Microsimulation calibration using automated video-based motor vehicle and bus trajectories

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Abstract: This study presents a method to calibrate microsimulation software using video data and an automated feature-tracking algorithm. This procedure is presented as an alternative to calibration methods including radar based traffic sensors, GPS and inductance loops since it allows for the collection and measurement of more traffic parameters. The methodology includes video data collection using a mobile video data collection system, data processing, and analysis of video-based trajectories. A calibration procedure is presented and uses an important bus corridor with an exclusive bus lane located in an arterial roadway in Montreal, Canada, as a case study. The vehicle-level speeds and bus dwell times are collected using the tracking algorithm and inputted into VISSIM, a microsimulation software. The microsimulation parameters are calibrated using an iterative process and the results are compared to the collected measurements. The results suggest that the automated video data and tracking algorithm provide accurate traffic data measurements and allow for the realistic calibration of microsimulation software. The study also presents the limitations of microsimulation default parameters and the effects they have on network performance. An emissions model is also developed to compare the default and calibrated outputs, presenting observable differences.

1   INTRODUCTION

Traffic microsimulation software has become an essential modeling tool in transportation research and practice. Many applications of traffic microsimulations are being used to analyze and evaluate transit projects and issues. However, the reliability and accuracy of these models relies on how precisely the field conditions are represented by the software parameters. Typical microsimulation software such as VISSIM, PARAMICS, AMSUM, etc (popular stochastic traffic microsimulation software) have a number of parameters that can be calibrated for specific traffic environments and situations. Calibrating parameters from microscopic data such as acceleration, speed distribution, lane changing parameters and driver behaviour as well as dwell time for bus transit in a bus corridor or roadway section are vital to the proper use of microsimulation software. A careful calibration is required to properly validate simulation output on a microscopic scale if one is to use simulation results to study microscopic behaviours, energy consumption or emissions. The challenge is to adjust or calibrate the set of vehicle parameters for the local conditions. This issue has attracted some attention in the past; for instance we can refer to the study presented in (Yu 2006) that uses GPS data to obtain speeds along a BRT corridor. Despite these advances, these studies do not adjust for other parameters such as speed distributions, vehicle characteristics and bus dwell times. Also, GPS data only provides speed profiles for a given bus, not for the whole population of buses and motor vehicles in a given link.

The main objective of this paper is to calibrate essential parameters for the microsimulation of a bus transit corridor using computing vision techniques for the generation of automatic video-based trajectories. Motor-vehicle speed profiles and bus arrival and departure times (also providing dwell times) are obtained based on a trajectory data analysis using collected video data and automated tracking

software. The advantages of video-based trajectory data for microsimulation model calibration are demonstrated using a case study of a major bus corridor in Montreal, Canada, that has an exclusive bus lane and articulated buses. This research also illustrates the advantages of the use of mobile video data collection systems.

2   BACKGROUND

2.1   Literature Review

A literature review has found a limited number of papers related to our subject. There are many publications that focus on the calibration of traffic microsimulation software but very few of them discuss the data collection methods. Furthermore, little has been written on the calibration of public transit networks within microsimulation software and to the best of our knowledge, video-tracking software has not been used in calibration studies. The authors in (Yang 2012) present an implementation of control strategies in a microsimulation program for bus rapid transit (BRT) networks and analyze the results using travel speed and average delay measures. They conclude that the application of the microsimulation software leads to accurate results and is useful for the planning and management of transit networks. In (Abdelghany 2007), a dynamic traffic assignment-simulation modeling framework (DYNASMART-P) that can plan and analyze a BRT network is presented. The primary operational attributes of the BRT are evaluated by running a number of simulation experiments with the objective to assess the potential change in transit ridership and overall traffic interactions within the network. The authors conducted five sets of experiments with respect to the following operational elements: right-of-way separation, prioritization at certain intersections, higher service frequency, stop-skipping and shorter dwell times. The work presented in (Cortés 2010) provides guidelines for incorporating certain elements of public transportation into microsimulation programs in order to properly model the interactions between general traffic and public transportation. The study looked at examples of software being developed specifically for public transportation simulation including the interaction of buses at stops and in networks. In (Yu 2006), the authors present a method to calibrate a microsimulation software BRT model using GPS data. The performance index is calculated as the Sum of Squared Error (SSE) between the collected speeds and the simulated speeds. A Genetic Algorithm is used to minimize the SSE by adjusting a number of the microsimulation software parameters. A method is presented in (Zhang 2010) to calibrate bus parameters using a car-following model within microsimulation software and to collect performance data automatically recorded in a bus system. The author of (Fernandez 2010) outlines a method to calibrate and validate bus stop modeling within microsimulation software and concludes that current software does not represent bus stops and their capacity properly, which may lead to the unrealistic simulation of bus networks and their performance. In terms of tracking software applications, (St-Aubin 2012) outlines a method to analyze the surrogate safety at freeway ramps using automated trajectory measurements. The video-collection method is proposed as an alternative to traditional methods including historical accident data analysis.

