Calibration of Microsimulation Models for Advance Warning Systems

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Abstract—The use of microscopic traffic simulation models in traffic operations, transportation design, and transportation planning has become widespread across the United States because of: (i) rapidly increasing computer power; (ii) the development of sophisticated traffic micro-simulation tools; and (iii) the need by transportation engineers to solve complex problems which do not lend themselves to traditional analysis techniques. This paper presents an application of traffic microsimulation to the analysis of actuated advance warning (AAW) system operations at high-speed signalized intersections. It has been shown that there is a greater-than 90% likelihood that the installation of an AAW system — consisting of one detector in advance of the intersection and active warning signs with the legend “PREPARE TO STOP WHEN FLASHING” — at a high-speed signalized intersection, enhances traffic safety [1]. Microscopic traffic simulation modeling is an ideal tool for the analyses of intersections equipped with AAW systems because it provides the ability to look more closely at the impacts these systems have on intersection safety and efficiency. It can also be a more convenient, less expensive, faster and safer alternative to field implementation and testing. The objective of this paper is to develop a microsimulation modeling approach that can be used to perform consistent, detailed analyses of AAW systems. Salient features of the methodology include: (i) modeling the expected changes in speeds while the advance warning signs are active; and (ii) modeling the subsequent reaction of drivers to the onset of the amber indication. The approach is demonstrated using VISSIM, a widely used psychophysical car-following model based microsimulation software. A signalized intersection in Lincoln, Nebraska equipped with AAW devices on two of its high-speed approaches is used as a case study.

Keywords- Dilemma zone; Advance warning; Microsimulation; Calibration

I. INTRODUCTION

As drivers approach high-speed signalized intersections at the onset of the yellow signal indication they often face a dilemma as to whether to stop or go through the intersection. This is because there might be neither sufficient yellow time to go through nor adequate braking distance to stop. The section of roadway upstream of the intersection where this indecision occurs is known as the dilemma zone. The dilemma zone poses a serious safety and operational challenge at isolated high-speed signalized intersections, especially when there are significant volumes of trucks and other heavy vehicles. A combination of poor driving decisions, poor acceleration and deceleration characteristics, and improper signal timing plans can lead to red-light running and rear-end or lateral collisions.

Dilemma zones generally occur due to improper signal timing [2]. Consequently, an important control objective at high-speed signalized intersections is to provide safe green-to-yellow light transition (dilemma zone protection) by minimizing the occurrence of high-speed vehicles in the dilemma zone [3, 4]. Two methods of providing dilemma zone protection are widely used. These are the use of: (i) advance warning systems; and (ii) advance detection.

Advance warning (AW) systems consist of static warning signs with the legend “Prepare to Stop when Flashing,” enhanced with flashing beacons located upstream of the intersection. The AW system is interconnected to the signal controller so that the beacons are activated at a predetermined time before the onset of yellow. The other method, advance detection (AD), involves the use of one or more detectors upstream of the intersection so that approaching vehicles are able to extend the green (and prevent the onset of yellow) while traveling in the dilemma zone. Both the AW and the AD system with multiple detectors have been widely studied and shown to be somewhat effective at minimizing conflicts and reducing crashes [5, 6, 7]. However, a significant drawback to the conventional AD system is that the long allowable gaps provided by these designs increase the frequency at which the green indication reaches its maximum allowable value [4]. When this happens, the green is immediately terminated and the signal changes directly to yellow without regard to the presence of vehicles in the dilemma zone. This could be hazardous to drivers.

An alternative implementation (called actuated advance warning, AAW system in this paper), which is widely used in Nebraska, provides a shorter maximum allowable headway and is a blend of AD and AW systems [4]. It consists of one advance detector and a flashing beacon — warning sign assembly interconnected to the traffic signal. The design algorithm continually monitors the upstream detector as well as traffic at the intersection in order to predict the onset of the yellow signal indication.

A. Actuated Advance Warning System Description

The detector layout for the AAW system is shown in Fig. 1. The system has one advance detector in each approach lane. In addition, stop line detection is provided in the through lanes.
and left-turn bays. The range of stop line detection is 30 to 40 ft in the through lanes and 40 to 50 ft in the left-turn bays. The advance detector operates in the pulse mode (i.e. each vehicle crossing the detector transmits a single pulse to the controller, regardless of the time the vehicle spends in the detection area). The stop line detectors operate in the presence mode (i.e. a continuous call is transmitted to the controller as long as a vehicle is within the detection area) but are not active during the extendible portion of the green interval [4].

