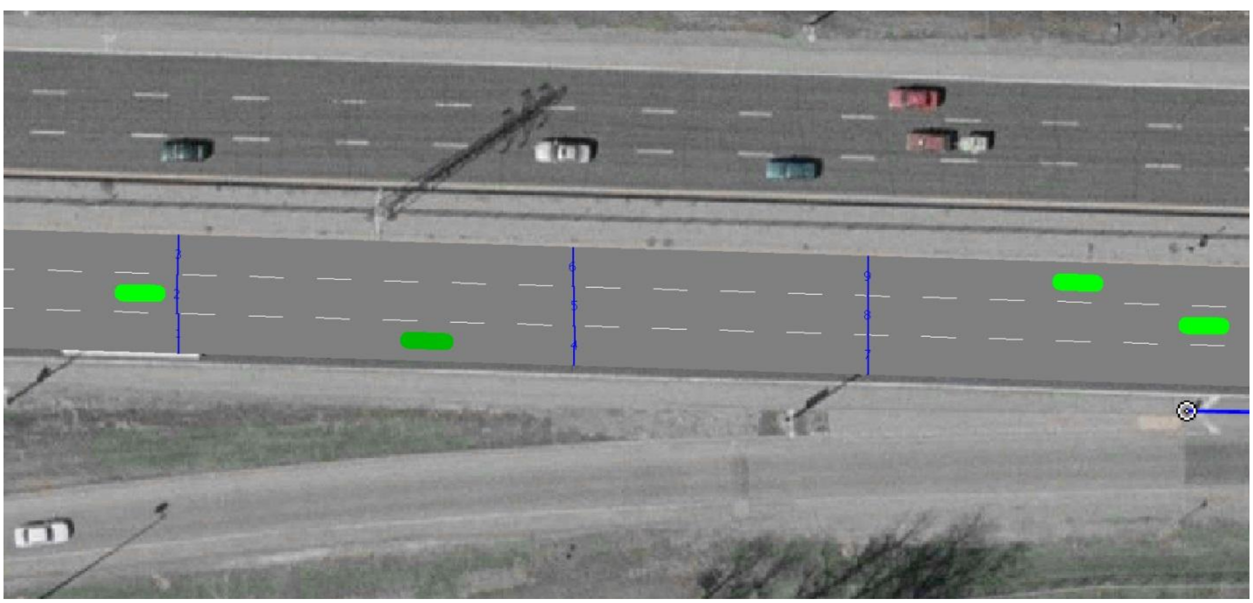


FIGURE 2 Test network as built in VISSIM

A similar approach is used to extract the gap time from the video trajectories.

Figure 2 shows the network as simulated in VISSIM: a simple, straight, 3-lane highway with no curves, a flow rate of approximately 2700 veh/h and a normal free-flow speed distribution centred on 95 km/h. The study area proper, as with the video data, is located just upstream of the entrance.

Validation

Validation work did not focus much on macroscopic measures, unlike many other papers. The network is simple enough to focus primarily on microscopic behaviour, e.g. the entire network consists of a short, single, straight, three-lane highway segment. Vehicle flows and speed distribution are input directly from the data collected from the video analysis. Video-measured gap distributions, however, are manually validated as part of the semi-automatic trajectory extraction technique to an acceptable level of error (roughly 5%).

EXPERIMENTAL RESULTS

Initial Observations

The full gap time distribution domains (i.e. over t = [0,+infinity[ ) are not comparable. This is because the vehicle arrival pattern in the simulation is purely stochastic, a distribution which was not calibrated at the outset of the experiment, while the vehicle arrival rate collected from the video demonstrates a clear pattern of vehicle clustering. The result is that the overall gap distribution from the video data is more biased towards short and long gap times, whereas the simulated vehicles tend to have a more gradual gap distribution. The vehicle clustering occurring from the video data might be attributed to users' preparatory exiting manoeuvres, signalized queues entering on-ramps, or simply more time allotted for vehicles to find a vehicle to follow. However, this is not a problem as long as we focus on short gap times, or in other words, gap times that are the result of one vehicle following another. We therefore limit ourselves to a time domain of t = [0,2]; longer than this and we can safely assume that most vehicles are not actively following each other (at highway speeds, about 50 metres apart). The significance of the cut-off threshold (CC3 of -8) used in VISSIM is not well understood at the time of writing, and so is ignored.

