ESTIMATING FUEL CONSUMPTION AND VEHICLE TAIL-PIPE EMISSIONS AT SIGNALISED INTERSECTIONS

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ABSTRACT: Concern over the negative impact that gasoline powered automobiles have on air quality has prompted renewed interest in methods for quantifying vehicle tailpipe emissions. This paper describes the development of several non-linear regression models that can be used to estimate the additional mass of carbon monoxide, hydrocarbon, and nitrogen oxide that would be expected to be produced by vehicles traversing a roadway, if a traffic signal with known timing parameters was to be installed. One class of regression models uses traffic demands, roadway characteristics, and traffic signal timing parameters as explanatory variables. A second class of models uses number of stops and stopped delay as explanatory variables. The relative merits of these classes of models are discussed. A comparison of the proposed models to similar models contained within the Canadian Capacity Guide indicates marked differences in the relative and absolute impact that traffic signals have on the quantity of pollutants produced.

1. INTRODUCTION

Increasingly, traffic and transportation engineers are becoming sensitive to the environmental impacts that gasoline powered automobiles have on air quality. Unfortunately, a limited number of methods is available for quantifying the relative impact of different traffic management and control strategies. The goal of this research was to derive analytical expressions for estimating vehicle tailpipe emissions and fuel consumption that could be used in practice to quantify the environmental impact of candidate traffic signal control strategies.

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 are 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 to 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 the 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 requires 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 carbon monoxide (CO), hydro carbon (HC), and nitrogen oxide (NO_x) emitted and fuel consumed as a 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 traffic 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 speed and acceleration behaviour of vehicles 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 emission 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 traffic simulation 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 allocated 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.

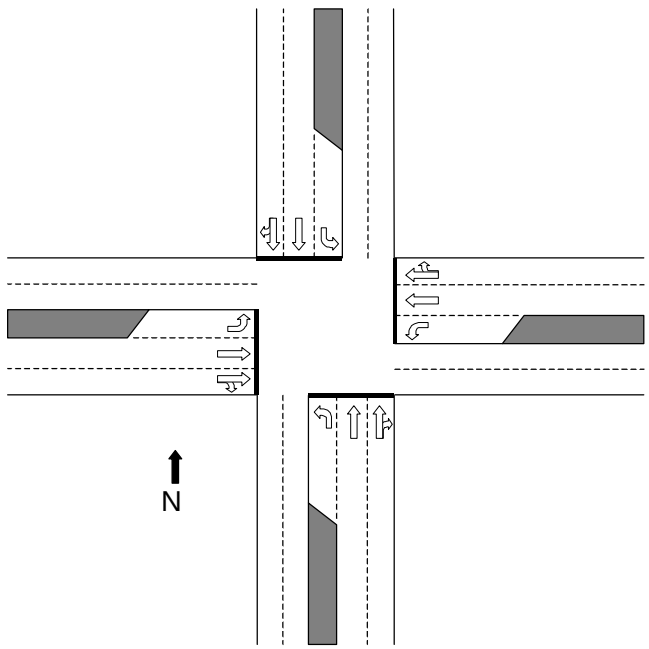

Figure 1: Intersection used for model evaluation

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 a cycle length of 100 seconds. Each phase consists of a green interval of 46 seconds and an amber and all-red 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 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 kph/s < deceleration ≤ 0.0 kph/s) and underestimates more severe decelerations (i.e. –9.6 kph/s < deceleration ≤ –1.6 kph/s). The accuracy of model predictions in reflecting the observed field data can be quantified using Equation 1.

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

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 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.