In addition to the advance detector, two flashing signal heads are mounted on top of advance warning signs with the legend “Prepare to stop when flashing.” One warning sign / flashing signal heads assembly is positioned on either side of the approach roadway downstream of the advance detector. The design algorithm continually monitors the upstream detector as well as traffic at the intersection in order to predict the onset of the yellow signal indication. The signal heads are designed to flash 5 to 7 s (depending on the approach speed) before the onset of the yellow indication.

For each vehicle detected during the extendible portion of the green interval, the controller extends the green by an amount of time equal to the passage time setting on the controller. The extensions are based on vehicle detections at the advance detector location. The detector layout shown in Fig. 1 ensures that the maximum allowable headway (largest headway at which no further green time extensions are allowed) equals the passage time setting on the controller (approximately 3 s). This is much shorter than the maximum allowable headway for conventional AD systems (approximately 10 s). As a result of this, the frequency of losing the dilemma zone protection through max-out (i.e. terminating the green interval at the preset maximum) as well as the average waiting time of vehicles on the cross road are substantially reduced [4]. A recent study indicated that there is a greater-than 90% likelihood that the installation of an AAW system at a high-speed signalized intersection enhances traffic safety [1].

B. Microscopic Traffic Simulation

Applications of microscopic traffic simulation models for the analysis of several complex issues have become a common practice in transportation engineering. Microscopic traffic simulation models are built around the concept of realistic movement of individual vehicles. They consist of a number of components that interact to model the movement of individual vehicles, both in response to each other’s motions and in response to the presence of geometric features on the highway and to the operation of the traffic control system. Each vehicle that enters the network is stochastically assigned a unique set of operational characteristics (for example vehicle type and corresponding vehicle performance and vehicle characteristics) which it maintains as it travels through the network. The interactions among system entities (vehicle-to-vehicle, vehicle-to-roadway, and vehicle-to-traffic control device) are modeled based on specific car-following and lane-changing models [8]. Dynamic behavior is modeled by scanning the network every second or micro-second and updating relevant information associated with each vehicle’s movement such as position and speed. Some of the more well-known microscopic traffic simulation models available for commercial and research purposes in the United States are CORSIM, VISSIM, PARAMICS, INTEGRATION, and SimTraffic.

VISSIM was chosen for this study because of the flexibility provided by its vehicle actuated programming (VAP) language. VISSIM is a stochastic microscopic traffic simulation model developed by PTV AG, Germany (VISSIM Manual 2009). The model consists internally of two distinct components that communicate through an interface – first, a traffic simulator that simulates the movement of vehicles and generates the corresponding output and second, a signal state generator that determines and updates the signal status using detector information from the traffic simulator on a discrete time step basis. The input data required for VISSIM include network geometry, traffic demand, phase assignment, signal control timing plan, vehicle speed distribution, and the acceleration and deceleration characteristics of vehicles. VISSIM allows the user to model traffic signals with different control types including: pre-timed, Ring Barrier Control (RBC) standard signal control emulator (which can operate in fully actuated, coordinated, or semi-actuated coordinated modes), and vehicle actuated programming (VAP). The model is also capable of producing measures of effectiveness commonly used in the traffic engineering profession such as average delay, queue lengths, and fuel emissions [9].

The objective of this paper is to develop a modeling framework that can be used to perform consistent, detailed analyses of AAW systems on high-speed signalized intersection approaches. Traffic conditions at an intersection equipped with AAW systems on two of its high-speed approaches are emulated using the VISSIM microscopic traffic simulation model.

II. MODEL DEVELOPMENT

The test bed for this study is the isolated intersection of Highway 77 and Saltillo Road located about 5 miles south of Lincoln, Nebraska. As may be seen in Fig. 2, Saltillo Road is a two-lane undivided highway. The eastbound and westbound approaches on Saltillo Road each has an exclusive left-turn lane and a shared through/right-turn lane. The speed limit on both approaches is 55 mph.

![Fig.2 Northbound approach on Highway 77 at Saltillo Road](image)

Highway 77 is a four-lane divided expressway. The northbound approach on Highway 77 has two through lanes, an exclusive left-turn lane, and an exclusive right-turn lane. The southbound approach also has two through lanes and an exclusive left-turn lane. However, right-turners on the southbound approach share the outer lane with through traffic. The speed limit on both the southbound and the northbound approaches is 65 mph (reduces to 55 mph at approximately 1,150 ft upstream of the intersection).