The gap distribution as measured from the video (shown in **Figure 3**) shows some interesting features. Firstly, it clearly depicts a road user's minimum acceptable safe following gap time of 0.6 seconds. It also has two distinguishing peaks, notably at 0.8 seconds and 1.4 seconds. These concentrations of observations are likely the following distance variation thresholds, i.e. users decrease their speed once they reach the minimum gap threshold to keep a constant or increasing gap. The tall, narrow profile of the minimum threshold is in contrast to the short, wide profile of the maximum threshold, indicating stricter behaviour of a leading vehicle on approach than when trailing away. Given a reaction time of around 1 to 1.5 seconds, this might demonstrate that the observed drivers are comfortable following others at slightly aggressive distances, although no direct comparisons are made with drivers of other areas.

When comparing measured gaps between each lane, no significant differences were found between lanes; although speed was slightly higher in the third lane, this was offset by slightly larger following lengths.

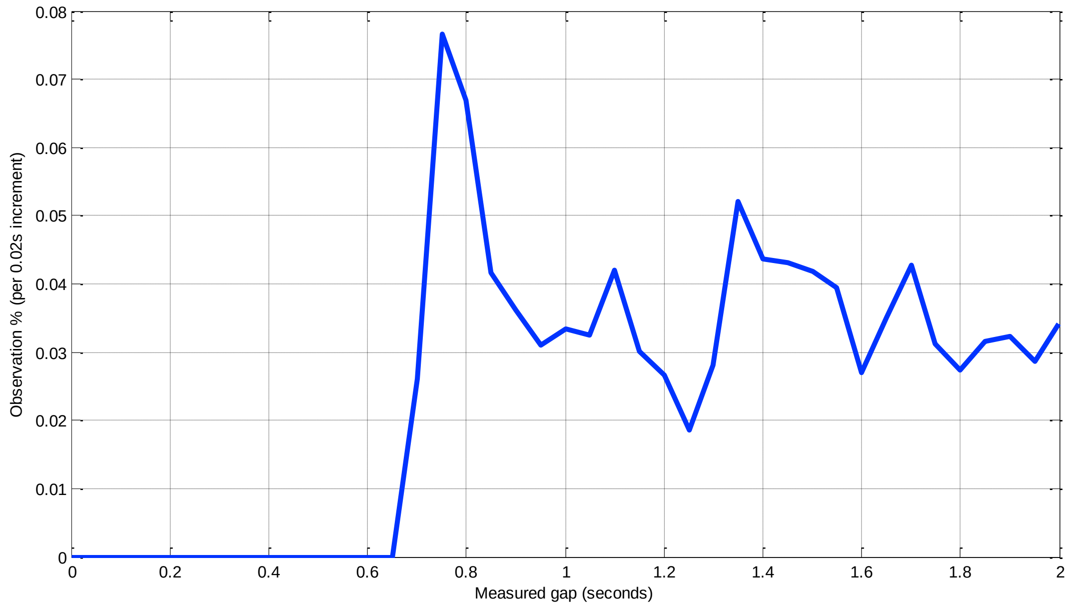


FIGURE 3 Control video-measured gap time distribution

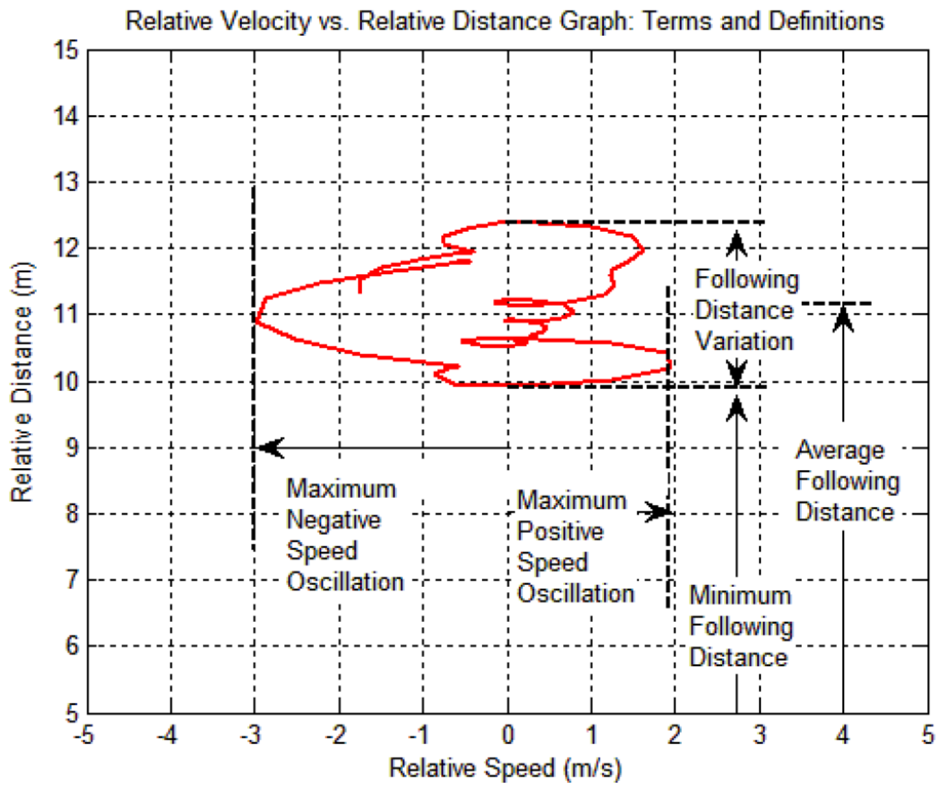


FIGURE 4 Following-oscillation graph (10). The driver of a vehicle approaching another slows down to keep a minimum safe distance between vehicles. The deceleration action eventually leads the trailing vehicle to lose some distance on the leading vehicle, enabling the driver to safely accelerate once more.

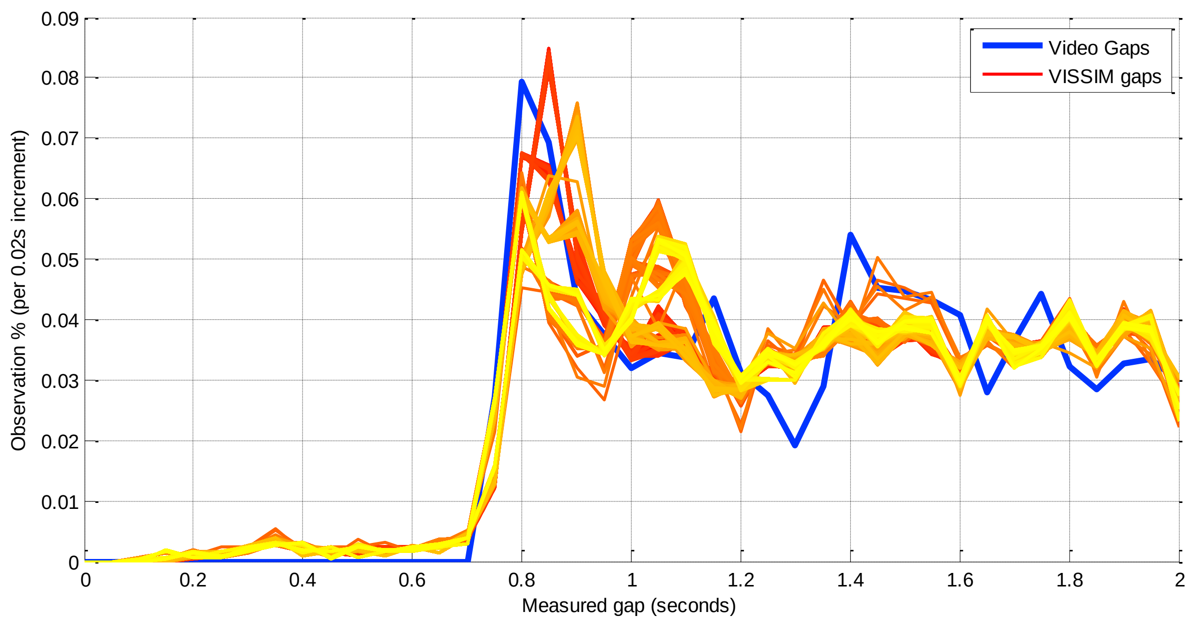
Some manual gap time counting was performed in an attempt to verify the shape of the video-measured gap distribution, with limited success however, as manual video counting is neither efficient nor particularly accurate. The minimum acceptable safe following distance was the easiest and most satisfactorily validated aspect of the video-measured gap distribution.

