# A GPS-BASED CALIBRATION TOOL FOR MICROSCOPIC TRAFFIC SIMULATION MODELS

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# INTRODUCTION

## TRAFFIC MICROSIMULATION

Microscopic simulation is one of the widely used techniques to solve a variety of complex problems in traffic engineering. The applications range from traffic forecasting to performance evaluation of alternative ITS applications with great benefits in terms of resources and time. Their ability to model finer details such as car following behaviour, lane changing, driver awareness, and driver aggressiveness provide the modeller with a high flexibility in modelling traffic networks with distinct characteristics. This added flexibility for modelling comes with a cost of a challenging parameter calibration for the modelling process. The simulator used in this research*, PARAMICS*, contains parameters ranging from properties of the driver population to individual driver behaviour parameters such as headway distribution and reaction times [3,6]. Model construction involves building the physical elements of the network such as roadways, junctions and modelling the traffic flow in terms of origin-destination tables. Calibrating the model is another critical element of the microsimulation. Information provided by probe vehicles could assist the calibration process to a great extent; however, the full potential of such data has not been exploited according to the current literature, primarily due to technological limitations in obtaining accurate individual vehicle level data (position, speed and gap between vehicles) for such applications [3].

## VEHICLE-BORNE GPS AND PROBE VEHICLES

### Using GPS equipped vehicles as probes

Researchers have exploited the capabilities of GPS for traffic applications since it became operational in the 1990's. GPS, being a precise positioning system, offers a great potential as a tool for collecting vehicle movement related information. It is capable of providing time tagged position and velocity observations at high rates. The accuracy of GPS observations ranges from several metres in standalone mode to 1-2 m in differential mode under open sky conditions. Complementary sensors such as self-contained devices can be used to augment GPS in order to improve the availability and accuracy in urban canyons. GPS operates in upper UHF frequency range and is therefore nominally a line-of-sight system. However a new generation of high sensitive GPS receivers combined with map-matching technologies, provide an ideal integrated positioning system for probe vehicle applications under GPS signal masking conditions.

### GPS and map-matching

Traffic engineering applications rely on information associated with the roadway features such as road links, intersections or traffic signals. Vehicle-borne GPS does not take into account the restrictions imposed on the vehicle by the road network, which is vital for the exploitation of the full potential of GPS in traffic engineering applications. The key element of this research is the building of this link to enhance the capability of GPS in traffic engineering applications, specifically as a tool for calibrating microsimulation models.

# TRAFFIC MODELLING WITH *PARAMICS*

## MODEL CONSTRUCTION

### Selection of the model area

The proposed method is illustrated using a section of a highway in Calgary: Deerfoot Trail from 16th Avenue to Beddington Trail. The selection was based on several factors. Firstly, the GPS processing algorithm uses standalone GPS at present and therefore clear reception of GPS signals is a preferable factor. Secondly, modelling a highway segment with restricted access by means of ramps, which are monitored by permanent traffic counting stations, eliminates the complexities associated with modelling urban origin-destination patterns. Adding more significance, Deerfoot Trail is one of the first highways in an Intelligent Transportation Systems (ITS) incorporation program in Alberta, Canada [1].

### Data sources and initial model calibration

The model construction could be considered as a two-stage process: infrastructure and traffic modelling. The geometrical construction of the model was based on a road centre line map of Calgary and construction drawings of Deerfoot Trail. Figure 1 depicts the map of the modelled segment of Deerfoot Trail along with the simulation model.

