Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

CALIBRATING DRIVER AGGRESSION PARAMETERS IN MICROSCOPIC SIMULATION USING SAFETY-SURROGATE MEASURES

Dawei (David) Hong[1] and Montasir Abbas[2]

[1]Rummel, Klepper & Kahl (RK&K), VA, USA
[2]Dept. of Civil and Environmental Eng., Virginia Tech, Blacksburg, VA, USA

ABSTRACT

This research aimed to develop a methodology and framework to calibrate microscopic simulation models that drive behaviors to reproduce safety conflicts observed in real-world environments. The Intelligent Driver Model (IDM) was selected as the car-following algorithm to be utilized in the External Driver Model (EDM) Application Programming Interface (API) in VISSIM to better represent real-world driving behavior. The calibration method starts with an experiment design in the statistical software JMP Pro 16, which provided 84 simulation runs, each with a distinct combination of the 11 EDM input variables. After 84 runs each with a unique variable configuration, the traffic trajectory was analyzed using the FHWA's Surrogate Safety Assessment Model (SSAM) to generate counts of crossing, rear-end, and lane-change conflicts. It is concluded that the proposed calibration method can closely match the conflict counts derived from real-world conditions.

1 INTRODUCTION

Safety is a critical aspect of transportation engineering, especially with rising public travel and vehicle ownership. Comparing safety performances for design decisions is a priority for engineering firms and transportation departments. Historically, empirical methods have been used to observe traffic conflicts through photographs and reports on the characteristics of conflict-prone intersections (Parker and Zegeer 1989). This type of approach is called traffic conflict techniques for safety (Parker and Zegeer 1989), and the goal is to identify such conflicts defined by the scenarios or events that can develop into a collision (Lund Institute of Technology 1977). However, this process is time-consuming, costly, and requires careful examination to cover the details (Parker and Zegeer 1989). In the last twenty years, surrogate safety measures have been proposed and applied in microscopic simulation to replace expensive crash studies and reconstructions (Essa and Sayed 2020; Parker and Zegeer 1989).

Using microsimulation software such as PTV VISSIM and its trajectory output for surrogate safety analysis in FHWA's SSAM has become a popular proposed method for researchers to identify safety issues within a roadway network (Argade 2014; Kim et al. 2018; Li et al. 2013; Vasconcelos et al. 2014). However, such an effort also resulted in criticism and concerns over the validation and calibration of such a claimed correlation between simulated conflicts and crashes (Essa and Sayed 2020; So et al. 2015). Some researchers hoped to use a calibration method to adjust driving behaviors for the safety studies to increase the modeling accuracy (So et al. 2015).

In a small city projected to double in growth over the next five years, increasing diversity in driver behavior is expected due to migration. Capturing this variation in VISSIM's default parameters, particularly in car-following scenarios, will be challenging. The Wiedemann model in VISSIM assumes that vehicle inputs are influenced solely by transient stimuli, not by planned decisions or driving preferences like acceleration and aggression. (Abdelhalim and Abbas 2022). Inaccurate modeling of driving behavior can lead to exponential growth of issues and limited safety assessments, resulting in damages, injuries, and fatalities. Accurately modeling driving aggressions and their relationship to crashes is essential.

This paper presents a method for calibrating driver aggression using SSAM and VISSIM's EDM API to improve simulations of driver behavior and associated conflicts for safety studies. The IDM car-following algorithm was chosen for its capacity to adjust desired speed and acceleration, effectively simulating aggressive driving behavior (Abdelhalim and Abbas 2022; Kesting et al. 2010; Shi 2019; Treiber et al. 2000; Treiber et al. 2007).

The following sections will outline the methodology selection process and highlight the gap in easily calibrated and accurate driver behavior modeling for safety assessment in microsimulation. Adjustments in the VISSIM microsimulation software for implementing an advanced car-following model will be detailed. The calibration procedure includes creating a roadway network in VISSIM, designing experiments using JMP Pro 16, compiling trajectory outputs, conducting SSAM analysis, fitting the final model, and performing sensitivity analysis. Each step will be discussed in detail, along with an introduction to VISSIM's EDM interface and the IDM car-following algorithm. Ultimately, a set of calibrated parameters will be generated to reflect driver aggression and vehicle conflicts.

2 STATE OF THE ART

VISSIM is a powerful microscopic traffic simulation tool that has not been widely used for safety analysis. Recently, its combination with SSAM has become an effective platform for researchers to identify safety threats using existing traffic data. This combination also allows for quantitative comparisons of different roadway designs and configurations. (Argade 2014; Kim et al. 2018). Many research efforts have utilized this VISSIM and SSAM combination for analyzing different roadside access management methods. (Argade 2014; Kim et al. 2018), innovative traffic patterns (Vasconcelos et al. 2014), and intersection control systems (Li et al. 2013). While not entirely accepted by the consultant industry, much research has shown promising safety analysis results (Abdelhalim and Abbas 2022; Fan et al. 2013). However, tools such as the SSAM could not be utilized to their full potential if the data used was not calibrated to represent the safety conditions of the local highway system accurately (Essa and Sayed 2015; Huang et al. 2013; Katrakazas et al. 2018; Fan et al. 2013). Research using SSAM to analyze safety conditions has been limited due to inadequate calibration and inaccurate representation of driving behaviors. (Essa and Sayed 2015, 2020; Huang et al. 2013; Katrakazas et al. 2018; Fan et al. 2013).