The papers identified in the literature review provide insights into the calibration of microsimulation software. However, the majority of the publications focuses strictly on the calibration of the models. Little has been done regarding the methods of data collection and the recent advances in video data analysis. This paper will present a method to incorporate video data collection and trajectory analysis into microsimulation calibration processes.

2.2   Test Location

The city of Montreal has been implementing a number of transit exclusive lanes over the past decade. Many of these lanes are time specific and reflect the general direction of peak traffic flows. The Côte-des-Neiges corridor is an 8 km (4.97 mi) section that includes bi-directional exclusive bus and taxi lanes which are active during the morning peak (southbound) and the evening peak (northbound). Currently, 50,000 daily trips are generated along this corridor (Genivar-Systra 2009), making it one of the most important corridors in the city of Montreal.

The test location for this study was chosen based on a number of factors. First, the site had to have appropriate utility poles along the roadway in order to properly install the camera equipment. Second, the site had to be free of any obstacles such as trees and overhanging structures that may affect the tracking algorithm. Third, the section had to be located along a stretch of road that would allow the vehicles to travel at design speeds. Fourth, the section had to be relatively straight in the horizontal and vertical axes in order to measure the vehicle trajectories as accurately as possible. Fifth, the section had to have a bus stop present. Based on these factors, the study area was located along chemin de la Côte-des-Neiges between avenue Decelles and avenue Forest Hill in the southbound direction. Figure 1 below presents a map (9) of the study area. An additional advantage of this section is the presence of three lanes of traffic. This allows vehicles to exhibit lane changing behaviour at all times, including the morning peak period. Between 6:30 am and 9:30 am the third lane of traffic is reserved for buses and taxis in the southbound direction.

2.3   Network and Data Collection

A microsimulation software network was built representing the Côte-des-Neiges corridor for this study. The corridor was extended at certain critical areas in order to properly observe its effects on a more macroscopic level. The network was built using City of Montreal traffic volume surveys collected at intersections between 2008 and 2009. The surveys include traffic composition (car, heavy goods vehicle (HGV), bus) and the time of day of the collection period. These values were validated through first-hand data collection at a selection of intersections and empirical expansion factors obtained from permanent counting stations in the city were applied to slightly dated collection records. Also, the public bus lines were inputted using scheduled headways and passenger boarding and alighting distributions. (Genivar-Systra 2009) Furthermore, the traffic signal timings were manually collected throughout the study area. The data was collected for the morning peak period of 7am to 9am in order to capture the exclusive bus lane in the southbound direction.

The video data was collected using a Vivotek IP8151 camera mounted atop a 25 ft (7.62 m) pole. The camera was fastened to a streetlamp along chemin de la Côte-Des-Neiges. The video inputted into the tracking software was collected over a two-hour period starting at 8am on a weekday.

3   METHODOLOGY

3.1   Video tracking

This work relies on a newly developed open source project called Traffic Intelligence (Saunier 2012) that consists of several tools for video analysis and the interpretation of the resulting trajectory data. A feature-based tracking algorithm (Saunier 2006) is used that yields the trajectories of all moving objects in the camera view or a user-defined zone. In order to obtain measurements in real world coordinates, e.g. meters, a homography matrix is needed to project the vehicle positions in the image space (in pixels) to the road plane. The homography is estimated from the coordinates in the image and world space of at least 4 non-collinear points, using a simple interface from Traffic Intelligence.