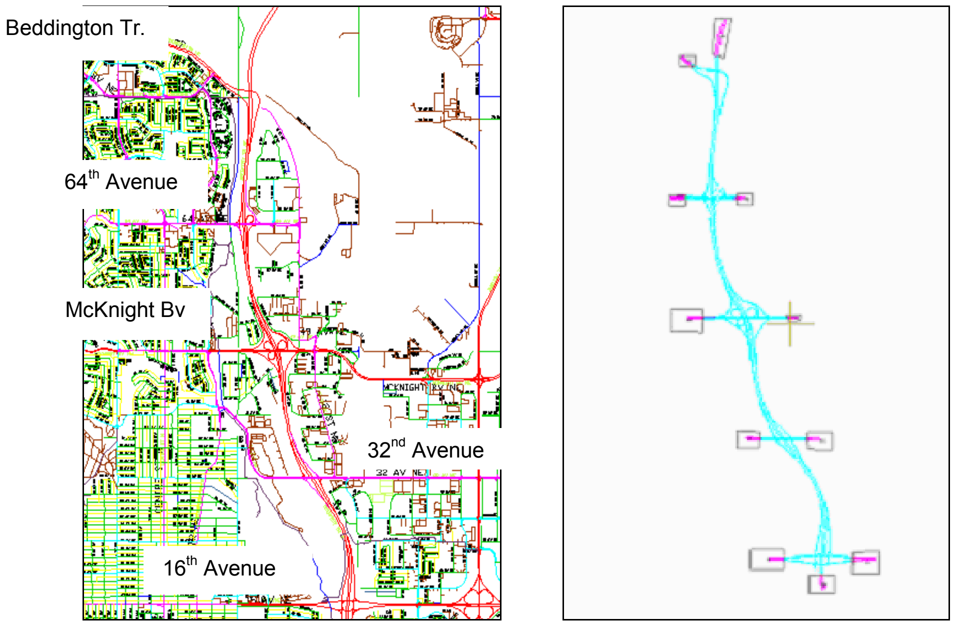


Figure 1: The Simulation Model of Deerfoot Trail, Calgary, Canada.

Traffic modelling was based on historical Average Annual Daily Traffic (AADT) scaled to fit the flows observed by a permanent counting station (PCS) on Deerfoot Trail between Beddington Trail and 64th Avenue. The *PARAMICS* Matrix Estimator tool was used for the origin-destination estimation. As depicted in Figure 2, total Northbound and Southbound traffic flows were obtained using the PCS lane flow counts and were matched with the flow counts of a simulated loop detector at the same location of the simulation model. In addition to the traffic flow calibration using AADT counts and data from PCS, speed data from GPS probe vehicles and driver characteristics data from an Alberta Transportation report on driver behaviour in Deerfoot Trail [8] were used for the initial calibration of the model. The probe vehicle speed profiles were combined into a speed contour map of the modelled area, which was used to calibrate the model in terms of operating speeds.