The signal at Highway 77 and Saltillo Road operates in the fully-actuated mode and is not coordinated with any other signal. The timing for the Highway 77 phases is 7 s minimum...
green, a 3 s extension, 30 s maximum green, and 3 s of yellow for the left-turn phases. The through phases have 15 s minimum green, a 3 s extension, 50 s maximum green, and a 4.5 s yellow followed by 0.5 s all-red. The through phase extensions are from advance detectors located 935 ft from the stop line. The timing for the Saltillo Road phases is 10 s minimum green, a 3 s extension, 30 s maximum green, and 4 s of yellow followed by 0.5 s all-red for all movements. The Saltillo Road phases have a 4 s delay on actuation. The through phases on Highway 77 are on “recall” and the signal “rests” in these phases when no traffic is present.

Anytime that there is a vehicle call on a conflicting phase (to the Highway 77 through phases), the signal would “wait” until there is no active call on Highway 77 (i.e. gap-out) or until there is only 7 s before the green time reaches the preset maximum value (i.e. max-out). At this time, the controller “freezes” and the active warning signs (located 650 ft from the stop bars) flash for 7 s to indicate the impending end of green. At the end of the 7 s “lead flash” interval, the controller resumes operation with the Highway 77 through phase yellow indication. The active advance warning signs continue to flash until the through phase(s) turn green again. The through phases on Highway 77 end together but may or may not start together depending upon which, if any, left turn phases are called. Because the signal is fully actuated, any phase, except for the Highway 77 through phases (which are on recall), may be skipped if no demand is present.

A. Input Parameters

Input data required for the VISSIM model were existing geometry, traffic counts, signal timing plans and phase sequencing, and posted speed limits. Geometric characteristics and signal timing plans were provided by the Nebraska Department of Roads (NDOR). Lane widths, approach grades, lengths of left-turn and right-turn lanes, and detector and advance warning flasher locations were retrieved from blueprints provided by NDOR.

Two JAMAR traffic data collectors (TDC-8) were used to record turning movement counts at the study intersections. Counts were collected from 2:00 to 4:00 pm on Wednesday September 29, 2010 and from 2:00 to 4:00 pm on Thursday September 29, Tuesday October 5, and Wednesday October 6, 2010. Average waiting times on conflicting phases and speed profiles (required for model calibration and validation) were collected with a mobile data collection trailer and by videotaping traffic operations and signal indications on the minor road approaches.

III. MODEL CALIBRATION AND VALIDATION

In this study, model calibration entailed modifying the default microsimulation parameters so that the model replicates the observed data (performance measures) as closely as possible. Proper calibration is crucial if the model is to be perceived as credible both to engineers and planners as well as the general public.

A. Measures of Performance

The first step in the model calibration and validation process was to determine appropriate performance measures. The measures selected for this study were the average waiting time on conflicting phases and the speed profiles on the high-speed approaches. Average waiting time was used to calibrate the model while speed profile was used to validate it. These performance measures were chosen because (i) they were considered reasonable indicators of the operational efficiency of an intersection equipped with AAW on its high-speed approaches and (ii) they were fairly easy to collect both in the field and from VISSIM.

B. Calibration Parameters

VISSIM has over 50 tunable model parameters. Thirteen of these parameters were identified as the most relevant to this study and were thus selected for calibration. These parameters were: (i-ii) mean and variance of the desired speed distribution; (iii) number of observed preceding vehicles; (iv) average standstill distance; (v) additive and multiplicative parts of desired safety distance; (vi) minimum headway; (vii) emergency stopping distance; (viii) reaction time for red stop sign; (ix) the coefficient of VISSIM’s “reaction-to-amber” function.

1) Desired Speed Distributions:

The desired speed distribution is an important factor that influences roadway capacity and the travel speeds that can be realized. The desired speed represents the speed at which a vehicle travels (with a small stochastic variation) when unimpeded. Of course, the presence of other vehicles on the roadway means that the speed that is actually realized by a vehicle may differ from its desired speed. Whenever possible, and if it is safe to do so, a vehicle that is traveling at a speed lower than its desired speed will overtake the vehicle ahead of it. A desired speed distribution is coded in VISSIM by specifying its shape as well as a minimum and a maximum speed value. Intermediate points such as the 15th, 50th, and 85th percentile speeds may also be specified.