The first step of the video tracking process is the extraction and grouping of feature trajectories into each moving vehicle. The program captures and tracks distinctive moving points called features within the frame which are then grouped together based on their proximity to one another and their relative motion. The main issues are over-segmentation (several trajectories for the same vehicle) and over-grouping (one trajectory for several vehicles). In order to minimize these issues, the parameters of the program are tuned by trial and error and consider the effect of factors such as the positioning of the video camera. Once the tracking parameters are properly set and the program analyzes the video, the vehicles are stored in a database that includes the vehicle unique number and the two-dimensional coordinates of the object at each time step, i.e. for each image frame in the video. Velocity data is also stored in the database by differentiating the positions over time.

This process can be tailored to extract a number of traffic parameters. In this study, speed distributions and bus dwell times are the target parameters.

3.2   Speed Distributions

The tracking software collects trajectory and velocity data for all the vehicles at each frame in the video, in this case at 15 frames per second. Filters are applied to the trajectories in order to collect measurements for all of the motor vehicle types. The presence of an exclusive lane in the study area means that vehicle types are segregated by lane. Areas or "speed boxes" are drawn manually for each zone where speed data is desired, e.g. for each lane of traffic. These speed boxes are similar to virtual loops. Running through the trajectory database, the average velocities of the vehicles passing through the boxes are collected and outputted and the mean and standard deviation are calculated from the speed distribution.

3.3   Dwell Times

A new method was developed to detect the times of arrival and departure of the buses. The task was simplified by the presence of an exclusive lanes for buses and taxis; therefore there was less traffic to process and differentiate. The feature-tracking algorithm was run on a specific window in the image space drawn in the bus lane before and after the bus stop (see the overlay in Figure 1). This allows for the detection of movement specifically in this zone. The next step was to group the features corresponding to the same vehicle together. A graph was built using the methodology provided in (Saunier and Sayed 2006) based on the temporal proximity of the feature trajectories (if the time interval between features was equal or less than two frames, the features were grouped together). Other vehicles did not stop at the bus stop and could therefore be filtered out by ignoring through features. To identify stopping and departing buses, the slope of the regression line of the speed as a function of time had to be respectively negative and positive. Finally, a group had to contain a minimum number of feature trajectories to be considered (15 and 3 respectively for stopping and departing buses, determined based on software calibration).

The results of the methods are satisfactory for arrivals, as all were successfully detected without any false alarms. The results are mixed for departures since few features can be tracked so far from the camera, and the perspective makes it difficult to measure how the speed is changing (the homography loses accuracy as the distance from the camera increases and, combined with some lens distortion, measured speeds tend to "naturally" diminish as vehicles are further and further away from the camera). It follows that many dwell times cannot be accurately measured. The ones that could be automatically measured were validated by comparing them to the manually recorded times (recorded in-field using a stopwatch). The average dwell time for the first hour of the collected data using the tracking software was 17.25 seconds and the manually recorded times were 16.57, resulting in a difference of 4 %.
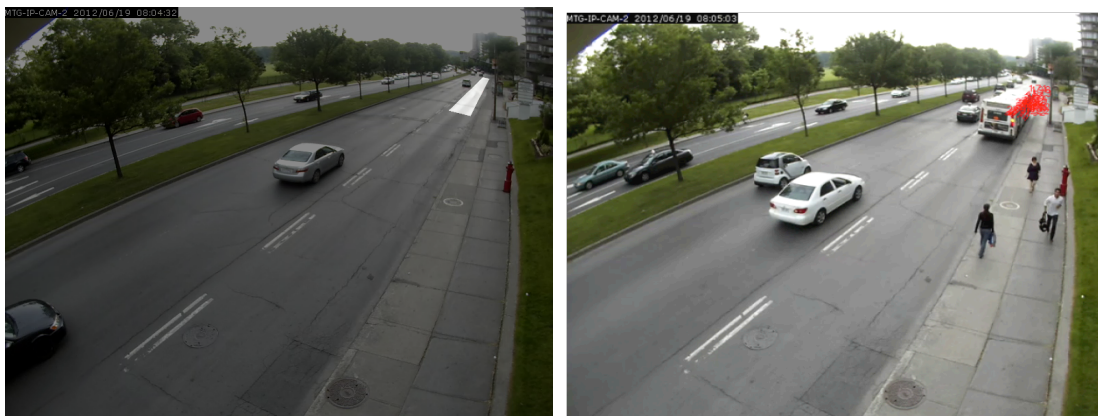

Figure 1 (a) Feature-tracking area overlaid in light color over a video frame (left) and (b) Dots on the side of the bus represent the feature-trajectories in the area at the arrival of a bus (right)

3.4   Calibration

The following calibration procedure was developed for this study.