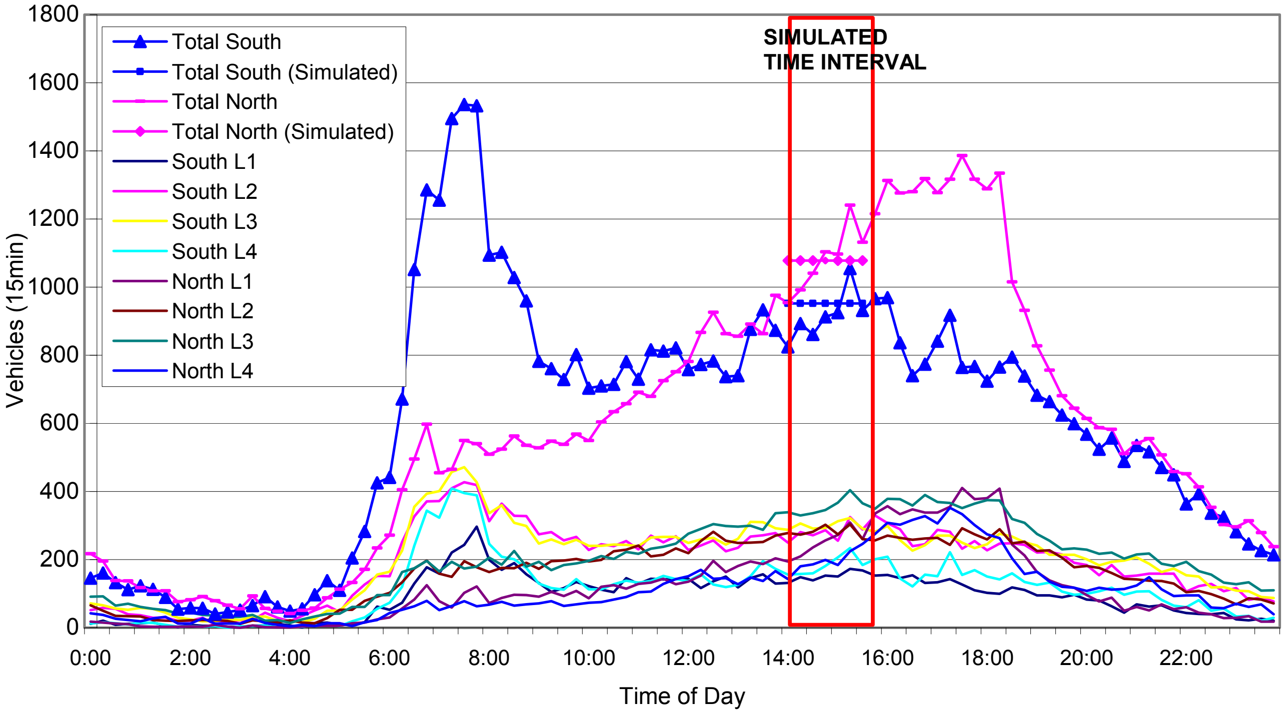


Figure 2: Permanent Counting Station Flow Data With Simulated Traffic Flow

# USING GPS FOR CALIBRATION

## METHODOLOGY

The proposed method involves enhancing the calibration of the *PARAMICS* model using speed profiles from probe vehicles traversing the road network. This enhances the initially calibrated model which used traffic flows and speeds for the calibration, thus enabling the modeller to go one step further as it analyses the behaviour of individual vehicles in the model rather than considering only the traffic counts, which is a function of many variables. Therefore, the key element in the proposed method is the tool that maps vehicle-borne GPS data onto vehicle trajectories on the road network. The GPS tool serves as the source of information for the proposed calibration. The calibration process comprises four modules: GPS map-matching tool, model building and initial calibration, *PARAMICS* simulator, and the optimisation module, as shown in Figure 3.

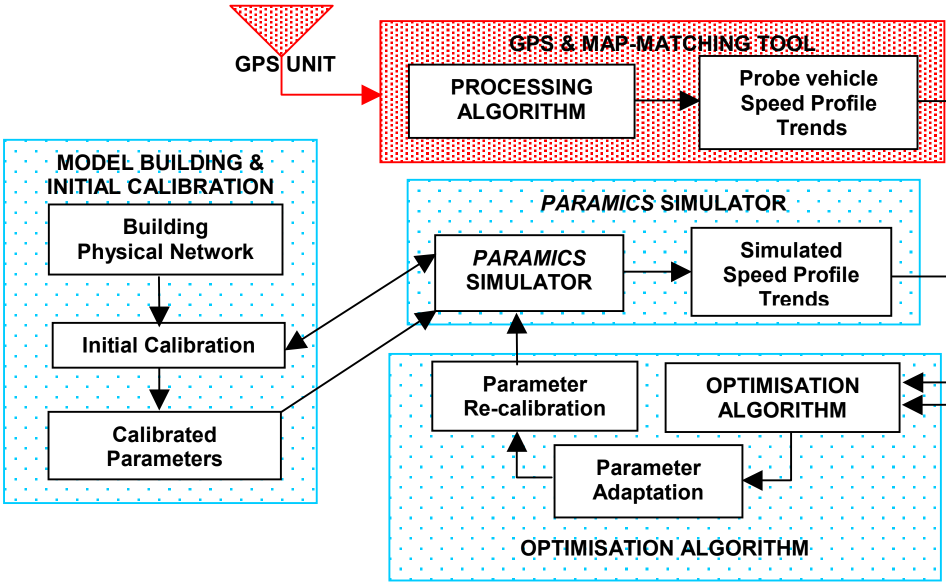


Figure 3: Proposed Calibration Algorithm

## DATA PROCESSING ALGORITHM

The data processing algorithm for map-matching GPS was developed with the primary objective of making GPS a ready-to-use tool for traffic engineering applications. The algorithm is provided with vehicle-borne GPS or a similar positioning system that is capable of estimating the vehicle position and velocity with covariance information and a digital road map of the area. The data-processing algorithm map-match the trajectories of vehicles to the road network in post-mission on an epoch-by-epoch basis (at the rate of one observation per second with the system used in this research). The data processing algorithm consists of two stages as shown in Figure 4. Firstly, GPS position and velocity estimates are mapped into the road network using GPS accuracy estimates provided by the receiver. This could result in more than one mapping per epoch depending on the estimation accuracy. Secondly the mapping outputs are introduced to the Kalman filter. The Kalman filter predict the vehicle position using filter dynamic model and uses a Nearest Neighbour Standard Filtering (NNSF) approach to select and combine the best mapped observation to the vehicle state model.

