

ANALYTICAL EMISSION MODELS FOR SIGNALISED ARTERIALS

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ABSTRACT: Concern over the negative impact that automobiles have on air quality has prompted renewed interest in methods for quantifying vehicle tailpipe emissions. In this paper we present non-linear regression models that can be used to estimate the additional mass of carbon monoxide, hydrocarbons, and nitrogen oxides that would be expected to be produced by vehicles traversing a roadway, if a traffic signal was to be installed. The regression models use traffic demands, roadway characteristics, and traffic signal timing parameters as explanatory variables. Data for calibrating these models are obtained from the application of Integration, a microscopic traffic simulation model, to 8100 individual scenarios. The validity of using Integration as a source for emission data is examined using field data. The proposed models have adjusted R^2 values ranging from 0.76 to 0.95. A comparison of the proposed models to similar models contained within the Canadian Capacity Guide indicate marked differences in the relative and absolute impact that traffic signals have on the quantity of pollutants produced.

1. INTRODUCTION

The goal of this research was to derive analytical expressions for estimating vehicle tailpipe emissions and fuel consumption as a function of traffic characteristics and signal timing parameters. These expressions could be used in practice to supplement existing techniques for comparing candidate traffic control strategies by permitting a comparison to be made on the basis of vehicle emissions, in addition to delay and stops.

Extensive research has been conducted to quantify vehicle emissions as a function of influencing factors, such as engine type and condition, driving characteristics (i.e. acceleration rate, speed, etc.), air temperature, type of pollution controls, etc. Many different models have been developed, which in general fall into three broad categories.

The first category of models is driving cycle based, in which specific driving cycles are defined, and expressions developed on the basis of emission measurements made on vehicles driving that specific cycle. The US EPA model, Mobile 5 (and most recently Mobile 6) is an example of this approach (USEPA, 1994). The drawback to this approach is that it is often not clear how similar a specific pre-defined driving cycle is with the conditions being examined. Prior to the release of Mobile 6, there existed only two driving cycles, an Urban cycle and a Freeway cycle. This limited number of cycles also constrained the accuracy of applying Mobile 5 to traffic scenarios that were not similar to the Urban or Freeway cycles. In Mobile 6, 16 driving cycles are defined, expanding the range of conditions over which the model can be applied, however, the accuracy of the emission estimate still remains a function of similarity between a selected driving cycle and the conditions being examined.

The second category is microscopic simulation modelling, in which individual vehicle behaviour is represented and emissions are estimated over each time step (typically on the order of 1 second) as a function of the vehicle's current speed and acceleration. These models have the benefit of being able to estimate emissions for any traffic scenario, rather than a limited set of pre-defined scenarios. Furthermore, these estimates are automatically sensitive to all factors that influence vehicle speed and/or accelerations. However, the use of these models often require significant effort, as the network must be coded and suitably calibrated before an estimate can be made. For many applications the effort required to apply these simulation models is not justified.

The third category of estimation techniques is aggregate analytical models, in which estimates of emissions are made as a function of average vehicle travel characteristics, such as speed, delay, and/or number of stops. The estimation method contained within the Canadian Capacity Guide falls within this category. The advantage of these models is that they can be applied with relatively little effort and can be incorporated within the existing signal timing design process.

The objective of this paper is to describe the derivation of a set of analytical emission models that can be used to estimate the additional quantity of CO, HC, and NO_x emitted as result of the presence of a traffic signal. The models make direct use of the signal timing parameters and traffic demands as independent causal factors.

1.1 Research Approach

The approach taken in this research was to make use of Integration, a microscopic simulation model (Van Aerde, 1999), to generate emission data over a wide range of traffic, roadway, and signal conditions. These data were then used to calibrate regression models that have been proposed to represent the underlying relationship between vehicle emissions and various factors.

It is recognised that the validity of the proposed regression models is largely dependent on the validity of the microscopic simulation model that was used to generate the emission data. Therefore, an examination of the validity of Integration was made in two key areas. The first was to examine the degree to which the model is able to realistically model the microscopic behaviour of vehicles in terms of speeds and accelerations, in the vicinity of traffic signals, as

the amount of emissions that are produced by individual vehicles is closely dependent on their second-by-second motion. The second examination was made to determine the validity of the emission sub-models that are used within Integration to estimate vehicle tailpipe emissions every second. These sub-models have been verified by other researchers and have been described in the literature. In this paper we provide only a brief assessment of the validity and credibility of these emission sub-models.