Figure 4 briefly summarizes the oscillation that occurs between the relative distance and relative speed during typical car-following behaviour as measured in **Figure 3**. More advanced car-following models might also take into account the behaviour of a leading vehicle whose driver may be influenced into modifying his or her speed under pressure from tailgaters.

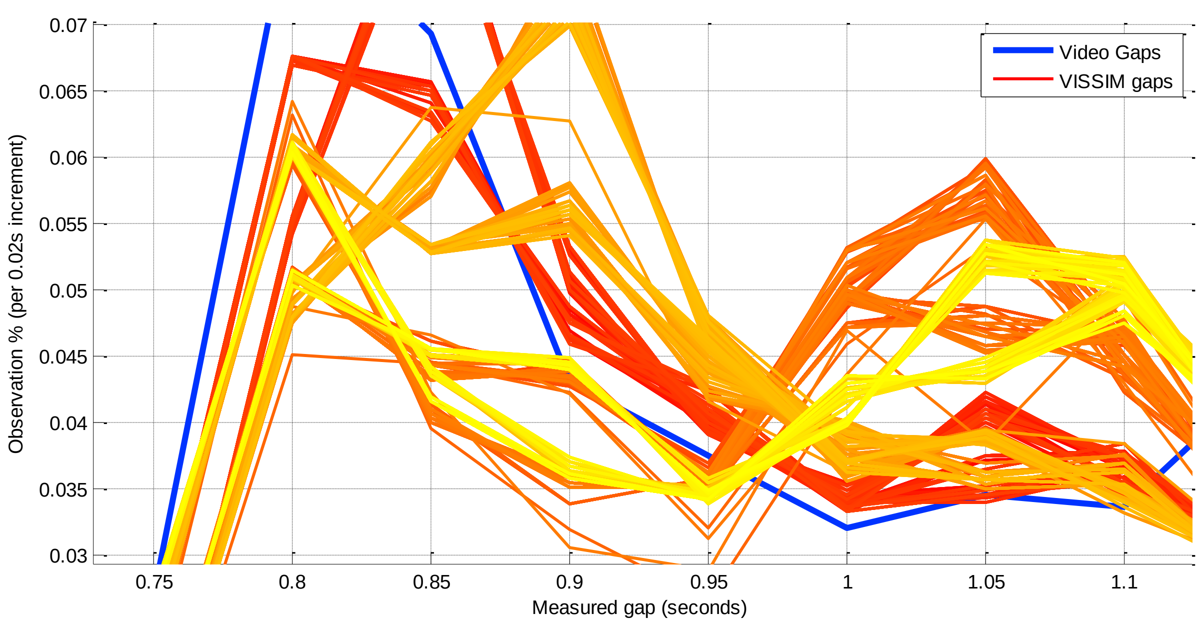
Identification of Significant Model Parameters