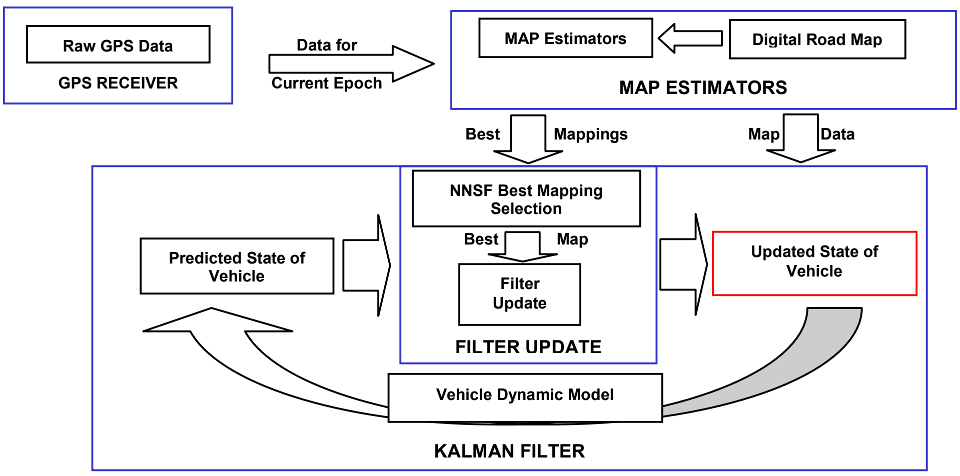


Figure 4: The Data Processing Algorithm

### Positioning System

The positioning system provides GPS time tagged instantaneous position, velocity with covariance information of the vehicle. Positioning system accuracy varies with the technology used and a standalone GPS receiver similar to the one used for this research provides an instantaneous horizontal position accuracy of 5-10m and a corresponding velocity accuracy of 5-10 cm/s under favourable open sky conditions. This accuracy degrades under conditions such as urban canyons where integration with appropriate self-contained sensors could still provide the same accuracy [7]. The algorithm was developed such that it could process data from any of these sources.

### Mapping System

The task of the algorithm is to map the raw position and velocity estimates to a vehicle trajectory on the road network and for each observation epoch the first requirement is to find the most likely mapping of the raw observation to a segment in the road network. There could be more than one probable mapping of an observation in a dense road network. A probable true position zone is established using the position covariance information and road segments within the zone are selected as possible candidates for the true road segment traversed by the vehicle. A maximum a posteriori (MAP) position and velocity estimator is used to map the observation on to each one of these possible segments along with a reliability estimate for each of these mappings. The mappings for a time epoch is ranked according to their likelihood based on three features: the distance between the raw position observation and the mapping, the agreement of the observed direction of the velocity vector with the direction of travel of the road segment, and the continuity of the vehicle along the road network. The most likely mappings are then directed to the Kalman filter.

### Vehicle Movement Modelling

A Kalman filter is used to model the movements of the vehicle and the filter process can be updated with observations as they become available [4]. The prediction capability of the Kalman filter is a vital feature used in the map matching process and is critical in two aspects. Firstly, the best mapping of the observation is selected by minimising the weighted innovation of the filter, which is similar to selecting the mapping closest to the Kalman filter prediction. This approach is known as the Nearest Neighbour Standard filtering (NNSF) approach. Secondly, at time epochs where no reliable mappings are available, the filter could continue predicting vehicle trajectory until a reliable mapping is available.

The filtering process contains a measurement model and a dynamic model with a two-stage operation, prediction and updating. The filter-updating module obtains most likely mappings of a particular time epoch from the mapping module as depicted in Figure 4. The dynamic model is critical in capturing and modelling the movements of a ground vehicle and a time correlated velocity and acceleration model was used for this research, as it is able to model a range of dynamic conditions. The observation mode defines the relationship between the observations and the state vector.

## *PARAMICS* CALIBRATION DATA

The filter generates the vehicle trajectory mapped on-to the road network. This enables the extraction of features in speed variation at different locations of the road network. Figure 5 illustrates the methodology of the filter in map matching, the raw GPS observation, mapped estimates, the Kalman filter prediction, and the final filtered estimate.

