THE INTEGRATION OF PEDESTRIAN-VEHICLE INTERACTION INTO VEHICLE EMISSION AND EMISSION DISPERSION MODELLING

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Introduction

Vehicle emissions are often associated with their negative effects on global climate changes. However, in addition to contributing to global warming, emissions from internal combustion engines also include carbon monoxide (CO), hydrocarbons (HC), black carbon, nitrogen oxides (NOx), and particulate matters, which present adverse health effects to those exposed to them.

In urban centres, pedestrians along busy urban streets are particularly susceptible to vehicle emissions due to their proximity to large volumes of vehicles. In addition, roads in urban centres are generally lined with buildings that restrict air flow, thus reducing the dispersion of emitted pollutants. This further increases the concentration of pollutants to which pedestrians in these areas are exposed.

Previous work by Misra et al. (2012) produced an integrated approach to estimate urban traffic emissions at the St. George Street and College Street intersection. A microscopic simulation of vehicle traffic was performed (Paramics) in conjunction with a vehicle emission model (CMEM) to calculate emission factors for Carbon Monoxide (CO) and Nitrogen Oxides (NOx) along streets in an urban setting. The emission factors were then used as input to emission dispersion models (AERMOD and QUIC) to determine the concentration of pollutants in the study area (Misra 2012).

This paper presents the integration of pedestrian micro-simulation into the existing approach to estimate urban traffic emissions. By simulating pedestrian movement and capturing the interaction between pedestrians and vehicles, it is possible to model the delay experienced by vehicles when they are yielding to pedestrians, which leads to the generation of additional vehicle emissions.

Literature Review

This paper is based on the existing work by Misra et al. (2012), which has used Paramics for vehicle micro-simulation, CMEM for vehicle emission generation, and AERMOD and QUIC for emission dispersion (Misra 2012). Therefore, similar software packages for the vehicle simulation, emission generation, and emission dispersion modelling are used again for this study. The major component that is introduced by this paper is the pedestrian simulation and the interaction between pedestrians and vehicles.

Pedestrian Modelling Software

There are many attempts at modelling pedestrian movement in the literature. They can be put into three different categories. They are sketch plan models, network analysis models, and agent based models (Raford and Ragland 2006). Sketch plan models are high-level analysis tools that aim to associate pedestrian volumes to factors such as land uses, vehicle volumes, and population densities of adjacent areas (Federal Highway Administration 1999). Network analysis models are more complex than sketch plan models. They often aim to determine pedestrian volumes on specific links in a study area (Raford and Ragland 2006). Agent-based models recreate the environment and generate virtual agents that mimic the walking behaviour of pedestrians. Agent based models thereby introduce a greater degree of precision. Since this study requires a large amount of detail, an agent-based pedestrian model is required.

Several agent-based pedestrian simulation packages are commercially available. Four of the most prominent packages are Vissim, Paramics Urban Analytics Framework (UAF), Legion, and MassMotion. MassMotion is chosen for this study for its ability to perform strategic routing for its agents, and for its efficiency in simulating large numbers of agents. There exist also several MassMotion models for the Toronto downtown area and key infrastructure nodes in the area such as Union Station, Yonge/Bloor Subway Station, and St. George Subway station (Oasys Software 2014). Integrating MassMotion with vehicle micro-simulation software leads to additional potential to expand the capabilities of these models.

Vehicle Modelling Software

Vehicle modelling can be broken down into macroscopic and microscopic models. For this study, a microscopic traffic model is preferred for its ability to describe the highly detailed movements of vehicles as they interact with pedestrians. The model would also be required to have a working interface with the pedestrian simulation and the emission model. With these criteria, Paramics was chosen as the vehicle simulator. It is highly configurable with its application program interface (API), in which users can develop their own plugins to change and improve the functions of the program. In addition, there is an existing Paramics network available for the study area, from Misra et al's paper (2012).