SSAM analyzes the trajectory of vehicles in the network and uses the proximity model to predict the closeness to the accident by Time to Collision (TTC) and Post-Encroachment Time (PET) (Abdelhalim and Abbas 2022; Pu and Joshi 2008). TTC and PET are parameters that represent conflicts, which is a surrogate of crashes (So et al. 2015). However, as a new post-processing analysis platform for the existing microsimulation tools, SSAM received mixed reviews from scholars (So et al. 2015). The mixed impression came down to the modeling inaccuracy in the default microsimulation settings that require extensive calibration (Essa and Sayed 2020), the inability of VISSIM to violate traffic laws as in real life (Huang et al. 2013), the feasibility of analysis accuracy improvement using calibration (Essa and Sayed 2015), or even simply the question of whether the act of using VISSIM data for the SSAM analysis is statistically relevant because of the random nature of the driving behaviors (Fan et al. 2013). On the other hand, many studies have also laid out the solution to those problems, such as the fact that, with purposeful calibrations, the VISSIM and SSAM combination has promising improvements in its safety prediction accuracy (Essa and Sayed 2015; Huang et al. 2013; Katrakazas et al. 2018; Fan et al. 2013).

SSAM is sensitive to modeling inaccuracies and requires careful calibration. One proposed method involves two steps: first, calibrating the average delay per vehicle using observed speed data, and then adjusting the VISSIM Wiedemann driver model parameters based on rear-end conflict results (Essa and Sayed 2015). The author found that while calibration improved accuracy at one intersection, only a few driver model characteristics were transferable (Essa and Sayed 2015). The untransferable parameters may need calibration per intersection or could remain unchanged using system defaults. A study in Croatia also found that the VISSIM default Wiedemann 74, calibrated in Germany, was unsuitable for their area (Otković et al. 2020). These transferability conclusions affirmed the conclusions drawn by other authors as well (Abdelhalim and Abbas July 31, 2022; Fan et al. 2013).

Due to the limited transferability of the default VISSIM Wiedemann driver model parameters, many researchers opted to calibrate the simulation model for individual intersections or networks rather than creating a universal method. Some focused on calibrating driver behaviors based on specific simulation outcomes, like SSAM-determined conflicts (Otković et al. 2020). Other researchers preferred using an extra calibration step for the speed and delay (Essa and Sayed 2015), and some even used a complex function to analyze the calibration results (Katrakazas et al. 2018). AI calibration approaches have been examined, but they fall short in conducting sensitivity analysis to identify the most influential parameters affecting responses (Al-Msari et al. 2024).

Research has primarily focused on calibrating the Wiedemann driver model in VISSIM, but there is also literature on using VISSIM's EDM API to enhance driver following behavior modeling and employ the VISSIM and SSAM combination for quantitative validation (Abdelhalim and Abbas July 31, 2022; Li et al. 2013). The EDM replaces the car-following algorithm of the Wiedemann 74 or 99 model in the VISSIM microscopic simulation (Abdelhalim and Abbas July 31, 2022). This allows for a more accurate representation of driver aggression in vehicle-following scenarios compared to the default Wiedemann models. Notably, the EDM has been used to apply a driver model algorithm that calibrates itself based on SSAM results (Abdelhalim and Abbas July 31, 2022). The research introduced an innovative method showing the SSAM's capability in safety analysis through a new driver model, though its transferability to other locations remains uncertain. VISSIM's EDM API (Shi 2019) provides an easy-to-calibrate alternative to the Wiedemann model for car-following, as it can incorporate other driver models like IDM to better mimic driving behaviors (Abdelhalim and Abbas July 31, 2022; Kesting et al. 2010). Improved driver aggression calibration allows state or local officials to estimate potential crashes when comparing roadway designs or analyzing existing roads, bypassing costly crash studies. (Argade 2014).

The use of VISSIM and SSAM for safety analysis faces issues such as insufficient calibration, non-standardized calibration methods, and the inability to accurately represent driving behaviors. Thus, a surrogate analysis method with greater accuracy and easier calibration is needed.

3 METHODOLOGY

The research methodology included three key components: (1) observing safety-critical conflicts in real-world scenarios, (2) developing a simulation model for the case study, and (3) calibrating driving behavior parameters to replicate observed conflicts. The simulation comprised a VISSIM model of a 5-mile circular road network in Blacksburg with peak-hour traffic, Ring-Barrier Controllers to emulate Signal Phase and Timing (SPaT) data, and an IDM model for car-following behavior using VISSIM's EDM API.

To validate the methodology, we employed a statistical analysis model (JMP Pro 16) and designed experiments with 11 IDM independent variables for VISSIM runs. A VBScript automated the loading of a Dynamic Link Library (DLL) for 84 continuous runs. The SSAM converted VISSIM trajectory data into conflict counts, and JMP Pro 16 was used for fitting, sensitivity analysis, and calibrating IDM values to generate targeted conflict counts from near-conflict data.

3.1 Roadway Network

The experiment used a 5-mile loop roadway based on research showing that looped networks effectively represent vehicle-to-vehicle interactions, similar to real traffic. Notable studies using this setup focused on phantom traffic and the role of autonomous vehicles in alleviating such issues (Stern et al. 2018; Sugiyama et al. 2008; Tadaki et al. 2013). To calibrate vehicular conflict detection, a loop road network was modeled in VISSIM, based on the roadway network in Blacksburg, VA. This network includes a mix of rural principal arterials, urban minor arterials, major collectors, and minor collectors (Federal Highway Administration 2000).

Blacksburg, a college town with diverse growth prospects, is the chosen location. The network layout is illustrated in Figure 1. Turning volumes and SPaT data for the VISSIM setup were sourced from

Blacksburg and VDOT. Data from Blacksburg covers intersections 1 to 8, while VDOT provides information on the US-460 bypass and Southgate Drive Interchange (Figure 1).

Figure 1: Roadway Network's Satellite Imagery and the VISSIM Network (Blacksburg, VA, 2019).

The timing plan from Blacksburg and VDOT is utilized to reflect actual field conditions. Data for modeling the 5-mile roadway network were collected between 2018 and 2023 to accurately represent current traffic. The 5 PM to 6 PM peak hour was selected due to the typically high traffic volume, which increases the likelihood of collisions. To simplify the simulation, minor intersections without traffic controllers were excluded, as specific turning counts could not be determined. Additionally, driveways, turnouts, bus stops, and facility entrances were not included due to a lack of data.