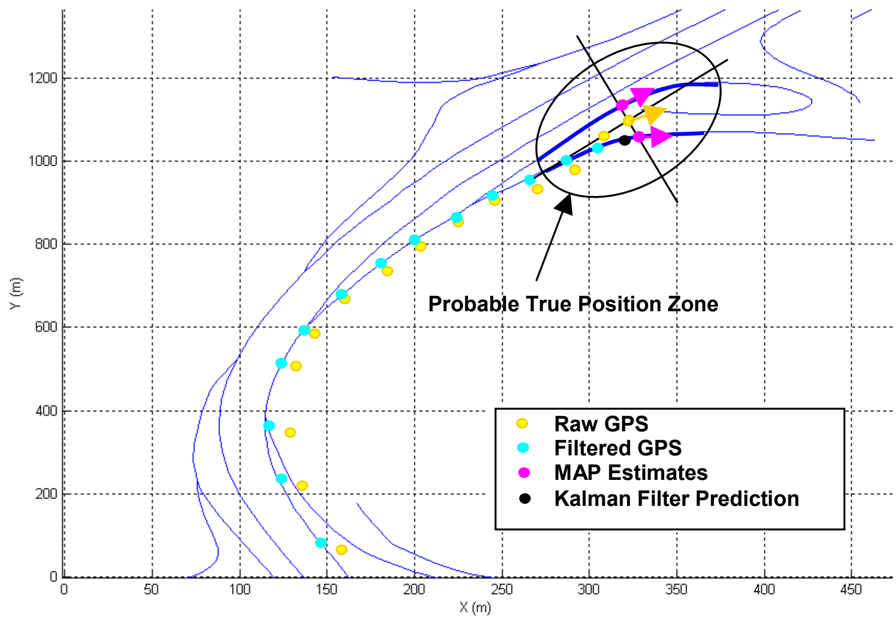


Figure 5: The Map-matching Process

The most significant result for the proposed calibration method, namely speed variations along the vehicle trajectory, is a part of the filter state estimates. Speed profiles for these vehicle trajectories are constructed and are then used for the calibration process. The simulator provides the facility to select virtual probe vehicles logging similar information on their movements in the network. This function is used to obtain the speed profiles from the simulated model.

## DATA COLLECTION

The field tests were conducted in the highway segment modelled in the simulator, between 16th Avenue and Beddington Trail of Deerfoot Trail, Calgary. Test trajectories were designed to traverse most of the entry and exit ramps and the entire highway segment under consideration. Two drivers were used for the tests. A NovAtel 600 antenna with a SiRF high sensitive GPS receiver was used for the data collection. Tests were done using two instrumented vehicles equipped with a GPS antenna-receiver configuration, one of which from the Wireless Location Research Group of the Department of Geomatics Engineering. The performance characteristics of the SiRF high sensitive receiver were researched [5]. The test set-up on one of the test vehicles is shown in Figure 6.

 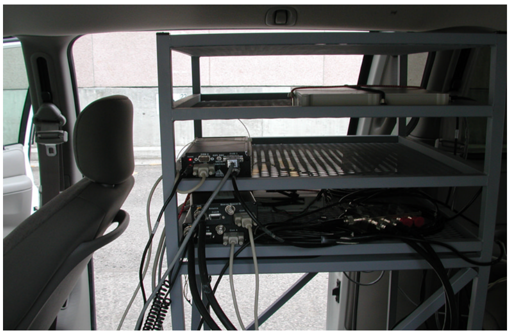

Figure 6: The Test Set-up

# CALIBRATION ALGORITHM

## PROPOSED CALIBRATION CRITERION

The proposed approach for calibration is to use the speed profiles of the probe vehicle to improve the calibration of the model. Once the initial calibration is conducted using the flow counts and speed measures available, virtual probe vehicles are generated in the simulation. The *PARAMICS* modeller is able to generate vehicles with different driver behaviours. Driver properties modelled include driver age, aggression, and awareness. Each of these properties changes the way a vehicle would behave under various driving conditions. For example, a less aggressive driver would wait for a larger gap between vehicles in case of a priority merge whereas a more aggressive driver would accept a smaller gap and merge into the traffic stream. A driver population has to be inferred based on the information available such as a normal distribution for driver aggression. At the same time, drivers of the probe vehicles have to be categorized into several aggression and awareness levels based on their knowledge of the area, age, driving experience, and driving habits.

The evaluation of the agreement between the simulated speed profiles and the probe vehicle speed profiles is formulated as an optimisation process. A popular method of optimising such problems is simulated annealing [2, 9]. As opposed to a simple parameter optimisation, this optimisation should take into account the randomness associated with the real and virtual speed profiles. The speed profiles of a test run by a probe vehicle is a random sample obtained from a population of many speed profiles by different drivers and driving conditions and a virtual probe vehicle speed profile is another random sample taken from a population of different simulated drivers and driving conditions. Therefore, the optimisation of agreement between the two should take into account the randomness associated with the two samples.