Pedestrian Vehicle Interaction

On most North American streets, pedestrians and vehicles interact in two different cases. The first type occurs at signalized intersections, signalized crosswalks, and stop signs, where vehicles are to yield to pedestrians. The second type occurs at uncontrolled intersections and unsignalized crosswalks, where pedestrians are to wait for gaps between vehicles before crossing. The goal of this project is to accurately implement both of these cases in a pedestrian-vehicle interaction model that integrates MassMotion and Paramics.

Cases where *Pedestrians affect vehicles* occur most prominently for turning vehicles at intersections. In these cases, vehicles would simply slow, stop, and wait for the lane to be cleared of pedestrians to avoid collisions. These vehicles would assess the positions and velocities of the pedestrians on the crosswalk and look for opportunities to proceed. This is most commonly known as gap and lag acceptance, where drivers predict a period of time where their lane in the crosswalk is clear of pedestrians. Alhajyaseen et al examined this with video data collected at a number of intersections in Japan and determined left turning drivers' acceptance to gaps between pedestrians for driving through a crosswalk (left hand traffic) (Alhajyaseen, Asano and Nakamura, Estimation of left-turning vehicle maneuvers for the assessment of pedestrian safety at intersections 2012) (Alhajyaseen, Asano, et al., Gap acceptance models for left-turning vehicles facing pedestrians at signalized crosswalks 2011). From their data, the average gap and lag that was accepted ranged from 2.9 seconds to 6.7 seconds.

Cases where *Vehicles affect pedestrians* occur most prominently for jaywalking pedestrians, and pedestrians at crosswalks who do not have right of way over vehicles, such as at crosswalks with a "Wait for Gap" sign. In these cases, the pedestrians wait on the curb for all lanes on the road to be cleared with an acceptable gap between vehicles before stepping onto the road. Oxley et al (1996) used observed data from an arterial road in Melbourne, Australia to determine the average distance of gap that was accepted by jaywalkers to be between 8 to 9 seconds. Wang et al. used observed data from an arterial road in Beijing, China to estimate a binary logit model to determine the probability of crossing as a function of vehicle gap, age, and number of pedestrians in the group (Wang, et al. 2010). Their study shows that the gap length that yields 50% probability of crossing for a single young pedestrian is 4.75 seconds. This large difference between the two values of acceptable gap time is likely caused by the cultural difference between the two cities.

Emission Generation Software

Emission generation models can be broken down into macroscopic and microscopic models. Macroscopic models generally focus on using average vehicle operation characteristics over a large study area. Microscopic emission models use instantaneous driving behaviour and traffic conditions to calculate emission generation. Due to the versatility of microscopic models, they have been integrated with vehicle microsimulation software packages in several cases. This study is focused on pedestrian-vehicle interactions at urban intersections and their effect on emissions. Therefore, it generates a large amount of detail in dynamic vehicle behaviour. Pursuant to this, microscopic models were considered for this study. CMEM's availability as a plugin for Paramics makes it the software package of choice for this project.

Emission Dispersion Software

The dispersion of emission is carried out by the movement and turbulence of air in which the pollutants reside. As a result, the study of emission dispersion involves understanding atmospheric conditions. This ranges in scale from global atmospheric conditions, such as jet streams, air masses, and cyclones, to local weather conditions, such as urban heat island effects and obstacle wakes (Arya, Air Pollution Meteorology and Dispersion 1999). In Misra et al's study (2012), two models, AERMOD and QUIC, were utilized to investigate the dispersion of CO and NOx (Misra 2012).

Misra et al (2012) determined that the NOx concentrations calculated by AERMOD matched the observed values better, whereas the CO concentrations calculated by QUIC had a better match with the observed values (Misra 2012). Both models have advantages and limitations. AERMOD's ability to use high-altitude meteorological data allows it to be potentially more accurate than QUIC. However, this high-altitude data is not available and had to be obtained using interpolation techniques from Lakes Environmental. In addition, AERMOD is only able to incorporate building geometries into its dispersion model for point sources of pollutants, and its time frame for varying weather data and emission sources is set to a minimum of one hour. This makes it inadequate for modelling the dispersion of pollutants generated along a road, and for an intersection at rush hour. It was also found that QUIC was able to explicitly calculate street canyon effects, and its results had better correlation with the measured values (Misra 2012). Thus, for the purpose of this study, QUIC is the software of choice for modelling emission dispersion.