A first set of hypotheses is generated and tested in VISSIM using a 0.1 second timestep, all other conditions and input parameters being equal. This test focuses primarily on identifying the most significant parameters to test in a more fine-grained second simulation. In order to keep the number of simulations around or lower than 1000, 2 cases (10^2 = 1024) are explored for each CC parameter, generally evaluated at approximately +/-10% of the default value. CC0 is tested for 1 and 2 (default 1.5), CC1 is tested for 0.8 and 1 (default 0.9), CC2 is tested for 3.9 and 4.1 (default 4), CC3 is tested for -8.1 and -7.9 (default -8), CC4 is tested for -0.4 and -0.3 (default -0.3), CC5 is tested for 0.3 and 0.4 (default 3.5), CC6 is tested for 11 and 11.88 (default 11.44), CC7 is tested for 0.2 and 0.3 (default 0.25), CC8 is tested for 3.4 and 3.6 (default 3.5), and CC9 is tested for 1.4 and 1.6 (default 1.5).

Figure 5(a) compares the control video-measured gap-time distribution with all the simulation generated gap-time distributions (each hypothesis). The control distribution already generally matches the shape of simulated distributions, however each parameter’s testing range was limited. Each simulation gap-time distribution is colour-coded from red to yellow according to the hypothesis order. The testing order leads to an increment of each parameter range from CC9 to CC0 (in that order) similar to binary structure (base 2). Therefore, clusters of similar colours indicate sensitivity to higher-order (i.e. CC0, CC1) parameters, as depicted in **Figure 5(b)**. Compared with parameters CC2-CC9, CC0 and CC1 change the shape of the distribution dramatically.



a)



b)

FIGURE 5 (a) First set of hypotheses compared with distribution measured from video data.

5(b) The majority of hypotheses are super-imposed over each other, but CC0 and CC1 stand out as the most significant. Red: CC0 = 1, CC1 = 0.8; Dark Orange: CC0 = 1, CC1 = 1; Light Orange: CC0 = 2, CC0.8; Yellow: CC0 = 2, CC1

Calibration of Model Parameters

A second set of hypotheses is generated to test the CC0 and CC1 parameters. This time, a wider and finer range can be easily simulated, as the complexity of varying parameters has decreased. We use a range of [0,4] with an increment of 0.25 for CC0 and a range of [0.2,3] with an increment of 0.2 for CC1 for a total of 255 simulations. Values of CC2 to CC9 are left at the default settings because they were not found to impact the results significantly. All other parameters, including speed distributions, geometry, and flows, were not changed.

Figure 6 shows the simulated and video-measured gap distributions. This time we find some lateral variance with the minimum acceptable safety gap, and a much noisier left tail end and right end. The following-distance variation thresholds are still clearly visible.