3.2 Mathematical Model

The mathematical expression of the open-source code modified for this experiment is the IDM, a time-continuous car-following function commonly used in traffic engineering research (Shi 2019; Treiber et al. August 30, 2000; Treiber et al. 2007). The IDM functions are shown below in Equations 1 and 2. The a_{IDM} is the acceleration calculated from the IDM and fed back into the VISSIM API at each time step. The $s, v, \Delta v$ are the VISSIM parameters following distance, vehicle speed, and vehicle speed differential (from the surrounding vehicles) being input into the IDM from the EDM API. Besides a free acceleration component denoted by "δ" that generally has a value of "4", the meaning of the rest of the parameters is shown below (Table 1). Below is IDM Equation (1):

$$a_{IDM}(s, v, \Delta v) = \frac{dv}{dt} = a[1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v, \Delta v)}{s}\right)^2] \quad (1)$$

IDM Equation (2):

$$s^*(v, \Delta v) = s_0 + vT + \frac{v \Delta v}{2\sqrt{ab}} \quad (2)$$

3.3 EDM Script, Experiment Design, and Variables

The EDM utilized in this research is a set of open-source scripts (Shi 2019) that utilized the IDM in its algorithm for calculating the VISSIM's virtual drivers' behavioral response to the change in the input EDM's parameters. This open-source C++ script builds a DLL for VISSIM's EDM API, using 11 major input parameters for user calibration (Table 1). These parameters allow users to replace VISSIM's default Wiedemann 74 or 99 car-following model with behavior calculated by the IDM algorithm. In an experiment designed in JMP Pro 16, these parameters were assigned reasonable ranges, resulting in 84 distinct parameter combinations for the EDM scripts, leading to 84 VISSIM simulation runs. Each combination corresponds to one simulation run due to the lack of stochastic nature of the same random seed, ensuring identical outcomes with the same VISSIM file and inputs. The "turning_indicator" parameter, with designated values of "-1," "2," and a corrected "0" instead of "0.5," was handled accordingly in JMP Pro 16. A script was also created to automate the compilation of these 84 DLLs.

Table 1: EDM input variables and possible range.

	Possible Range	
Independent Variables	**Low**	**High**
desired_acceleration	0	8.5
desired_lane_angle	-1.57	1.57
active_lane_change	-1	1
rel_target_lane	-1	1
desired_velocity	5	35
turning_indicator	-1	2
a = IDM_max_acceleration	0	8.5
b = IDM_max_deceleration	0	10
v0 = IDM_desired_velocity	5	35
S0 = jam_distance	0	10
T = safe_time_headway	0	3

Below are the explanations for each of the variables. Most of the variables below either describe a desired state to be in or describe an active desire to complete a certain driving movement. "desired_acceleration" is an EDM default variable that has a unit of m/s^2. This variable corresponds to the desired acceleration of the driver at the current time step (Rahal et al. 2017). A range of "0" to "8.5" was used for this variable because an acceleration of 8.5 is about the quickest acceleration to be expected of street vehicles. "desired_lane_angle" is another default EDM variable that has a unit of rad. It is the desired lane angle relative to the middle of the lane (Rahal et al. 2017) (Table 1). A positive value in rad would be a state of desiring to turn to the left, and a negative value indicates a desire to turn right, while a "0" value denotes no desire to turn either left or right concerning the middle of the lane (Rahal et al. 2017). A range of "-1.57" to "1.57" rad is used for it equates to about 90 degrees turn to the left and the right. "active_lane_change" is an EDM default variable that has no unit, but it simply indicates the direction of the active lane change movement or a desired lane change movement (Rahal et al. 2017). A "+1" value would indicate an active leftward lane change, a "0" value means no lane change, and a "-1" value means an active rightward lane change (Rahal et al. 2017). "rel_target_lane" is a default EDM variable that has no unit, but similar to the previous variable, it indicates a desired lane to be in.

For example, one lane to the left would be "+1", one lane to the right would be "-1", and a "0" value would indicate the current lane is the desired lane (Rahal et al. 2017). "Desired_velocity" is another default EDM variable in a unit of m/s. It straightforwardly indicates the travel speed the driver desires to run during the current time step (Rahal et al. 2017). A range of "5" to "35" was used because a speed of 11 mph to 78 mph could be expected in the roadway network. "turning_indicator" is a default EDM parameter similar to the "active_lane_change" parameter mentioned previously. "turning_indicator" has no unit. A value of "+1" indicates the left turn signal is on, a value of "-1" indicates the right turn signal is on, a value of "0" indicates no signal was used in the lane change, and a value of "2" indicates both indicators or the hazard light was used (Rahal et al. 2017). It is noted that the turning indicator variable not only allows the VISSIM visualization during the simulation run to show blinkers used by the ego vehicle, but it also allows other drivers to notice and respond to the use of the blinkers (Rahal et al. 2017). “vehicle_color” is a default EDM variable neglected in this experiment due to its insignificance in affecting driver behaviors under the no-driver-error default settings in VISSIM.

The IDM variables are added to the default EDM by researcher Yunpeng Shi in the open-source script used in this experiment (Shi 2019). These IDM variables are essentially the Kesting and Treiber IDM variables incorporated into the script (Kesting et al. 2010). “IDM_max_acceleration” or “a” as noted in the original open-source script, is an IDM variable with a unit of m/s^2. “IDM_max_deceleration”, or “b” as noted in the original open-source script, is an IDM variable with a unit of m/s^2. Both “a” and “b” are positive values used for the IDM calculations to determine the acceleration and the following distance at the current time step (Kesting et al. 2010; Shi 2019). For “a”, a range between “0” to “8.5” like the one given to the “desired_acceleration” is given. For “b”, a range between “0” to “10” was given due to the slightly higher deceleration that could be expected from street vehicles than that of their acceleration. “IDM_desired_velocity” or “v0”, is another IDM variable with a unit of m/s like the “desired_velocity”. Thus, a similar range between “5” and “35” is given. “jam_distance” or “S0” is an IDM variable with a unit of meters. A range between “0” and “10” was given since following a vehicle with as much as two-car-length distance is acceptable. “safe_time_headway” or “T” is the final IDM variable with a unit of seconds. A range between “0” and “3” is used in this experiment because the “3-second rule” is a commonly recommended car-following rule when driving at 65 mph.