The proposed regression models are compared to the models presented in the Canadian Capacity Guide (CCG) and conclusions regarding differences between these models are made.

2. EVALUATION OF SIMULATION MODEL

2.1 Evaluation Network

An evaluation of the accuracy of the microscopic vehicle behaviour was conducted by comparing the vehicle speed and acceleration values predicted by the Integration model to field observations. The accuracy of the Integration model predictions was also compared to similar predictions from the NETSIM model. The observed data and the NETSIM results were determined by Hallmark and Guensler (1999a, 1999b). It is important to note that both of these publications describe the same research. This first paper (Hallmark and Guensler, 1999a) was presented at the 1999 meeting of the Transportation Research Board. The second paper (Hallmark and Guensler, 1999b) is the same paper (albeit with minor revisions) published in the Transportation Research Record.

On the basis of the descriptions provided in these two papers, a single 4-leg signalised intersection was modelled with Integration (Figure 1). All approaches consisted of an exclusive left-turn lane, an exclusive through lane, and a shared through and right-turn lane. An unadjusted saturation flow of 1800 vph was selected for all lanes. The traffic demands applied to the intersection are provided in Table 1. The papers by Hallmark and Guensler only specify total approach demand, but do not specify the individual turning movement volumes. Therefore, a portion of each approach volume was apportioned to each movement such that the over-all intersection level of service was compatible with LOS C as specified by Hallmark and Guensler. All vehicle demands enter the approach links with exponentially distributed time headways.

Table 1: Traffic demands on signalised intersection

Intersection Approach	Demand (vph)		
	Left-Turn	Through	Right-Turn
Eastbound	66	1119	132
Westbound	90	765	45
Northbound	70	1200	141
Southbound	10	1150	129

The intersection is modelled with a 2-phase fixed time signal having cycle length of 100 seconds. Each phase consists of an effective green interval of 46 seconds and a loss time of 4 seconds.

The intersection was modelled for 1 hour. Simulation output describing vehicle position, speed, and acceleration was obtained for each vehicle each second. These data were processed to obtain the proportion of time spent by vehicles in each speed and acceleration range. To be consistent with the results provided by Hallmark and Guensler, data were only obtained for vehicles within 76m of the stop line on the approach link and 76m after the intersection on the outbound link. Also, when estimating the percent of vehicle activity by bin, stop delay was minimised to 1 second per vehicle so that high delay values (i.e. speed = 0) did not overwhelm all other vehicle activity fractions.

2.2 Results

Figure 2 illustrates the percent time spent by vehicles in each acceleration range for the observed field data, predicted by NETSIM, and predicted by Integration. The Integration results reflect a selected free speed of 60 km/h, speed at capacity of 55 km/h and a speed dispersion factor of 0.3. The two papers by Hallmark and Guensler provide significantly different NETSIM results. The NETSIM results provided in the TRB reference (1999a) more closely reflect the field data than do the NETSIM results provided in the TRR reference (1999b). It is not clear why the results are