Parameter definition: Choose the calibration parameters (speed distribution, bus dwell times and vehicle characteristics) based on the data collection method.
Parameter collection: Extract the measurements from the data using tracking software and manual verification.
Microsimulation input: Tailor the measurements for the microsimulation software and adjust the appropriate parameters.
Microsimulation output: Record the performance of the network and compare the output to the collected measurements.
Calibration: Calibrate the chosen parameters and repeat step 4 until results are acceptable.

3.4.1   Calibration Parameters

The microsimulation software has a number of parameters that can be calibrated. The controlling processes within the software include a psycho-physical model for longitudinal movements and an algorithm for lateral movements. The following list presents the most important microsimulation parameters that involve components of vehicle interactions and driver behaviour.

- **Speed Distribution:** Distribution curve that is focused around the median value.
- **Headway:** The minimum headway between vehicles at all times within the network.
- **Acceleration/Deceleration:** Maximum and minimum values for accepted acceleration/deceleration within the network
- **Look Ahead Distance:** The number of vehicles that can be analyzed by a driver in order for it to react accordingly.
- **Dwell Times:** The boarding and alighting rates for public transportation.
- **Lane Change Distance:** The distance before a destination that a vehicle begins to attempt a lane change.
- **Distance of Standing:** The lateral distance between vehicles while they are in motion.

In order to calibrate the microsimulation software for this study, the following parameters are measured in the field using specific measurement processes. First, the speed distribution of all the vehicles travelling along the corridor is collected using the video tracking software that was applied to the raw footage collected on site. Based on the characteristics of the motor vehicles, distinct speed distributions are collected. Second, bus dwell times are calculated by manual observation as well as automatic detection using the tracking software. The number of passengers boarding and alighting was counted manually by studying the video footage. Average boarding and alighting rates are then calculated based on the dwell times.

3.4.2   Vehicle Models

The first parameter to calibrate within the microsimulation software is the vehicle models and performance characteristics since the microsimulation software's default parameters use European vehicles. Given the important differences in the vehicle fleet in Canada with respect to the European default parameters, a Canadian template was inputted into the microsimulation software in order to simulate a more accurate traffic environment. The template included vehicle dimensions and acceleration profiles that were collected from a vehicle survey.

3.4.3   Speed Distribution

The video tracking software output was processed to produce a speed distribution for the general traffic. Figure 2 presents a histogram of the video-based motor vehicle collected speeds. The profile displays the properties of a normal distribution and the average speed of 42.9 km/h (26.7 mph) accurately fits the

traffic environment because the speed limit is 50 km/h (31 mph) and the study area is located immediately after a signalized intersection.