Once the user changes the input parameters to their desired numbers and the vehicle class according to the desired VISSIM vehicle class in the C++ script, the script is then developed into a DLL file ready for VISSIM’s API to call. For this experiment, all vehicle classes, including the passenger cars, buses, and Heavy Goods Vehicle (HGV) classes, used the external driver. However, in a scenario where the other vehicle classes are added, the scripts are easily modifiable by changing a single parameter “vehicle_type” to the corresponding vehicle classes. During the simulation run, VISSIM will supply the EDM with information such as the vehicle ID, lane number, total distance traveled (or odometer), lane angle, velocity, acceleration, length, and weight at every time step. The algorithm in the DLL will take these values and supply VISSIM with the updated values after the parameters run through the IDM model at each of the time steps incrementally (Rahal et al. 2017; Shi 2019).

4 RESULTS AND DISCUSSION

The following section will focus on the calibration process from the simulation output parameters and a discussion of the calibration results. The calibration process consists of four parts: (1) Create 84 simulation runs generating 84 distinct trajectory files (.trj) using a script file, (2) Input the trajectory files in SSAM to translate the files into conflict types and conflict counts for each of the runs, (3) Input the conflict types and their counts for each run into their corresponding response variable in JMP Pro 16 for model fitting, and (4) Fine-tune each parameter within the acceptable ranges to match the pre-determined conflict count translated from the real-world data. After the DLL generation, a script file was written for the VISSIM interface to initiate the EDM API, load all the DLLs consecutively, and run the simulations consecutively.

After the 84 simulation runs, the trajectory data was examined by the SSAM and output three types of conflicts and their counts. The SSAM was then used to identify incidents where the vehicle’s trajectory was in proximity to the other vehicles. TTC and PET were used to describe such proximity. TTC is the time before two vehicles in the roadway network collide if they continue in their trajectory. PET is the time between one vehicle occupying a specific location in the roadway network and the next vehicle arriving at the same location (Pu and Joshi May 2008). The TTC and PET were then used as a filter to identify the most critical conflicts among all the conflicts, specifically those with 0 seconds (equal to collision) or 0.1 seconds of TTC or PET. The crossing, rear end, and lane change conflicts of each scenario or trajectory file were compared against the VISSIM default as well as the EDM’s default trajectory output. TTC thresholds were set at “0” to “1.5” seconds, while PET thresholds were set at “0” to “4.9” seconds. The conflict data taken into consideration were 55,394 crossing conflicts, 434,143 rear-end conflicts, and 43,157 lane change conflicts. All of these factors came from the sum of the conflicts in all 84 simulation runs. Various levels of conflict severity were scattered throughout the roadway network used in this investigation (Figure 2**).**

Prices Fork Road, the east-west running arterial on the top part of the roadway network, showed the highest concentration of conflicts of all severity levels, while the southern part of the roadway network experienced the least number of conflicts. Also, from the concentration of the conflicts on Prices Fork Road, it is worth mentioning that there is a possible correlation between the number of vehicles and the number of surrogate conflicts. On the US-460 bypass, the north-south running freeway on the left side of the roadway network barely has any conflicts. This is because of a lack of vehicles on the freeway US-460 compared to the vehicles traveling on the arterial Prices Fork Road.

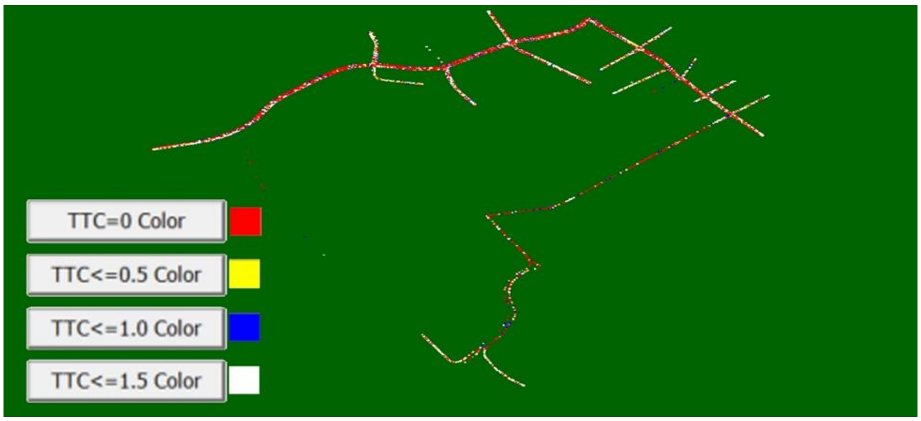

Figure 2: Conflict map visualization by SSAM.

Since the conflicts happened throughout the 84 simulation runs and were all projected as a summary of the conflicts, the concentration of the conflicts may seem as if it is higher than normal (Figure 2). To further explain the number of conflicts in individual VISSIM runs, the following is the data acquired from the SSAM after the analysis and the filtration of the included unnecessary trajectory conflicts. The table only shows the SSAM conflict summary data from the 27th to the 37th run as an example (Table 2). All 84 lines of data were loaded into JMP Pro 16 for final model fitting and calibration target-matching. Before the JMP model fitting and sensitivity analysis, the visual inspection indicates a high fluctuation of all three types of conflicts throughout the 11 simulation runs because of the change in EDM driver model parameters.

Table 2: EDM input variables and corresponding VISSIM conflicts.