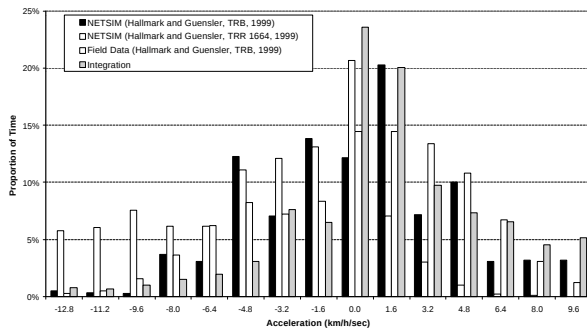


Figure 2: Comparison of proportion of time spent in each acceleration range

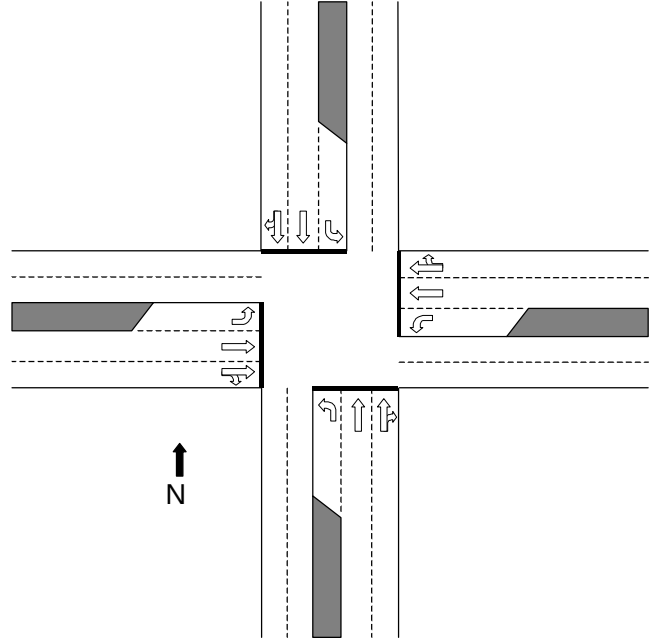


Figure 1: Intersection used for model evaluation

different, since both papers describe the same research.

The results depicted in Figure 2 suggest that Integration overestimates the proportion of time vehicles spend at very low deceleration rates (i.e. $-1.6 \text{ kph/s} < \text{deceleration} \leq 0.0 \text{ kph/s}$) and underestimates more severe decelerations (i.e. $-9.6 \text{ kph/s} < \text{deceleration} \leq -1.6 \text{ kph/s}$). The accuracy of model predictions in reflecting the observed field data can be quantified using Equation 1.

$$E = \sum_{i=1}^n \frac{(p_i - P_i)^2}{P_i} \quad (1)$$

where:

p_i = percent time predicted by model (NETSIM or Integration) for range i

P_i = percent time from field data for range i

n = number of ranges

Using Equation 1, the total error associated with the proportion of vehicle time associated with acceleration ranges as predicted by NETSIM (1999a), NETSIM (1999b) and Integration was calculated to be 0.19, 2.42, and 0.32, respectively.

A similar examination was conducted on the percent time spent in each speed range. Figure 3 illustrates the distribution of vehicle activities across the speed ranges. Both papers by Hallmark and Guensler (1999a, 1999b) present the same data for the field data and the NETSIM results. The results indicate

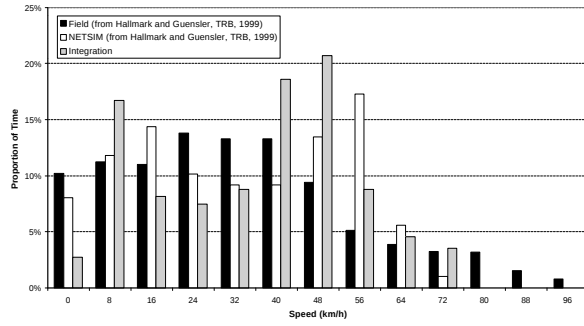


Figure 3: Comparison of proportion of time spent in each speed range

that Integration tends to overestimate the proportion of time that vehicles spend at speeds greater than 32 km/h and underestimate the time associated with speeds less than 32 km/h. Applying Equation 1, the total error associated the proportion of vehicle time associated with speed ranges as predicted by NETSIM and Integration was calculated to be 0.38 and 0.35 respectively.

These results seem to support two conclusions.

First, both NETSIM and Integration appear to provide similar levels of overall accuracy in modelling the microscopic acceleration and speed behaviour of vehicles at signalised intersections.

Second, while both models provide distributions of speed and acceleration that reflect general trends in observed conditions, there remain significant discrepancies between the model predictions and the field data as collected and described by Hallmark and Guensler. Unfortunately, it is not possible to make conclusions regarding the source or cause of these discrepancies. They may be a result of the modelling logic employed within NETSIM and within Integration. Conversely, they may result from inadequate specification of the field conditions within the simulation models. In fact, the field data collected by Hallmark and Guensler were obtained from up to 30 different intersection sites, and data collected for a random sample of vehicles at each site. The data set used for comparison to the simulation models was composed of data from several different field sites having similar level of service.

3. EVALUATION OF MICROSCOPIC EMISSION SUB-MODELS

The previous section examined the ability of the Integration simulation model to represent the microscopic speed and acceleration behaviour of individual vehicles at traversing a signalised

intersection. This section briefly examines the microscopic emissions models that are embedded within the Integration model.

The emissions models have been described in detail by Ahn et al (1999) and Rakha et al. (2000). A brief description is provided here to present the degree to which these microscopic emission models reflect field data.