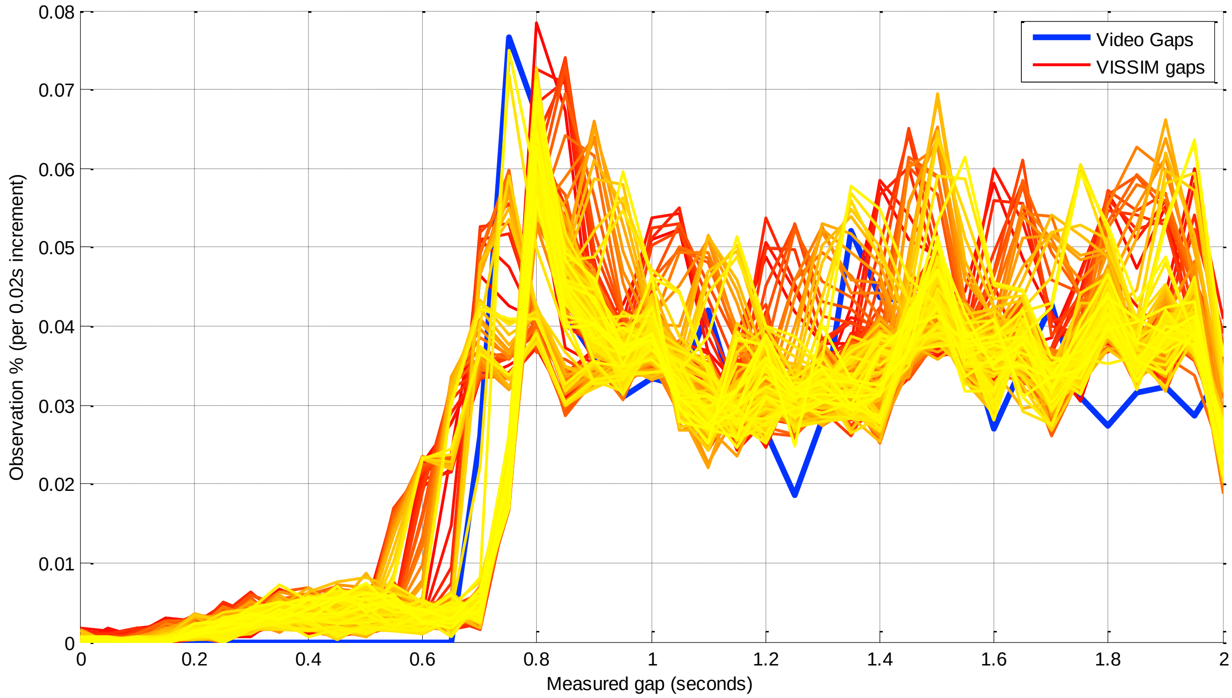


FIGURE 6 Second set of hypotheses compared with control video-measured gap-time distribution.

Figure 7 shows a quartile-quartile plot of the observation percentage for the video-measured gaps versus a single simulated distribution of gaps (in this case simulation #228). This type of analysis is useful for comparing discrete non-parametric distributions. For each simulation, we run a simple linear regression analysis on the quartile-quartile plot and record the CC values for which we have the closest fit with the shape of the video-measured gap distribution.

Figure 8 demonstrates the five best-fitting simulation distributions with respect to the video-measured distributions. **Table 4** lists the CC parameters that match the video gap distribution most closely in terms of linear residuals from the quartile-quartile plot. A value of 0.6 for CC1 was the most significant parameter for all distributions, along with a CC0 in the range of 3.75 to 4.