Desired_a	**desired_lane_angle**	**active_lane_change**	**rel_targetlane**	**Desiredvelocity**	**turning indicator**	**a**	**b**	**v0**	**S0**	**T**	**Crossing**	**Rear End**	**Lane Change**
4.25	1.57	1	0	35	2	8.5	10	35	10	0	226	2492	215
0	1.57	1	-1	20	-1	0	10	20	0	0	135	1592	130
8.5	1.57	1	1	35	-1	0	10	35	10	1.5	137	2196	96
8.5	-1.57	1	-1	5	0	8.5	10	20	10	0	495	34	123
0	0	1	-1	35	0	0	0	35	5	1.5	138	2061	110
0	-1.57	1	1	5	-1	0	10	5	5	1.5	146	2053	112
4.25	-1.57	0	1	5	-1	8.5	0	20	10	0	318	1821	212

0	-1.57	-1	1	35	2	0	5	5	0	3	135	1592	130
0	0	0	-1	5	0	8.5	10	35	5	1.5	579	536	617
4.25	1.57	-1	1	20	-1	8.5	5	35	0	1.5	259	64	127
8.5	-1.57	-1	1	35	2	0	0	35	5	0	146	2053	112

Comparing the 1st, 7th, and 10th runs in Table 2, the IDM deceleration parameter seems to have a large impact on the rear-end conflicts. In real life, decelerating too slow or too fast could result in a rear-end collision. Similarly, in the VISSIM simulation, if the drivers dictated by the EDM parameters brake too fast or do not have enough braking, it will likely result in more collisions. The first simulation run above has the most amount of rear-end conflicts as well as the highest IDM maximum deceleration of 10 m/s^2, which is approximately the highest deceleration possible on a street-legal vehicle. The violent braking is likely the cause of such conflicts. The seventh simulation run has the lowest IDM maximum deceleration of 0 m/s^2. By not having enough braking in a car-following episode, the vehicles will likely collide with each other in the event of turning into another street or in a roundabout. Thus, while the deceleration parameter changed, the number of rear-end conflicts did not dramatically decrease.

However, when compared to the tenth simulation run, the previous two experiment runs had deceleration values that were too extreme. A maximum deceleration value of 5 m/s^2 is like that of moderate to hard braking in daily commutes. In the tenth run, the rear-end conflict count dropped dramatically to only 64, indicating a more modest braking behavior will likely result in fewer rear-end conflicts.

These visual inspections of the simulation data, however, could not replace the statistical analysis. While visual inspections could indicate possible correlations between a singular driver model parameter and a single VISSIM surrogate conflict output parameter, it is impossible to determine the exact correlation or the impact of other driver model parameters on this correlation. For example, how would the increase in safe-time headway impact the correlation between the IDM maximum deceleration and the rear-end conflicts? JMP Pro 16 was used to examine the output of all 84 simulation runs based on its experiment design, and it reports all trends or correlations observed. A model fitting is completed producing the visualization of the model-fitting results in (Figure 3) and (Figure 4). All three response parameters show statistically significant correlations to the 11 input variables under 95% confidence intervals with the lane change being the response variable with the highest R-square value.

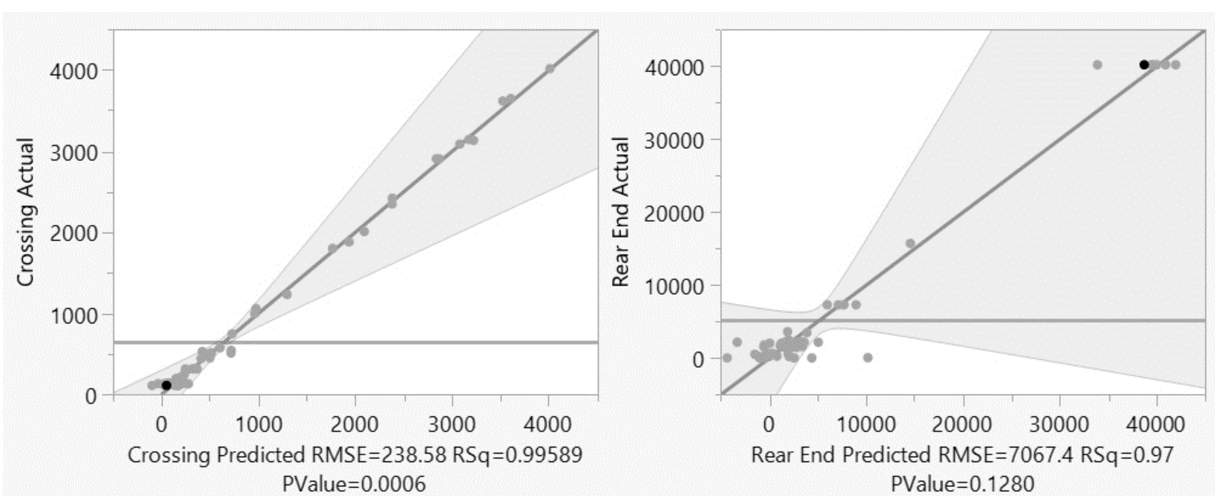

Figure 3: Crossing and rear end conflicts model goodness of fit.

After the model fitting, a sensitivity analysis was performed. As shown below in Figure 5 and Figure 6, each of the 11 input parameters has demonstrated its influence on each response variable. The correlation profiles shown for all 11 driver model variables and 3 conflict response variables revealed correlations that were impossible to discover visually. When moving the parameter value needle on one of the eleven parameter's correlation profilers, the rest of the correlation profilers' profile changes as the needle moves. This evidence confirmed the findings of the visual inspection above: the impact of one parameter on the correlation between other parameters. Also, the correlation profilers confirmed the finding that the IDM max deceleration value has a significant impact on the rear-end conflict count (Figure 6).