Separate models exists for carbon monoxide (CO), hydro carbons (HC) and oxides of nitrogen (NOx). Each model is a multivariate non-linear third degree model of the form

$$\log Z_k = \sum_{i=0}^3 \sum_{j=0}^3 B_{ij}^k u^i a^j \quad \forall k \quad (2)$$

where:

- Z_k = estimated quantity of emission (g/sec)
- B_{ij}^k = regression coefficient for speed range i , acceleration range j and emission k
- u^j = vehicle speed (km/h)
- a^j = vehicle acceleration (kph/s)

Observed data were obtained by testing 8 light duty gasoline powered vehicles on a dynamometer. Vehicles ranged in model year from 1988 to 1995. Each vehicle was tested over a range of speeds (0 to 120 km/h at increments of 1.1 km/h) and a range of acceleration rates (-1.5 m/s² to 3.6 m/s² at increments of 0.3 m/s²). All testing was done under hot stabilised conditions. The resulting emission data were averaged across the eight vehicles to create emission rates for a composite vehicle. Regression models of the general form of Equation 2 were fit to these composite emission data for each of the three emissions. The models explained more than 90% of the variance observed in the composite emissions indicating a high degree of explanatory power. It must be noted that these relationships do not consider the impacts of cold starts, high emitting vehicles, ambient temperatures, or heavy vehicles.

4. DEVELOPMENT OF ANALYTICAL EMISSION MODELS

The Integration simulation model was used to generate emission and fuel consumption data for a range of traffic and signal control conditions. These data were then used to calibrate regression models for estimating vehicle tailpipe emissions as a function of signal timing parameters and traffic conditions.

4.1 Data Generation

A total of 8100 scenarios were simulated using the Integration model. In each case the network consisted of a 4-leg intersection with a single two-phase signal controlling exit privileges from each approach (Figure 4). Traffic demands were generated on the eastbound approach with exponentially distributed time headways over a 60 minute period. No traffic demand was generated on the other three approaches. The simulation was permitted to continue until all vehicle trips had been completed. All approaches consisted of a single lane with an unadjusted saturation flow rate of 1800 vph. Average emissions of carbon monoxide (CO), hydrocarbon (HC), and nitrogen oxide (NO_x) per vehicle, as estimated by the emissions sub-models within the Integration model, were recorded for each scenario. The signal control parameters, namely degree of saturation, x , cycle length, c , green interval duration to cycle length ratio, g/c , and the traffic demand, q , and the link free speed, S_f , and speed at capacity, S_c , were recorded.

Each of the 8100 scenarios reflected a different combination of signal control parameters, traffic demand, link speed conditions, and random number generator seed. Parameter values and combinations are provided in Table 2.

Scenarios were also executed without the traffic signal for the same traffic demand, link speeds, and random seed combinations.

The resulting emission data was compiled by subtracting the average vehicle emission associated with a non-signal scenario from the corresponding average vehicle emission associated with the traffic signal. This quantity represented the additional average emission quantity that would be produced by each vehicle traversing a single approach as a result of the installation of a traffic signal.

4.2 Model Calibration

Emission models were developed by calibrating regression models to the generated emission data. A

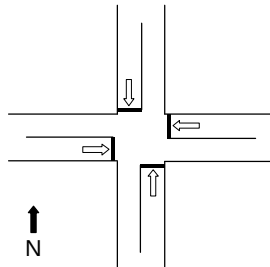


Figure 4: Intersection used for model evaluation

variety of model structures were considered including first and second order linear models, and first and second order exponential models. The exponential models, having the general structure as in Equation 3, were selected on the basis of their superior explanatory powers.

$$E = e^a \times e^{b_1 Z_1^{n_1}} \times e^{b_2 Z_2^{n_2}} \dots \times e^{b_m Z_m^{n_m}} \quad (3)$$

where:

E = emission estimate (kg)

a = regression constant

b_m = regression coefficient associated with independent variable m

Z_m = independent variable m (e.g. X , c , S_f , S_c , etc.)

n_m = exponent for independent variable m

In each case, a step-wise approach was adopted for determining the independent variables that should be included within the models. The F-test was used to decide whether an independent variable made a significant contribution to the model's ability to explain the variance observed in the data. A level of significance of 5% was chosen for adding independent variables to the model. A level of significance of 10% was chosen for removing variables.