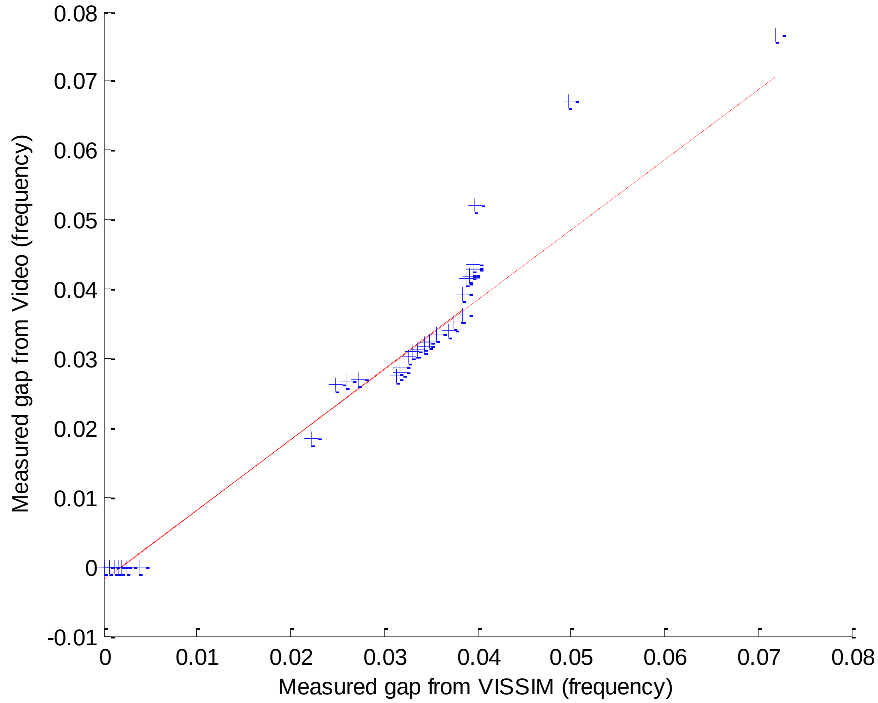


FIGURE 7 Quartile-quartile plot (Q-Q plot) of video-based versus simulation-based distributions.

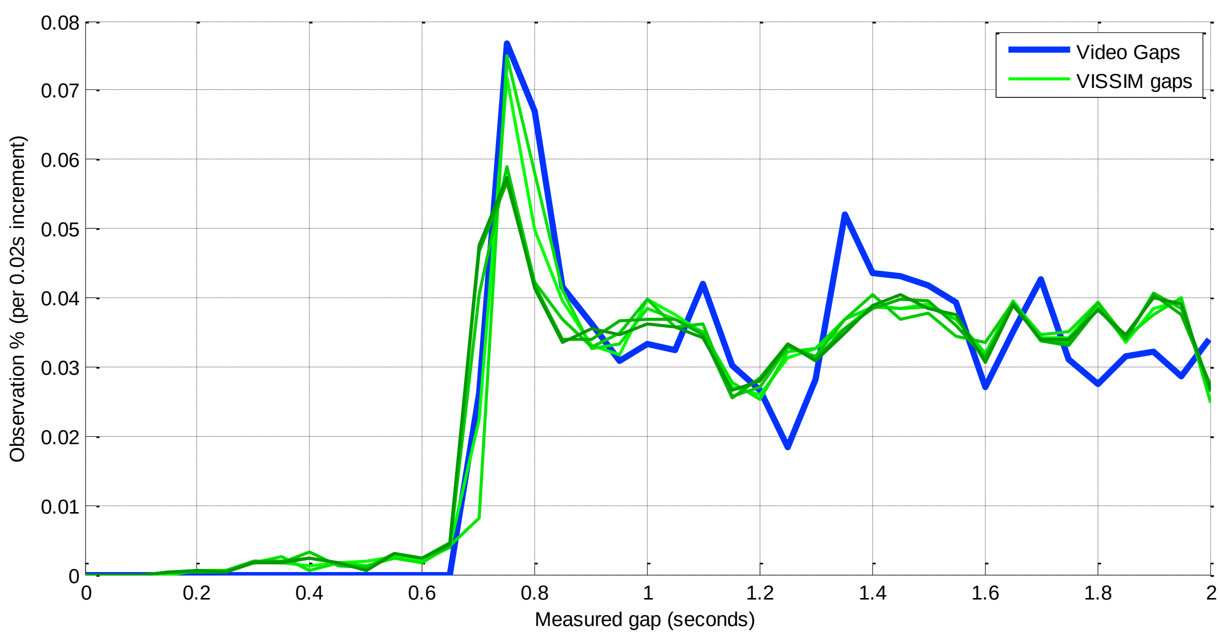


FIGURE 8 Top five fitting hypotheses; all have a CC1 of 0.6. Lightest green has the highest R^2 value.