The collected speed distribution was transformed into a cumulative function in order to be inputted into the microsimulation software Desired Speed distributions. Once the speed profile was assigned to the fleet, a one-hour simulation was performed five times using different seed numbers to insure variation between the runs. In order to measure the speeds of the vehicles within the simulation, a series of data collection points were installed in the network where the video data was retrieved. The data collection points were designed to collect the speed of vehicles moving across them and outputted an average value for the entire simulation. The implementation of the collected speed profile within the microsimulation resulted in an average speed of 41.0 km/h (25.5 mph) in the collection area, a relative error of 4.4 %. In order to reduce the error, the speed profile was modified. Since the average speed had shifted to the left, the profile had to be moved to the right. The calibration process involved shifting the speed profile to the right incrementally and running the simulation. After fifteen runs, the average speed was 42.46 km/h (26.37 mph), within 1 % of the collected speeds.
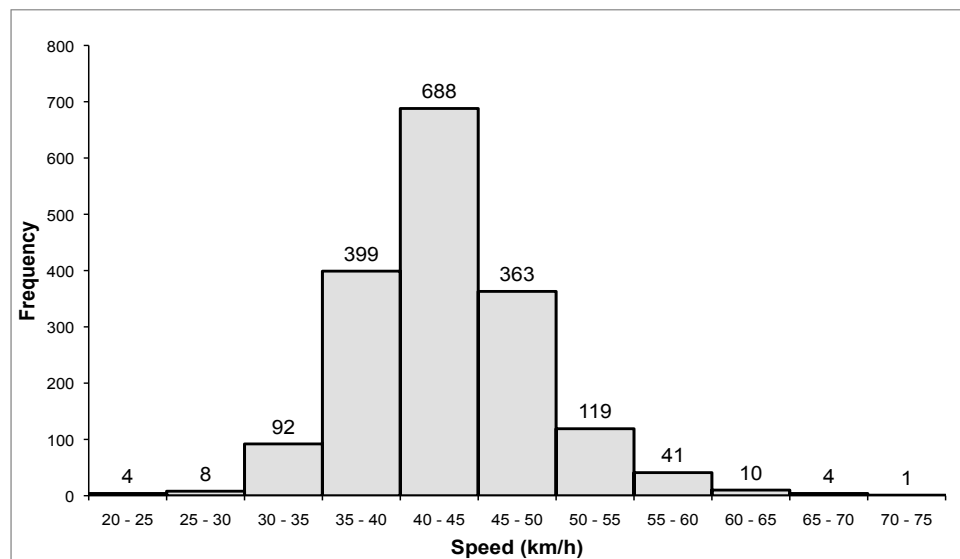
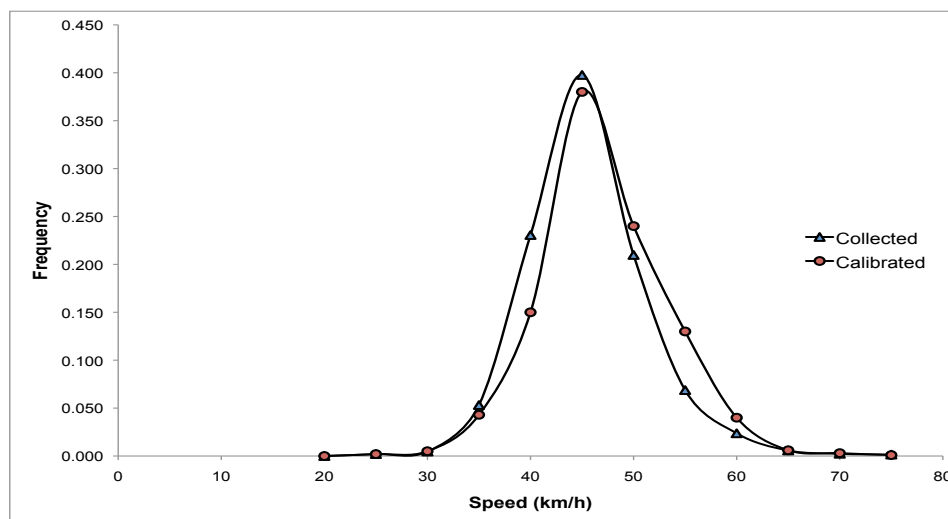Figure 2: Histogram displaying the video collected speeds

Figure 6: Graph comparing the collected and calibrated speed distributions

In Figure 6, a comparison of the collected and calibrated distributions is exhibited. From visual observation, the distributions seem relatively similar, exhibiting comparable shape and skew. In order to statistically validate their similarity, an independent two-sample Welch's t-test is performed with a null hypothesis declaring that the distributions have the same mean and these results are shown in Table 1. Since the calculated t-statistic of 2.43 is smaller than the critical value of 2.58, the null hypothesis is not discarded and the distributions are shown to exhibit the same mean at a significance level of 0.01.

Table 1: Results from the Welch's t-test

Values	Collected	Calibrated
Mean	42.99	42.46
Standard Deviation	5.77	5.23
Population	1730	960
Degrees of freedom	2148	
T statistic	2.43	
T table (p, d.f.)	2.58 (0.01, 2148)	

3.4.4 Dwell times

Once the dwell times were collected both manually and using the tracking software, the values were entered into the microsimulation software. Since the data collection focused on an individual stop, inputting a distribution for the total dwell time at all stops in the network would lead to inaccurate results because each stop exhibits different behaviour due to distinct passenger distributions. However, the assumption was made that the boarding and alighting rates throughout the network were constant. The boarding and alighting rates are calculated by dividing the number of passengers alighting and boarding over the dwell time for every recorded bus. The average boarding time was found to be 5.94 seconds/passenger and the alighting time was 2 seconds/passenger since the buses had 3 exit points and only a single entrance point.