The speed limit on Highway 77 was 65 mph and it was reduced to 55 mph at approximately 1,150 ft in advance of the intersection. A desired speed distribution of 50 to 70 mph was used for the 65 mph speed limit. This corresponds approximately to the lower and upper bounds of the 95 % confidence interval for speeds that are approximately normally distributed with mean 60 mph and standard deviation 5 mph. The approximate 15th and 85th percentile speeds were 55 mph and 65 mph, respectively. Similarly, a desired speed distribution range of 40 to 60 mph was used to model the reduced speed limit of 55 mph. Thus vehicles were assigned a desired speed from the 50 to 70 mph distribution as they entered the network on Highway 77. However, as they crossed the speed limit sign at the beginning of the reduced speed section, they were reassigned “new” desired speeds from the 40 to 60 mph distribution. This was done in VISSIM by placing a “desired speed decision” point at the location of the speed limit sign. The approach speed on Saltillo Road was 55 mph and thus vehicles entering the network from this roadway were also assigned desired speeds from the 40 to 60 mph distribution.

In order to model expected changes in speed while the active advance warning signs flashed, another “desired speed decision” point (with a different desired speed distribution) was placed at the location of the advance warning flashers. Exact parameter values of this desired speed distribution were not specified, a priori, but were instead estimated as part of the model calibration process. This reflects the observation that drivers’ response to the flasher is not known, a priori. This decision is also consistent with the findings of previous research that have indicated that, while there may be a general decrease in speeds following the installation of advance warning flashers, some drivers tend to accelerate in order to make the green [4].
The desired speed distribution used in this exercise was assumed to be normal with an unknown mean assumed to be in the range 40 to 50 mph and standard deviation of 7 mph. With the mean, μ and standard deviation, σ calibrated, approximate values of the minimum, the maximum, and the 15th and 85th percentile speeds were calculated. For example, a calibrated mean speed of 48 mph and a standard deviation of 7 mph would suggest approximately normally distributed speeds between 34 mph and 62 mph with approximate 15th and 85th percentile speeds of 41 mph and 55 mph, respectively.

2) Number of Observed Vehicles

The “number of observed vehicles” variable affects how well vehicles in the network can predict, and react to, other vehicles’ movements. VISSIM uses a default value of four for urban driving behavior and two for all others. A range of one to four vehicles was considered in this study.

3) Car-Following Parameters

VISSIM includes two versions of the Wiedemann model – urban driver and freeway driver. The car-following mode of the urban driver model was used in this study. The model has three tunable parameters; average standstill distance, additive part of desired safety distance, and multiplicative part of desired safety distance. The safe distance between vehicles is given by [10]:

\[
d_{\text{safe}} = d_1 + (a_1 + a_2 z) \sqrt{v}
\]

where,

- \( d_1 \): average standstill distance. This is the average desired distance between stopped vehicles. The VISSIM default is 2.0 m. Values considered reasonable for this study were 1.0 m to 3.0 m.
- \( a_1, a_2 \): coefficients that affect computation of the desired safety distance. The default value for the additive part \( a_1 \) is 2.0. Values considered in this study were 1.0 to 3.0. The multiplicative part \( a_2 \) has a default value of 3.0. Values used in this study were 2.0 to 4.0.

4) Minimum Headway

The minimum headway distance defines the minimum distance to the vehicle in front that must be available for a lane change in stable condition. The default value is 0.5 m. The range of values used for this parameter was 0.5 m to 3.0 m. Larger or smaller values appeared to be unreasonable.

5) Emergency Stop Position

For a vehicle following its route, the emergency stop position defines the last possible position from where a lane change can be made. If the lane change is not possible because of high traffic volumes, the vehicle will stop at this point and wait for an acceptable gap to do so. The default is 5.0 m. A range of 2.0 m to 7.0 m was considered reasonable for this study.

6) Waiting Time before Diffusion

The “waiting time before diffusion” variable defines the maximum amount of time a vehicle can remain at the emergency stop position waiting for a gap to change lanes in order to stay on its route. When this time is reached the vehicle is taken out of the network (diffusion). The default waiting time in VISSIM is 60 s. Values in the range 20 s to 60 s were used in this study.

7) Lane-Change Distance

The lane-change distance parameter is used along with the emergency stop distance parameter to model drivers’ lane-change behavior as they follow their routes. It is the distance, in anticipation of a lane change, at which a driver will begin maneuvering towards the desired lane. The default is 200.0 m. Values considered reasonable for this study were 150.0 m to 300.0 m.