Data and Method

As input to the MassMotion and Paramics software, data on vehicle and pedestrian volume were collected. The data collection took place on April 2nd, 2013, from 8:00 AM to 10:30 AM. Vehicle turning information was collected at street intersections, and pedestrian volume information was collected at intersections and building entrances/exits. A total of 11 and 17 locations are monitored for vehicles and pedestrians, respectively. It was noted that there was construction taking place on College Street at the St. George Street and College Street intersection, which reduced the number of lanes on College Street. The network was modified to reflect this change.

Vehicle data collection was conducted with the TrafficDuco™. TrafficDuco™ is a traffic surveying software that allows real-time turning movement counting for intersections. Pedestrian data was collected on paper. Each pedestrian data collector was given a spot and two bi-directional links to monitor for every 5-minute intervals between 8:00 AM and 10:30 AM. These data are then used for Origin-Destination matrix generation and modelling.

Pedestrian OD Estimation

A series of pedestrian OD matrices were estimated to produce the link volumes that matched the observed values. An entropy maximization approach was used to estimate the OD matrix (Xie, Kockelman and Waller 2010). The OD estimation process for pedestrians was carried out as an optimization problem, where the objective was to minimize difference between calculated link volumes and measured link volumes and to maximize entropy. The final objective function was defined as follows:

$$Min\left(\sum_{k}\left(x_{k,calculated}-x_{k,observed}\right)^{2}+\sum_{ij}\left(V_{ij}\ln V_{ij}-V_{ij}\right)\right)$$

Where $x_{k,calculated}$ and $x_{k,observed}$ are the calculated and observed volumes, respectively, on link k; and V_{ij}'s the entries in the OD matrix from origin i to destination j. The OD matrix contains 31 nodes, and there are 34 links within the network. This objective function was minimized using a genetic algorithm.

The genetic algorithm used in this case used an initial population of 300 randomly generated OD matrices. At every generation, the entries in every OD matrix are encoded into binary to form "chromosomes". Using each OD matrix's fitness function, candidates for crossover and mutation are selected. During crossover, a random number of bits in each chromosome of the two parent OD matrices are swapped; during mutation, a random number of bits in each candidate matrix are flipped. This process is then repeated for 2000 generations.

Vehicle OD Estimation

Vehicle OD Matrix was estimated using turning movement percentages. Since information for all turning movements was collected, vehicle volume between OD pairs was calculated by the following equation:

$$V_{ij} = x_O \prod_{k=0}^{K} P_k(turning)$$

Where x_O is the volume of vehicles counted leaving the origin point, and $P_k(turning)$ is the probability of making the required turn at intersection k out of all K intersections to get to the destination j. The study period is broken down into 10 different 15-minute segments, and two matrices were estimated for each time segment, one for light vehicles, and one for medium and heavy vehicles.

Software structure

For the purpose of this study, MassMotion is modified and compiled as an API to Paramics (Figure 1). The two major types of interactions between vehicles and pedestrians are represented by two different mechanisms in MassMotion and Paramics.

The pedestrians' vehicle gap acceptance for crossing at unsignalized crossings is modelled by opening and closing gates to these unsignalized crosswalks. These gates are controlled by the MassMotion API. At each simulation frame, MassMotion's unsignalized crosswalk gates check for oncoming vehicles and evaluate whether the crossing is safe. This evaluation is based on pedestrians' assured gap acceptance of 10 seconds for vehicles when crossing at unsignalized crosswalks.

The vehicles' pedestrian gap acceptance is represented by implementing "watch areas" for vehicles in which they detect pedestrians' future locations based on their current locations and velocities. These watch areas are defined as trapezoids extending forward from the front of each vehicle. These trapezoids are tapered outward at 5^{o}, and their lengths are based on the stopping distance of the vehicles as a function of their speed. For turning vehicles, the trapezoids are rotated in the direction of turning. In addition, left turning vehicles have their watch areas extended to monitor pedestrian crossings on the far end of the intersection.