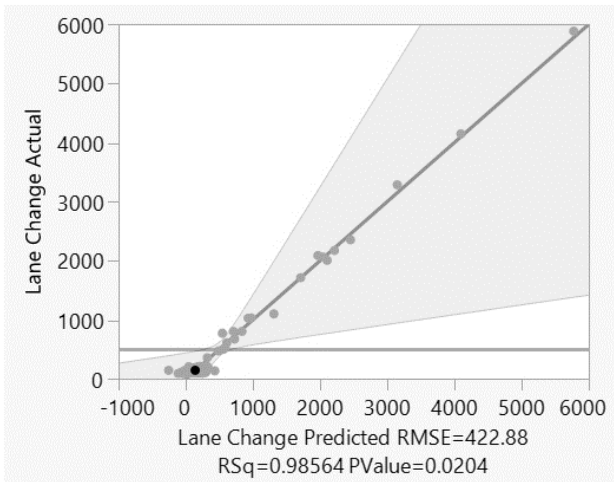

Figure 4: Lane change conflicts model goodness of fit.

The next step is to use the slider for each of the 11 parameters in the sensitivity analysis to change their values and observe the change in the response variables crossing, rear-end, as well as lane change conflicts. The curves show the correlation trends of each input parameter, changing their shapes with the movement of the sliders and indicating the cooperative influence of the 11 input parameters together. It is important to note that the inputs for "active_lane_change", "rel_target_lane", and "turning_indicator" are only acceptable as they are integers. For this experiment, a conflict count target is 280 crossing conflicts, 270 rear-end conflicts, and 55 lane-change conflicts. The sliders for each input variable were adjusted so that all three response variables from the new input variables would be matched to those of the calibration target.

The purpose of such calibration is to find a set of driving behavior parameters in the car-following episodes to best represent the driving behavior of a roadway network. After the simulation runs, SSAM, and the sensitivity analysis, the value of each parameter that is most effective in detecting conflicts and potential collisions was found. The effectiveness is determined by a good match between the calibration targeting conflict counts and the simulation conflict count based on the sensitivity analysis. Shown below are the calibrated parameters to best represent the targeted calibration values in (Figure 5) and (Figure 6). A crossing, rear-end, and lane-change conflict count of 281.35, 272.33, and 55.71 are within acceptable proximity to the calibration targets of 280, 270, and 55.

One benefit of such a calibration process is that it is mostly automatic, sans the SSAM's involvement and the sensitivity analysis in JMP Pro 16 due to their inability to support an API interface for automatic processing. In the event of a future application utilizing such calibration in a different locality, the scripts only need to be modified slightly to accommodate the setup on different computers, software versions, and roadway networks.

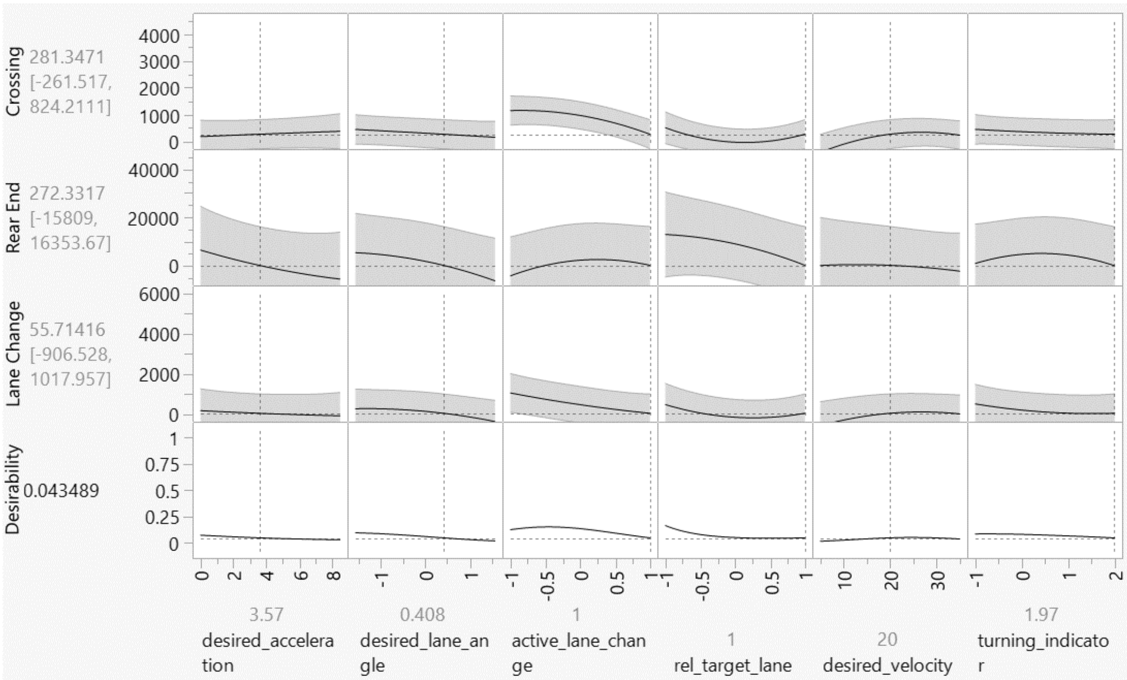

Figure 5: Calibrated EDM default input parameters.