8) Reaction-to-Amber

VISSIM’s probabilistic reaction-to-amber function is used to define vehicle behavior as it approaches a signal control showing amber. It is a binary logistic function that uses three parameters (\( \alpha, \beta_1, \) and \( \beta_2 \)) to calculate the probability of a driver stopping when the signal indication is yellow. A decision is kept until the vehicle passes the stop line. For a vehicle traveling at a speed \( v \) and at a distance \( dx \) from the stop line (at the start of the yellow indication), the stop probability is calculated as:

\[
P_{\text{stop}} = \frac{1}{1 + e^{-a - \beta_1 v - \beta_2 dx}}
\]  

The default parameter values used in VISSIM are \( \alpha = 1.59, \beta_1 = -0.26, \) and \( \beta_2 = 0.27. \) Acceptable ranges used in this study were \( \alpha = [0.08, 3.10], \beta_1 = [-0.50, -0.01], \) and \( \beta_2 = [0.01, 0.50]. \)

C. Calibration Procedure

The model calibration problem can be viewed as an optimization problem that seeks to match simulation model output and values observed in the field. A number of research projects related to the calibration of microsimulation models can be found in the literature [11, 12, 13]. The methods range in level of sophistication from simple manual adjustments to automated adjustments using evolutionary algorithms. The Genetic Algorithm (GA) was selected as the optimization tool for this study because of the following reasons: (i) it has been shown that it has advantages in dealing with non-convexity, locality, and the complex nature of transportation optimization; (ii) it searches over multiple locations and therefore has a very high likelihood of identifying a globally optimal solution; (iii) genetic algorithms only require the evaluation of an objective function with no need for gradient information; and (iv) they are rather robust when used in conjunction with simulation model calibration and can overcome the combinatorial explosion of model parameters [12, 14, 15].

Genetic algorithms are stochastic algorithms whose search methods are based on the evolutionary ideas of natural selection or the survival of the fittest. The GA calibration procedure starts with a randomly generated set or population of chromosomes each of which represents a potential solution to the problem under consideration; in this case a combination of simulation model parameters. The individual chromosomes undergo selection in the presence of variation-inducing operators such as mutation and crossover. A fitness function is used to evaluate each chromosome. Reproductive success varies with fitness. The processes of evaluation, selection, crossover, and mutation are repeated until a satisfactory solution is found. The main features of the GA calibration procedure are described in the following sections. A simplified...
flowchart of the main components is shown in Fig. 3. The GA was coded in Perl and integrated with VISSIM.

![Flowchart](image)

1) **Initial Population**
An initial population of 40 candidate solutions or chromosomes was used. Each chromosome is a string containing model parameter values (genes). In order to avoid any bias at the beginning of the evolutionary run, each of the 13 genes defining a chromosome was initialized with a random number within the predefined search space limits described in the preceding section.

2) **Simulation Run**
A VISSIM simulation model was developed with the input parameters described earlier. The Perl control program was called to run the simulation for each of the 40 chromosomes. The time period for each simulation run was four hours. The main output collected at the end of every run was the average waiting time on conflicting phases (minor road approaches).

3) **Fitness Calculation**
The quality of the solution provided by each chromosome was evaluated using a fitness function. The fitness function adopted for this study was the mean absolute error ratio (MAER) which measures the average discrepancy between simulated and observed waiting times and is given by:

\[
MAER_j = \frac{1}{m} \sum_{i=1}^{m} \left| \frac{TSIM_{ij} - TOBS_i}{TOBS_i} \right|
\]

where,
- \(MAER_j\): estimated MAER using chromosome \(j\);
- \(TSIM_{ij}\): simulated average waiting time on minor approach \(i\) using chromosome \(j\);
- \(TOBS_i\): observed average waiting time on minor road approach \(i\);
- \(m\): number of minor road approaches considered (\(m = 2\)).

4) **Stop Criterion**
The stopping criterion used was a preset maximum number of generations (iterations) of the GA. This number was set equal to 100. Once this criterion was met, the chromosome with the smallest MAER was selected as the best solution.

5) **New Generation**
An elitist selection strategy and the genetic operators of crossover and mutation were used to produce a new generation of chromosomes.

If the stop criterion was not satisfied, then after evaluating the fitness function for the current generation of chromosomes, a subset of chromosomes was selected for use as parents in succeeding generations. The chromosomes were chosen according to their fitness value. In this study, an “elitist” selection strategy was used to ensure that the best chromosomes were preserved at each generation. This involved directly placing the best two chromosomes (as determined from their fitness values) into the next generation. A stochastic roulette wheel selection scheme was used for the process of choosing parents for subsequent recombination. That is, each chromosome was assigned a slice on a Monte Carlo-based roulette wheel proportional to its fitness. The “wheel” was spun in a simulated fashion 38 times and the parents were chosen based on where the “pointer” stopped [14].