On the basis of the step-wise regression results regression models were selected for each emission type. The regression coefficients for each selected model are provided in Table 3. The selected models had R^2 values of 0.953, 0.922, and 0.756 for CO, HC,

Table 3: Regression model coefficients

Model	Coefficients		Student t
	(Constant)	b_i	
CO	(Constant)	-5.687	-256.7
	S_f	0.0529	118.8
	X	1.506	124.5
	S_c	0.0282	72.5

Table 2: Parameter value combinations used for data generation

Parameter	No.	Values
Link Speed (km/h) $\{S_f, S_c\}$	12	$\{(80,75), (80,70), (80,60), (70,65), (70,60), (70,50), (60,55), (60,50), (60,40), (50,45), (50,40), (50,30)\}$
Cycle Length (sec)	5	$\{60, 75, 90, 105, 120\}$
g/c ratio	3	$\{0.3, 0.5, 0.7\}$
Degree of Saturation	9	$\{0.4, 0.6, 0.8, 0.9, 0.95, 0.97, 0.99, 1.0, 1.01\}$
Random Seed	5	$\{1, 2, 3, 4, 5\}$

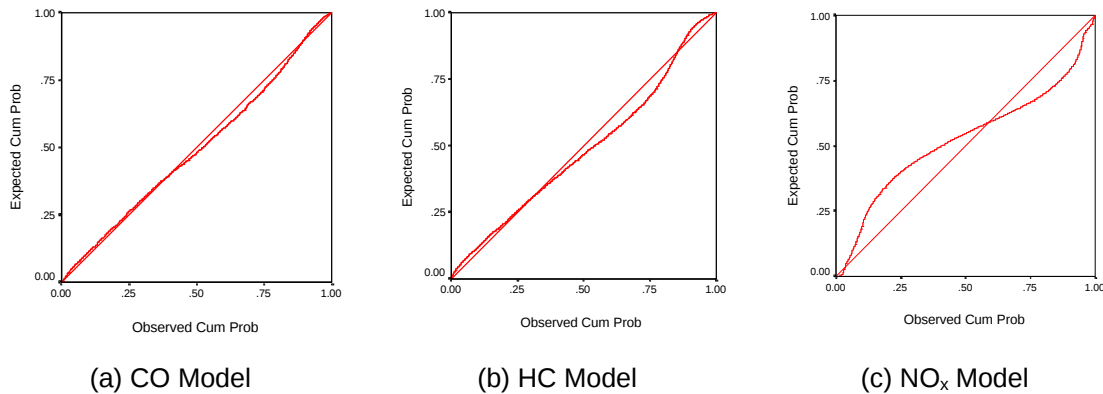


Figure 5: Cumulative probability plots of Normalised residuals for the emission regression models

and NO_x , respectively.

An examination of the residuals (Figure 5) indicates that for the CO and HC models, the residuals are near-Normally distributed with no apparent changes in variance. The residuals associated with the NO_x model are not as well behaved. For NO_x two distinct regions of large estimation error (one associated with over estimation and the other with under estimation) imply that the regression model for NO_x fails to capture at least one causal factor. A number of other model structures using the set of available explanatory variables were examined for NO_x , however, a model with greater explanatory power was not found.

5. COMPARISON OF PROPOSED MODELS TO EXISTING TECHNIQUES

A review of the literature was conducted to identify other analytical models for estimating emissions with the intent of comparing these models with the models proposed in this paper. The literature review revealed that very little work has been carried out previously to develop analytical emission models that explicitly include signal timing parameters as independent variable. One notable emission model that does provide emission estimates as an indirect function of signal timing parameters is the model proposed in the 2nd Edition of the Canadian Capacity Guide (Teply et al., 1995). This model estimates CO, HC, and NO_x , as a function of the number of stops in each lane during each phase, the average stopped delay in each lane during each phase, and the average cruise speed and distance. The model indirectly associates emissions with signal timing parameters in that the number of stops and average stopped delay are first estimated from the traffic demands and signal control parameters, and then these estimated of stops and delay are used to estimate emissions.

The background of the derivation of the model proposed in the CCG is not available in the literature, although personal communication with Prof. Stan Teply, the editor of the CCG, revealed that the model is based on results obtained from the Mobile 4 model developed by the US EPA.

A single scenario was used to compare the results from the CCG with those obtained from the proposed regression models. The hypothetical scenario consists of a single lane intersection approach, with a base saturation flow rate of 1800 vph. A signal cycle length of 90 seconds and a g/c ratio of 0.5 are assumed. An average cruise speed of 50 km/h is assumed for application of the CCG method. The scenario represents an isolated intersection so no progression adjustments were made. A free speed of 65 km/h and a speed at capacity of 55 km/h are assumed for application of the regression models. Emission estimates were made for 11 values of X , ranging from 0.4 to 1.01. The resulting emission estimates represent the additional emission that would result from the impact of the traffic signal. Therefore, emissions resulting from cruising (i.e. the last term of the CCG model) are ignored.