TABLE 4 Top five simulations with CC0 and CC1 parameters as well as corresponding R^2

R^2 fit	Simulation ID	CC0	CC1
0.910733	228	3.75	0.6
0.904714	243	4	0.6
0.861583	213	3.5	0.6
0.84076	168	2.75	0.6
0.83905	153	2.5	0.6

CONCLUSIONS

Several conclusions were arrived at while these simulations were being performed. The first is that the overall distribution of following-distances is affected by more than just the Wiedemann 99 model. It can also be influenced by vehicle-clustering conditions on the highway when the entire gap-time distribution is considered. The gap-time might also be significantly affected by some of the parameters in the lane-change model (notably the safety distance reduction factor) in very dense flows, and if one simultaneously treats the second half of a lane-change action as a car-following situation.

The parameters CC0 and CC1 were adequately obtained for this particular section of highway. It might be interesting to see how this compares with other highway sections and whether recalibration is necessary for every highway sub-segment.

The shortcomings of the methodology used are clear: guessing and testing the software's algorithm is not the preferred method of calibrating the software's car-following model. Unless the model used is formally published, or at least some very specific guidelines are provided for the selection of CC parameters, there is little room for use of VISSIM and other microsimulation software in highly detailed, driver-behaviour-sensitive studies, such as highway conflict analysis, short of attempting to reverse engineer the parameters.

Future developments could include more attempted simulations with more optimized processing, now that the framework for mass batch simulations is in place. Some more solid statistical tests could be employed to increase reliability, although video processing introduces a certain amount of error too.

It would be interesting to test under conditions of high traffic flow, where all vehicles are following each other. However, this data might be difficult to obtain reliably from automated or semi-automated video trajectory extraction.

REFERENCES

1. *Automated Road Safety Analysis Using Video Data.* **Saunier, N. and Sayed, T.** Washington : s.n., 2007. 2007 TRB Annual Meeting. p. 21.

2. *Analysis of Driver Behaviour and Collision Risks for Protected Freeway Entrance and Exit Ramps: Trajectories and Surrogate Safety Measures.* **St-Aubin, P., Miranda-Moreno, L. and Saunier, N.** Halifax : Canadian Multidisciplinary Road Safety Conference, 2011.

3. *Some remarks on macroscopic traffic flow modelling.* **Papageorgiou, Markos.** 1998, Transportation Research Part A : Policy and Practice, pp. 323-329.

4. *Simulation des Straßenverkehrsflusses.* **Wiedemann, R.** 1974, Schriftenreihe des Instituts für Verkehrswesen der Universität Karlsruhe, p. 8.

5. *Validation of the Microscopic Traffic Flow Model VISSIM in Different Real-World Situations.* **Fellendorf, M. and Vortisch, P.** 2001, Transportation Research Board.

6. *An Integrated Microscopic and Macroscopic Calibration for Psycho-Physical Car Following Models.* **Menneni, S., Sun, C. and Vortisch, P.** 2009, TRB 88th annual meeting compendium of papers DVD, pp. 1-17.

7. *Guidelines for Calibration of Microsimulation Models: Framework and Applications.* **Dowling, R., et al., et al.** 2004, Transportation Research Record: Journal of the Transportation Research Board, No. 1876, pp. 1-9.

8. *Practical Procedure for Calibrating Microscopic Traffic Simulation Models.* **Hourdakis, J., Michalopoulos, P. G. and Kottommannil, J.** 2003, Transportation Research Record: Journal of the Transportation Research Board, No. 1852, pp. 130-139.

9. *Microscopic Simulation Model Calibration and Validation: Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System.* **Park, B. and Schneeberger, J. D.** s.l. : Transportation Research Record, 2003, Microscopic Simulation Model Calibration and Validation: Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System, pp. 185-192.

10. *Microsimulation Calibration Using Speed–Flow Relationships.* **Menneni, S., Sun, C. and Vortisch, P.** 2088, Transportation Research Record: Journal of the Transportation Research Board, No. 2088, pp. 1-9.