4   EXPERIMENTAL RESULTS

4.1   Microsimulation calibration

In order to quantify the effects of the microsimulation calibration, measurements were taken throughout the study area and the entire network during simulation runs. The following five calibration scenarios were used and are compared in Table 2.

- **Calibration 1:** The default microsimulation software parameters were used in this scenario. First, the primary speed profile with a mean value of 50 km/h was used. Second, the default vehicle models were utilized along with their base characteristics and acceleration profiles. Third, the default bus dwell times were unaltered.

- **Calibration 2:** The collected speed distribution obtained from the tracking software was used as the speed profile in the microsimulation software. The Canadian vehicle models and characteristics were inputted in this scenario and the calibrated dwell times were added as well.

- **Calibration 3:** The calibrated speed profile was used in this scenario along with the other parameters employed in scenario 2.

- **Calibration 4:** The calibrated speed profile and dwell time were used in this scenario along with the default vehicle models and characteristics.

- **Calibration 5:** The calibrated speed profile and Canadian vehicle models and characteristics were used along with the default dwell times.

In order to compare the scenarios, the following measurements were recorded within the microsimulated network.

- **Average Speed:** The average speed of all vehicles passing through the speed boxes.
- **Travel Times:** A 1.2 km (0.75 mi) section spanning the length of the study area was used to measure the average travel time of cars, buses and HGVs.
- **Delay:** The average delay per vehicle within the travel time section.
- **Average Network Delay:** The average delay per vehicle at a macroscopic level.
- **Average Network Speed:** The average speed of all vehicles within the network.

Table 2: Results and percent difference of the microsimulation software calibration scenarios

Parameters	Calibration 1	Calibration 2	Calibration 3	Calibration 4	Calibration 5
Average Speed (km/h)	47.96	41.00	42.32	42.16	42.00
Boarding Time (s/pass)	5.00	5.94	5.94	5.94	5.00
Alighting Time (s/pass)	2.50	2.00	2.00	2.00	2.50
Travel Time car (s)	136.70	162.50	157.74	151.54	158.14
Travel Time HGV (s)	136.98	166.62	160.24	157.00	171.28
Travel Time bus (s)	390.80	259.86	295.90	459.10	326.08
Delay (s)	47.30	56.02	54.40	50.66	55.08
Avg. Delay (s)	135.13	257.72	252.42	137.90	250.77
Avg. Speed (km/h)	19.92	11.65	11.94	18.74	11.99

	Percent Difference (%) (eg. ((1/2) -1)*100)				
Parameters	Calibration 1-2	Calibration 1-3	Calibration 2-3	Calibration 3-4	Calibration 3-5
Average Speed (km/h)	17.0	13.3	3.2	-0.4	-0.8
Boarding Time (s/pass)	-15.8	-15.8	0.0	0.0	-15.8
Alighting Time (s/pass)	25.0	25.0	0.0	0.0	25.0
Travel Time car (s)	-15.9	-13.3	-2.9	-3.9	0.3
Travel Time HGV (s)	-17.8	-14.5	-3.8	-2.0	6.9
Travel Time bus (s)	50.4	32.1	13.9	55.2	10.2
Delay (s)	-15.6	-13.1	-2.9	-6.9	1.3
Avg. Delay (s)	-47.6	-46.5	-2.1	-45.4	-0.7
Avg. Speed (km/h)	71.0	66.9	2.5	57	0.5

The first noticeable difference between the default and calibrated parameters is the difference in average speed. Calibration scenario 1 has average speeds within the study area that are more than 10 % greater than the calibrated scenario. Moreover, the average speed within the network is over 65 % higher and the overall delay nearly 50 % lower using the default parameters. An error of this magnitude is important and can lead to very different behaviour being exhibited within the network. Second, the travel times of cars and HGVs are approximately 15 % slower in the calibrated scenarios. This is most likely related to the slower average speed in those scenarios. However, the bus travel times improved by more than 30 % in the calibrated scenarios possibly due to the faster alighting times in the calibrated scenarios. Overall, the experimental results reveal the possible limitations of the default microsimulation software parameters and how differently the network performs at a microscopic and macroscopic level when critical parameters are calibrated.