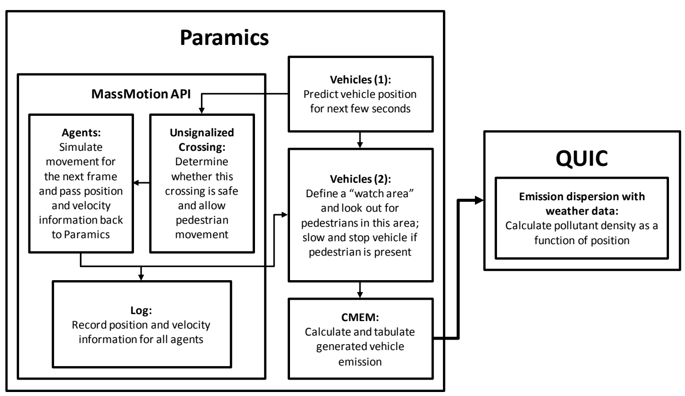

Figure 1 – General software structure

Vehicle type distribution in CMEM

CMEM breaks down vehicle fleet into 31 categories based on their emission patterns. To use these vehicle categories, Misra et al (2012) used an augmented distribution from the Canadian Vehicle Survey from Statistics Canada (2009) (Misra 2012)(Statistics Canada n.d.). Using the same approach as Misra's study (2012), the three vehicle categories used during data are broken down into 18 CMEM vehicle types.

CMEM runs concurrently with Paramics as an API, and tabulates the total amount of pollutants emitted on each link in 15-minute timeframes. This information is then exported and used as input to QUIC for emission dispersion modelling.

QUIC Settings

QUIC uses building geometries and weather data to calculate emission dispersion. Building geometry information is obtained from the University of Toronto's Maps and Data Library (Map and Data Library, University of Toronto n.d.), and weather data is obtained from the weather station located on 200 College Street, operated by the Southern Ontario Centre for Atmospheric Aerosol Research (SOCAAR). Pollutant sources are represented by constantly-emitting line sources along the streets in the study area. QUIC's emission model was run at 10-second timeframes over the 2.5-hour study period.

Results and Validation

To account for random variations, the models are run 16 separate times with different seeds in the MassMotion API, Paramics, and QUIC. A sample result from QUIC is in the figure below. It shows the pollutants following the wind (blowing from the southwest). Concentration for CO and NOx are modelled in g/m^3. These data are then validated with the observed CO and NOx concentrations on April 2nd, 2013. The observed data are provided by SOCAAR's sensors located at 200 College Street, at a height of 3 metres above ground.