## OBJECTIVE FUNCTION

The objective function is critical in obtaining good results in an optimisation problem. The speed profiles are categorised based on driver aggression and awareness levels and could be used in several ways to assess the level of calibration. The categorisation of drivers could consider factors such as different driver age groups, aggression levels, awareness levels, and driving environment properties such as peak or off-peak driving. The objective function could be formulated as a combination of macroscopic and microscopic measures from the speed profiles. For instance it can be formulated as a combination of travel time at the macroscopic level and acceleration/ deceleration behaviour at the microscopic level. The model for such an optimisation can be written as:

$$\text{Calibration Misfit} = \frac{1}{MN}\sum_{MN}^{1}\left|DT_{\text{Simulated}} - DT_{\text{Probe}}\right|$$

Where DT, M and N are the identified driver trends in simulated and probe vehicle speed profiles, number of routes considered for the calibration, and the number of identified driver trends for each route, respectively. As mentioned, DT could include travel time measurements, acceleration or deceleration behaviour from the simulation and GPS observations.

## RESULTS

The results from the optimally calibrated simulation model are presented using a set of figures with speed profiles from simulated and observed drivers selected at random from the simulation results and GPS observations.  Two routes were selected for the comparison, which are shown in Figures 7 and 8. Figure 7 shows the speed profiles of vehicles merging from 32nd Avenue East to Deerfoot Trail North and leaving the modelled area in Beddington Trail, which is labelled route 1. Figure 8 shows speed profiles of vehicles entering from Beddington Trail to the Deerfoot Trail South and leaving the Deerfoot Trail in 16th Avenue East, which is labelled route 2. These figures include speed profiles from drivers with different aggression and awareness levels. For example simulated probe 2 in Figure 7 is a driver above normal aggression and awareness levels where as simulated probe 3 in Figure 8 is a driver below normal.

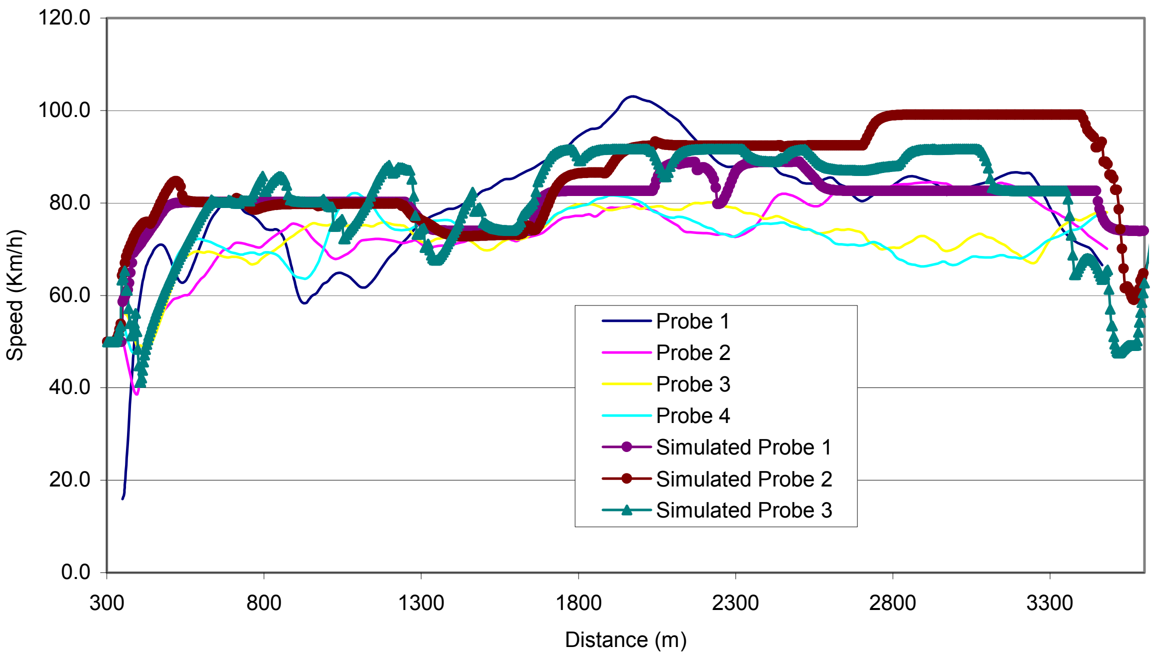


Figure 7: Virtual and real probe speed profiles: 32nd Avenue East to Beddington Trail (Route 1)