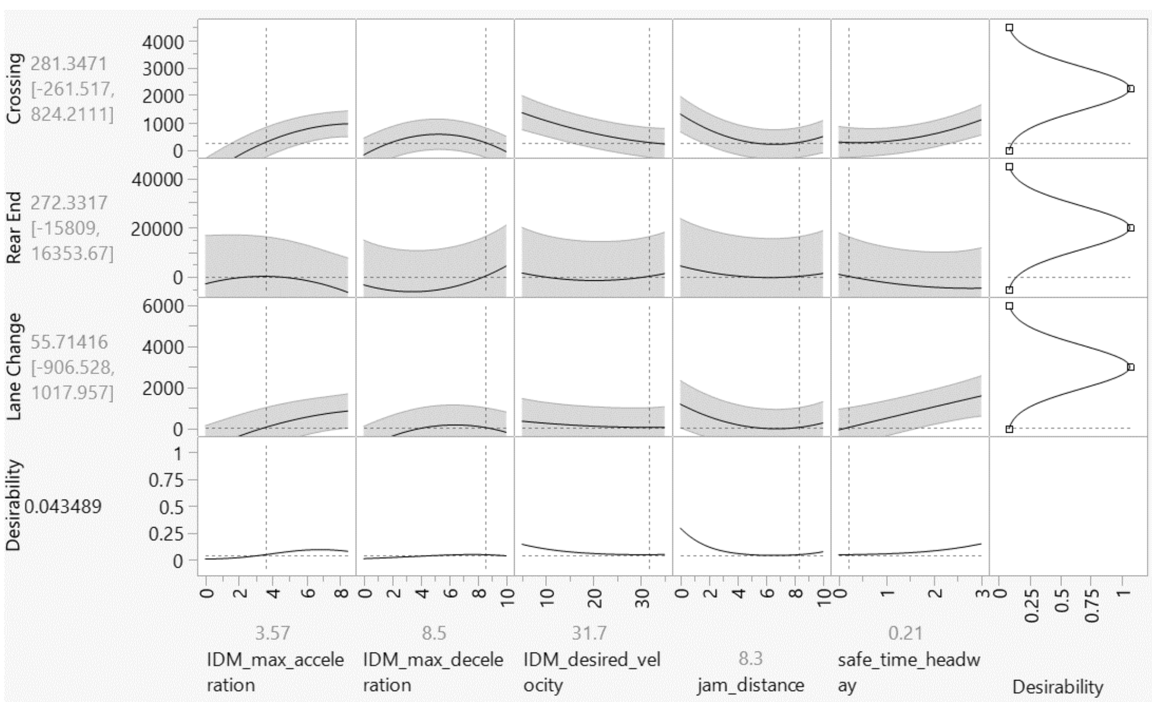

Figure 6: Calibrated IDM input parameters.

It is safe to conclude that the calibration method this experiment proposes effectively matches the surrogate conflicts translated from the real-world collision data. All potential crossing, rear-end, and lane change collision detections are optimized during this calibration. However, determining whether this calibration method has the adaptability to represent the surrogate of collisions in different localities or internationally still requires future research and development. With the availability of traffic turning volumes and SPaT data from different agencies, it is possible to come up with improvements on various steps of this calibration method and develop this method to be universally applicable to all roadway networks.

5 CONCLUSIONS

In this paper, a method of calibrating the VISSIM's EDM's car-following behaviors to best identify potential collisions through the surrogate conflict analysis of the microsimulation trajectories was introduced. The calibration methodology developed in this research can be applied to any adequately established simulation network model for other simulation tools with slight changes in the scripts and settings. This calibration method provides sufficient evidence to produce an accurate result matching real-world target metrics. With the availability of the calibration data, this method can be improved to accommodate more roadway networks. This methodology can potentially be used by researchers, engineering consultants, and officials to calibrate their microscopic simulation's car-following models to identify and alleviate safety-critical situations.

ACKNOWLEDGMENTS

This research was supported by the CIAMTIS Region 3 University Transportation Center, United States Department of Transportation. The traffic count data and the signal timing data for the US-460 interchange were provided by Dr. Andrew Nichols, the Signal & Freeway Operations Engineer from the Virginia Department of Transportation Salem District. The traffic count data and the signal timing data for the Blacksburg portion were provided by Mr. Joshua Middleton, the Public Works Assistant Director from the Town of Blacksburg, VA. Computer programming support was given by Amun Kharel from the Virginia Tech Department of Computer Science.

REFERENCES

Abdelhalim, A., and M. Abbas. 2022. *An Assessment of Safety-Based Driver Behavior Modeling in Microscopic Simulation Utilizing Real-Time Vehicle Trajectories.* 2210th ed. https://arxiv.org/pdf/2210.09076.pdf, accessed 22nd December 2023.

Al-Msari, H., Koting, S., Ahmed, A., El-shafie, A. 2024. "Review of driving-behaviour simulation: VISSIM and artificial intelligence approach". *Heliyon* 2024.e25936

Argade, P. D. 2014. "Quantifying the Safety Effects of Access Management Using VISSIM and SSAM: A Case Study". https://kuscholarworks.ku.edu/bitstream/handle/1808/18372/Argade_ku_0099M_13680_DATA_1.pdf.

Blacksburg, VA. 2019. Google. https://earth.google.com/web/@37.22269816,-80.43095489,624.27304692a,6857.08720796d,35y,0h,0t,0r/data=OgMKATA, accessed 13th January 2024.

Essa, M., and T. Sayed. 2015. "Transferability of calibrated microsimulation model parameters for safety assessment using simulated conflicts". *Accident Analysis & Prevention* 84:41–53.

Essa, M., and T. Sayed. 2020. "Comparison between Surrogate Safety Assessment Model and Real-Time Safety Models in Predicting Field-Measured Conflicts at Signalized Intersections". *Transportation Research Record: Journal of the Transportation Research Board* 2674(3):100–112.

Fan, R., H. Yu, P. Liu, and W. Wang. 2013. "Using VISSIM Simulation Model and Surrogate Safety Assessment Model for Estimating Field Measured Traffic Conflicts at Freeway Merge Areas". *IET Intelligent Transport Systems* 7(1):68–77.

Federal Highway Administration. 2000. Road Function Classifications The Interstate System The Interstate System Rural Interstate. https://safety.fhwa.dot.gov/speedmgt/data_facts/docs/rd_func_class_1_42.pdf.

Huang, F., P. Liu, H. Yu, and W. Wang. 2013. "Identifying if VISSIM simulation model and SSAM provide reasonable estimates for field measured traffic conflicts at signalized intersections". *Accident Analysis & Prevention* 50:1014–1024.

Institute of Transport Economics, Lund Institute of Technology. 1977. *Proceedings: First workshop on Traffic Conflicts*: *OSLO 77.* https://www.ictct.net/wp-content/uploads/XX-Oslo-1977/1977-Proceedings.pdf, accessed 22nd December 2023.