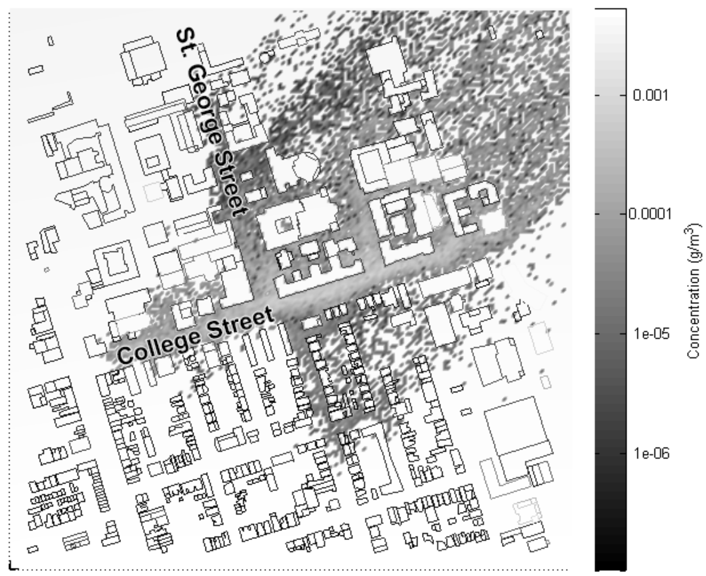

Figure 2 - CO concentrations at 8:45 at an elevation of 3m

For the data validation, observed concentrations at 3:00-5:00am were used as ambient concentrations, and were added to the modelled concentrations to obtain the predicted concentrations. The graphs below show the average of the 16 simulation runs and the observed concentrations. It is seen that the variance between each simulation run is large. The coefficients of variation in each of the 16 data points range between 0.12 and 0.31. By plotting the observed and modelled concentrations, it is evident that the concentration of CO is consistently over-predicted by this approach, and the concentration of NOx is closer to the measured concentration (Figure 3). This result is similar to the result obtained in Misra et al.'s study (2012), where the majority of the predicted CO concentration is considerably higher than the measured CO concentration, and the NOx concentrations are more accurate.

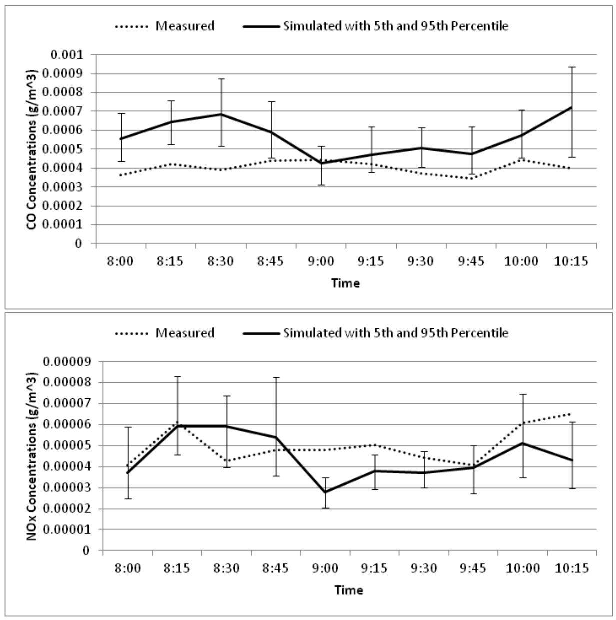

Figure 3 – Measured and Simulated CO and NOx concentrations during study period

To validate this model, a "factor of two" comparison is used. The "factor of two" comparison calculates the percentage of predicted concentration values that fall within a factor of two from the observed concentration values. This method is widely used to determine the significance of predicted concentrations for emission dispersion models (Arya, Air Pollution Meteorology and Dispersion 1999). For CO, 92.5% of the data points fall within the "factor of two" envelope, and for NOx, 95.6% of the data points fall within this envelope. Further examination using the correlation between the predicted data and measured data shows a coefficient of correlation of 0.31 for NOx and 0.03 for CO. This is in accord with the findings of Misra et al. (2012).

Conclusion and Future Directions

This paper describes the addition of pedestrian movements into an integrated approach to model vehicle emissions in an urban setting. In this new approach, MassMotion was compiled as an API plugin to Paramics to model the pedestrian-vehicle interaction, and CMEM was used to determine the generation of CO and NOx. The output from CMEM was then used in QUIC for dispersion analysis. The results were validated with measured CO and NOx concentrations. The results of the NOx dispersion model showed comparable results to the measured concentrations, while the results of the CO dispersion were consistently higher than measured results. However, predicted concentrations for both CO and NOx were within the "factor of two" envelope for more than 90% of the data points.

The next steps for this study would be to explicitly assess the amount of pollutants to which the pedestrians are exposed as they navigate through the study area by tabulating the concentrations of pollutants along the paths that are taken by pedestrians. It is also possible to assess the impact of several traffic policies, such as the effect of adding a scramble phase in the signalling of the intersection. The addition of a scramble phase would remove the need for turning vehicles to yield to pedestrians, but it would also cause the vehicles and the pedestrians to idle and wait longer at the intersection.

Acknowledgements

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