The calibrated scenarios 2 and 3 also reveal interesting characteristics when compared. Since calibration 3 uses the calibrated speed profile that results in a distribution that is nearly identical to the collected measurements, it is expected to represent the most realistic network performance factors. Seeing that the speed distribution is the only parameter that was changed between the scenarios, it is interesting to note that the 3 % difference in average speed displayed in the study area results in differences within a similar range between most of the other parameters. Although this seems logical since speed is the main factor for travel times and delay, it also indicates that the speed distribution parameter is possibly one of the most important parameters within the microsimulation software.

The calibrated scenarios 4 and 5 were collected in order to isolate the effects of the calibration parameters. In scenario 4, the application of the default vehicle characteristics revealed important changes to the network. The bus travel time along the study area was more than 50 % faster and the network delay and speed was similar to the default parameter scenario (Calibration 1). Also, the car and HGV travel times remained the same as well as the average speed within the study area. This indicates that the default acceleration and deceleration bus characteristics are not suited for North American microsimulation software networks and that the vehicle characteristics are an important parameter within the software. In scenario 5, the default dwell time values were inputted into the calibrated network. The results indicate that the default dwell times lead to a 10 % increase in bus travel time through the study area possibly due to the difference in alighting rates between the calibrated and default parameters. However, as expected, the other measurements taken within the network are unaffected by the dwell times.

4.2   Emissions modelling

The next step involved the modelling of emissions using the MOVES emission software in order to analyze the difference between the default and calibrated microsimulation scenarios. The emissions software required the following inputs and characteristics: geographical location, temporal and meteorological data, traffic volume, fuel type and vehicle drive cycles. The drive cycles (average speed along the corridor per time interval) were the only variable inputs as they relied on the microsimulation speed profiles from the default and calibrated scenarios. The emissions results compiled by the software for the corridor indicates that the default microsimulation settings underestimates the emissions (equivalent CO_2) within the network by 5% to 10%.

5   CONCLUSIONS AND FUTURE WORK

This study presents and demonstrates the application and reliability of video-based trajectory data in the calibration of a microsimulation software network. Using a mobile video-camera system, video data is collected and processed to obtain important microscopic parameters such as speed distributions and bus dwell times. These parameters can then be used in other applications such as emissions modelling. This study has exhibited the potential improvements that this method of data collection and trajectory analysis can have on the calibration of microsimulation software. The proposed approach allows for the collection of vehicle-level speed distributions and bus dwell time data in the field. With video collection, the entire traffic environment can be recorded along with the interactions between vehicles. The iterative process applied to the speed distribution calibration was done manually in this study. The collected data displayed an acceptable initial fit within the microsimulation that enabled the application of this manual calibration. The experimental results indicate that both the speed distribution and the vehicle characteristics are key factors within a microsimulation software bus corridor application.

However, more data needs to be collected in order to validate the results. Future work will include the collection of data at more sites within the microsimulation software network as well as the collection of additional data at each site in order to preserve data for validation and decrease the risk of over fitting the model. The case study results reveal a difference between the collected and simulated speed distribution. This may have resulted from the following factors. First, the collected samples may not represent the typical behaviour of the network. Second, the speed measurements in the simulation result from several factors, in particular the driver behaviour parameters, and from the complex interaction of the vehicles

that may prevent them from reaching their desired speed. In all likelihood, the reason for the discrepancy is a combination of both factors. Further research and more advanced analyses along with additional data collection will likely shine light on this issue.

Future work will include the collection and measurements of lane changing behaviour, gaps, vehicle classification and accelerations. Furthermore, the preliminary algorithm for the detection of arrivals and departures needs to be validated on other datasets. This feature-based algorithm is a promising method that could also be applied as virtual loops in other applications. Additionally, an automatic calibration system will be developed that would measure distribution metrics including mean, standard deviation and t-statistics and compare them to the observed distribution. This would lead to a more efficient and accurate calibration process and a more precise simulation. Additionally, the emissions modelling will be further refined by analyzing the effects of individual lanes and vehicle classes. Subsequent activities will involve the application of this method in other traffic environments including highway sections and High Occupancy Vehicle (HOV) facilities. The continual advances exhibited in intelligent transportation systems (ITS) will allow for the development of additional applications for automated feature-tracking and video data collection.

Acknowledgements

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