The results are illustrated in Figure 6 for CO. From the figure, it is evident that the CCG models are much more sensitive to the degree of saturation than the proposed regression models. This sensitivity results in estimates of emissions that are as much as 10 time greater than the estimates from the proposed models. The estimates from the CCG for a 1995 vehicle fleet and a 2000 vehicle fleet follow the same trend, with the year 2000 fleet producing marginally lower emissions (in the range of 5% for CO, 14% for HC and 17% for NO_x).

The most significant result is that unlike the CCG models, the proposed models indicate that emissions increase rather slowly with increases in the degree of saturation. For degree of saturation equal to 1.0, the

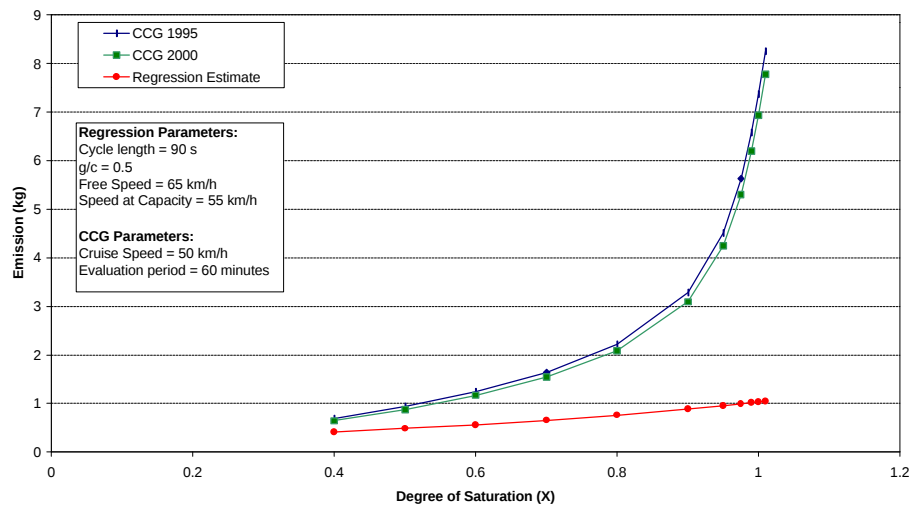


Figure 6: Comparison of proposed emission CO model and the models proposed by the Canadian Capacity Guide

proposed models indicate that emissions range from 2.5 (CO) to 4.9 (NO_x) times the emissions at a degree of saturation of 0.4. Conversely, the CCG models indicate that at $X=1.0$ emissions are 7 (NO_x) to 16 (HC) times the emissions at $X=0.4$.

Unfortunately, it is not possible to assess the validity of the CCG models as the derivation of the models has not been described in the literature. The evidence provided in this paper seems to indicate that the CCG models may significantly over estimate emissions for a wide range of typical signalised intersection operating conditions.

6. CONCLUSIONS AND RECOMMENDATIONS

A review of the literature indicates that while much research has been conducted to quantify vehicle tailpipe emissions, only one analytical model was found (the CCG model) that directly relates emissions to traffic signal control parameters. Unfortunately, the derivation of model has not been documented, with the result that the degree of accuracy of the model, and the level of confidence that can be placed in the model estimates, can not be established.

Microscopic traffic simulation models, such as the Integration model, are robust tools for estimating the impact of changes in traffic control strategies, on vehicle emissions. Unfortunately, in many applications, the additional effort required to code the network, calibrate the model, and execute the model for each alternative traffic control strategy, is not justified.

The proposed regression models explain a large proportion of the observed variance within the emission data generated by the Integration model. A comparison of the proposed models with those presented in the CCG revealed significant differences in emission estimates, especially at high degrees of saturation. The research results presented in this paper cannot conclusively determine that the proposed models are superior to those proposed by the CCG, however, the evidence seems to indicate that the estimates provided by the CCG models overestimate emissions by as much as a factor of 8.

It is recommended that the emission models proposed in this paper be used to examine the trade-offs between vehicle delay and emissions for signal timing designs. Furthermore, it is recommended that these models be expanded to explicitly include progression as an independent variable.

7. ACKNOWLEDEMENTS

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