Katrakazas, C., M. Quddus, and W. -H. Chen. 2018. "A Simulation Study of Predicting Real-Time Conflict-Prone Traffic Conditions". *IEEE Transactions on Intelligent Transportation Systems* 19(10):3196–3207.

Kesting, A., M. Treiber, and D. Helbing. 2010. "Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity". *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 368(1928):4585–4605.

Kim, K. M., M. Saito, G. G. Schultz, and D. L. Eggett. 2018. "Evaluating Safety Impacts of Access Management Alternatives with the Surrogate Safety Assessment Model". *Transportation Research Record: Journal of the Transportation Research Board* 2672(17):120–128.

Li, Z., M. V. Chitturi, D. Zheng, A. R. Bill, and D. A. Noyce. 2013. "Modeling Reservation-Based Autonomous Intersection Control in VISSIM". *Transportation Research Record: Journal of the Transportation Research Board* 2381(1):81–90.

Otković, I. I., A. Deluka-Tibljaš, and S. Šurdonja. 2020. "Validation of the calibration methodology of the micro-simulation traffic model". *Transportation Research Procedia* 45:684–691.

Parker, M.R., Jr., and C. V. Zegeer. 1989. "Traffic Conflict Techniques for Safety and Operations: Observers Manual", U.S. Department of Transportation Federal Highway Administration, Martin R. Parker and Associates, Inc. https://www.fhwa.dot.gov/publications/research/safety/88027/88027.pdf, accessed 22nd December 2023.

Pu, L., and R. Joshi. 2008. "Surrogate Safety Assessment Model (SSAM)-SOFTWARE USER MANUAL", Federal Highway Administration, Research, Development, and Technology Turner-Fairbank Highway Research Center. https://www.fhwa.dot.gov/publications/research/safety/08050/08050.pdf.

Rahal, M. C., S. Pechberti, B. Heijke, and P. Sukennik. 2017. D2.2_Technical_Report_on_connecting_AV-Control_Logic_and_AV_Simulator. https://www.h2020-coexist.eu/wp-content/uploads/2018/10/D2.2_Technical_Report_on_connecting_AV-Control_Logic_and_AV_Simulator.pdf, accessed 14th January 2024.

Rong Fan, Hao Yu, Pan Liu, and Wei Wang. 2013. "Using VISSIM Simulation Model and Surrogate Safety Assessment Model for Estimating Field Measured Traffic Conflicts at Freeway Merge Areas". *IET Intelligent Transport Systems* 7(1):68–77.

Shi, Y. 2019. *Using-VISSIM-External-Driver-Model-DLL-for-Modeling-Mixed-Traffic-with-Both-Automated-Vehicles-and-Human-Driven-Vehicles*. GitHub. https://github.com/YunpengShi/Using-VISSIM-External-Driver-Model-DLL-for-Modeling-Mixed-Traffic-with-Both-Automated-Vehicles-and-H, accessed 22nd December 2023.

So, J., B. Park, S. M. Wolfe, and G. Dedes. 2015. "Development and Validation of a Vehicle Dynamics Integrated Traffic Simulation Environment Assessing Surrogate Safety". *Journal of Computing in Civil Engineering* 29(5):4014080.

Stern, R. E., S. Cui, M. L. Delle Monache, R. Bhadani, M. Bunting, M. Churchill, N. Hamilton, R. Haulcy, H. Pohlmann, F. Wu, B. Piccoli, B. Seibold, J. Sprinkle, and D. B. Work. 2018. "Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments". *Transportation Research Part C: Emerging Technologies* 89:205–221.

Sugiyama, Y., M. Fukui, M. Kikuchi, K. Hasebe, A. Nakayama, K. Nishinari, S.-I. Tadaki, and S. Yukawa. 2008. "Traffic Jams Without Bottlenecks—Experimental Evidence for the Physical Mechanism of the Formation of a Jam". *New Journal of Physics* 10(3):33001.

Tadaki, S.-I., M. Kikuchi, M. Fukui, A. Nakayama, K. Nishinari, A. Shibata, Y. Sugiyama, T. Yosida, and S. Yukawa. 2013. "Phase Transition in Traffic Jam Experiment on a Circuit". *New Journal of Physics* 15(10):103034.

Treiber, M., A. Kesting, and D. Helbing. 2007. "Influence of Reaction Times and Anticipation on Stability of Vehicular Traffic Flow". *Transportation Research Record: Journal of the Transportation Research Board* 1999(1):23–29.

Treiber, M., A. Hennecke, and D. Helbing. 2000. *Congested Traffic States in Empirical Observations and Microscopic Simulations*. Institute of Theoretical Physics, University of Stuttgart. https://arxiv.org/abs/cond-mat/0002177v2, accessed 22nd December 2023.

Vasconcelos, L., L. Neto, Á. M. Seco, and A. B. Silva. 2014. "Validation of the Surrogate Safety Assessment Model for Assessment of Intersection Safety". *Transportation Research Record: Journal of the Transportation Research Board* 2432(1):1–9.

AUTHOR BIOGRAPHIES

DAWEI (DAVID) HONG is a traffic engineer at Rummel, Klepper & Kahl (RK&K) and a former student in the Department of Civil and Environmental Engineering at Virginia Tech in Blacksburg, Virginia, USA. His research interests include driving simulation, driving behavior modeling, connected and autonomous vehicles, and artificial intelligence. His email address is dhong@rkk.com.

MONTASIR ABBAS is a Professor of Civil Engineering at Virginia Tech University in the USA. He holds a B.Sc. degree in Civil Engineering from the University of Khartoum, Sudan, an M.Sc. in Civil Engineering from the University of Nebraska-Lincoln, and a Ph.D. in Civil Engineering from Purdue University in West Lafayette. His research interests include simulation, traffic operations and control, traffic flow theory, and the application of artificial intelligence in transportation engineering. His email address is abbas@vt.edu.