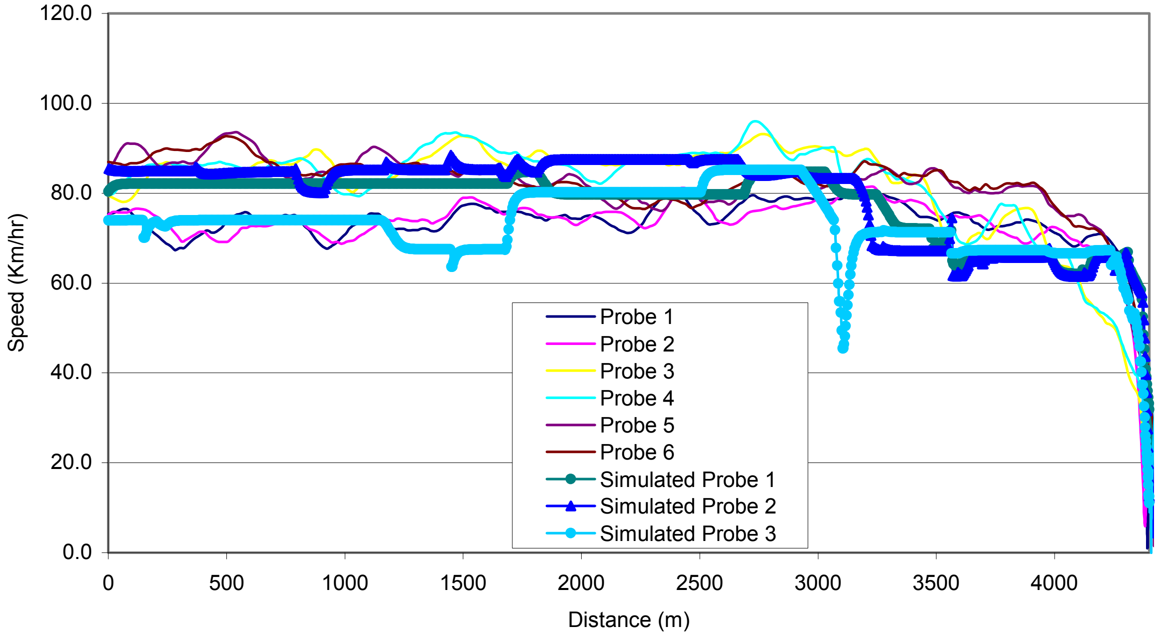


Figure 8: Virtual and real probe speed profiles: Beddington Trail to 16th Avenue East (Route 2)

The optimisation criteria used in the Deerfoot Trail simulation was a combination of travel times and driver acceleration behaviour. These two criteria for Routes 1 and 2 are presented in Figures 9 and 10. Figure 9 shows a comparison of simulated and measured travel times for Routes 1 and 2. For both routes, the simulated travel times are within one standard deviation of the GPS observed average travel times.

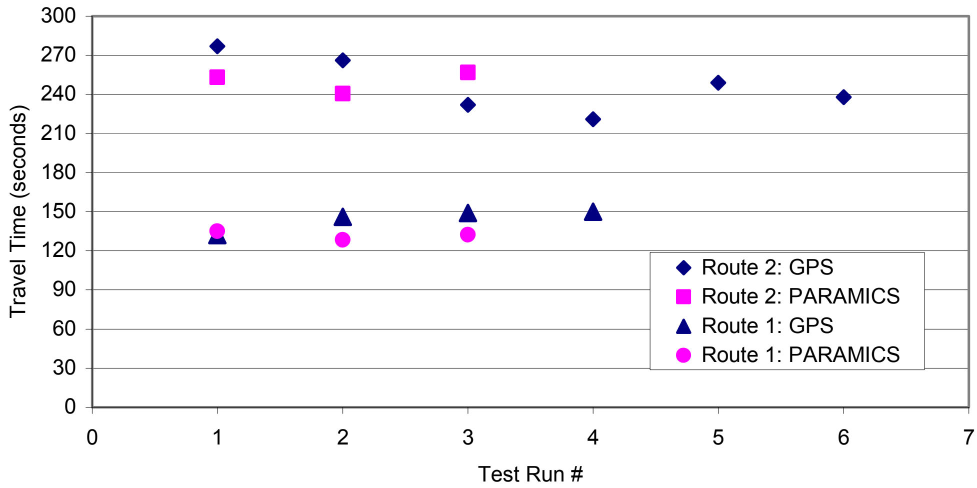


Figure 9: Observed and simulated travel times for Route 1 and 2.