The crossover operator was used to create offspring of the pairs of parent chromosomes identified from the selection step. The offspring could be either a blend or a clone of the two parents depending on a pre-specified probability of crossover. The crossover probability used was 0.75. If no crossover took place, then the two offspring were clones of the two parents. On the other hand if crossover occurred, then the two offspring were formed by an interchange of genetic material between the two parents. This was accomplished by swapping parts based on a randomly chosen splice point on the pair of parent chromosomes.

While keeping the two elite chromosomes, the remaining 38 chromosomes were replaced by the offspring produced from crossover. Because the initial population might not contain enough variability to find the solution via crossover alone, a mutation operator was used to introduce some variability in the new set of chromosomes by randomly changing genes with probability \(P_m\). The mutation rate \((P_m)\) was allowed to vary dynamically (between 0.0005 and 0.25) in the course of the evolutionary run. That is, the algorithm monitored the degree of convergence and adjusted the mutation rate accordingly. This was done to increase the chance that the algorithm did not converge prematurely to a local optimum.

The resulting population was the new generation of chromosomes. The simulation was re-run with each member of this new generation and the processes of fitness evaluation, selection, crossover, and mutation were repeated until the stop criterion was satisfied.
D. Calibration Results

The lowest value of the mean absolute error ratio (MAER) after 100 iterations of the GA for a population of size 40 was 0.067 (Fig. 4). The VISSIM parameter values that corresponded to this MAER value were:

- Number of observed vehicles: 2
- Average standstill distance: 2.8 m
- Desired safety distance (additive): 2.9
- Desired safety distance (multiplicative): 2.8
- Minimum headway: 1.8 m
- Amber coefficient, $\alpha$: 2.417
- Amber coefficient, $\beta$: -0.033
- Desired speed at Flasher location ($\mu$, $\sigma$): (42, 6) mph
- Waiting time before diffusion: 36 s
- Emergency stop position: 3.1 m
- Lane change distance: 172

Fig. 4 Observed and simulated average waiting times on minor road approaches.

As may be seen in the figure, the calibrated model compared much better with the field values (MAER = 0.067) than did the uncalibrated model (MAER = 0.189). The uncalibrated model indicated much shorter average waiting times than were observed in the field. Fig. 4 highlights the importance of the calibration of microscopic traffic simulation models.

E. Model Validation

Finally, the calibrated model was validated with speed profile data from the northbound and the southbound high-speed approaches. A comparison of the simulated speed profiles and the observed profiles is provided in Fig. 5 (Note that N0400 in this figure indicate average speed at a distance of 400 ft from the stop bar on the northbound approach etc.).

Fig. 5 Observed and simulated speed profiles on high-speed approaches.

As may be seen in Fig. 5, the plots suggest a good match (MAER = 0.055) between the observed and simulated speed profiles. This is an indication that the calibrated parameter values were appropriate for the test intersection.

IV. CONCLUSIONS

This paper developed a modeling framework that can be used to perform consistent, detailed analyses of actuated advance warning systems. Salient features of the methodology include: (i) modeling the expected changes in speeds while the advance warning signs are active; and (ii) modeling the subsequent reaction of drivers to the onset of the amber indication. The normal distribution was used to model the expected speed changes while a binary logistic function – of a vehicle’s speed and its distance from the stop line (at the start of amber) – were used to estimate the probability of a driver stopping on amber. Parameter values of the expected distribution of speed changes as well as those of the logistic reaction-to-amber function were estimated as part of the model calibration process using a GA based optimization process. The methodology was successfully applied to the calibration of a test intersection in Lincoln, Nebraska. The calibrated model provided more realistic results than the uncalibrated model (default values) and reaffirmed the importance of the proper calibration of microscopic traffic simulation models. In particular, the range of expected speed changes implied by the calibrated parameter values were consistent with previous studies that suggest that while speeds generally decrease following the installation of advance warning systems, some drivers may accelerate in order to make the green [4]. The proposed procedure appears to be effective for the calibration and validation of microsimulation models of traffic operations at high-speed signalized intersections equipped with actuated advance warning (AAW) systems. Although the data are specific to the test intersection, the procedure is readily transferrable.

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