Figure 10 shows a comparison of acceleration profiles from simulated vehicles and GPS observations taken from similar vehicle types. The observations correspond to the same location in both the simulation and the GPS based profiles (such as from a merge). This is vital as acceleration characteristics could vary, depending on vehicle type and the road gradient.

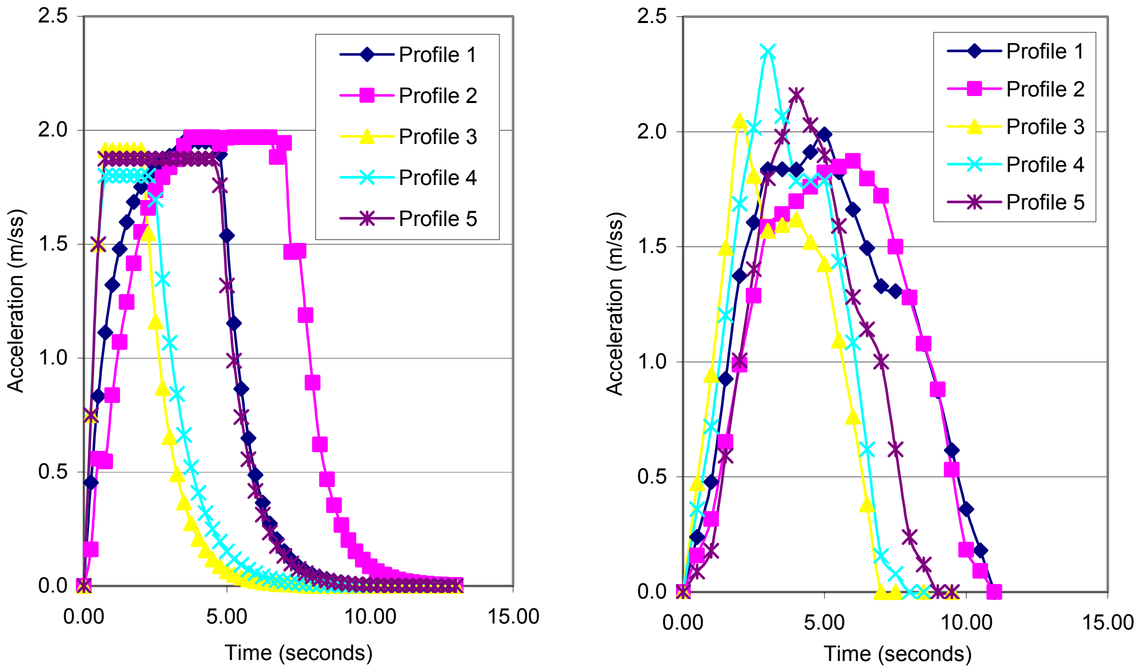


Figure 10: Simulated (Left) and observed (Right) acceleration profiles.

# CONCLUSIONS

A GPS and map-matching combined algorithm is developed as a tool for calibrating traffic microsimulation models. The methodology involves probe vehicles equipped with GPS to generate speed profiles of the vehicles travelling in different parts of the road network. These speed profiles are categorised based on different characteristics such as driver aggression and awareness. The simulation model is initially calibrated using conventional techniques. Virtual speed profiles generated by the simulator are then compared with the profiles generated by the GPS equipped probe vehicles using the agreement as an indicator of calibration. The search for the optimum calibration is formulated and presented as an optimisation problem solved using a simulated annealing-based algorithm.

The microscopic traffic simulator *PARAMICS* is used to model a segment of a highway. GPS-equipped test vehicles were deployed in the road network to collect vehicle movement related data and the algorithm was used to generate vehicle speed profiles for all roads in the modelled highway segment. The simulation model was initially calibrated using historical traffic counts and speed data provided by the probe vehicles. Virtual probe vehicles were generated in the simulation model and their speed profiles were logged in the simulator. The algorithm generated vehicle speed profiles were compared with the virtual speed profiles for optimising the model calibration and two such optimised speed profile sets were presented for two vehicle trajectories.

Further research will focus on two areas of the proposed method. Firstly, the enhancement of the GPS tool by using a GPS system aided by self-contained sensors instead of standalone GPS, thereby improving the availability and accuracy performance in urban canyons. Secondly, a sensitivity analysis will be conducted for the *PARAMICS* model parameters with the objective of selecting the critical parameters for the calibration. Further work will be done to develop the objective function and the optimisation algorithm.

# ACKNOWLEDGEMENTS

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