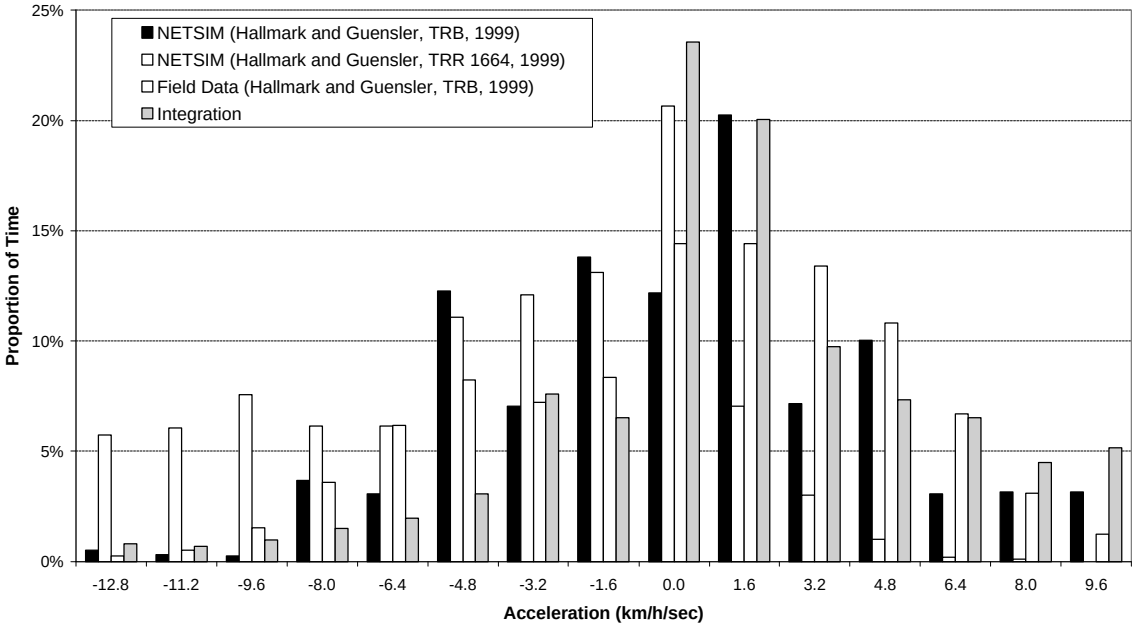

Figure 2: Comparison of proportion of time spent in each acceleration range

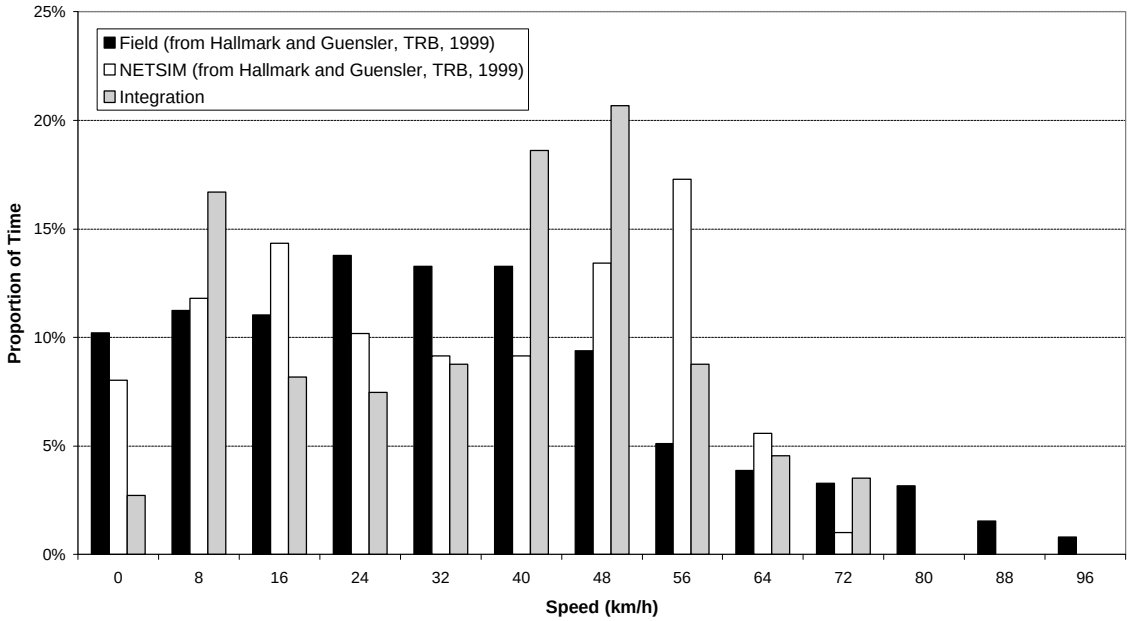

Figure 3: Comparison of proportion of time spent in each speed range

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

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

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^i = 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/s^2 to 3.6 m/s^2 at increments of 0.3 m/s^2). 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 and fuel consumption 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. Average fuel consumption as predicted by INTEGRATION was also 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.

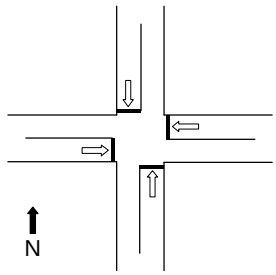

Figure 4: Intersection used for model evaluation

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 and fuel consumption data were compiled by subtracting the average vehicle emission (or fuel consumption) associated with a non-signal scenario from the corresponding average vehicle emission (or fuel consumption) associated with the traffic signal. This quantity represented the additional average emission (or fuel) quantity that would be produced (or consumed) by each vehicle traversing a single approach as a result of the installation of a traffic signal.

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}

4.2 Model Calibration

Emission models and the fuel consumption model were developed by calibrating regression models to the generated emission and fuel data. A 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.

$$E = e^{a+b_1 Z_1^{n_1} + b_2 Z_2^{n_2} + \ldots + b_m Z_m^{n_m}} \tag{3}$$

where:

E = estimate of additional emission (kg) produced or fuel (litre) consumed
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

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.

Two classes of models were considered. The first class, named *Direct Estimation Models*, estimated emissions and fuel consumption directly on the basis of signal timing parameters, traffic demands, and link characteristics. The second class, named *Indirect Estimation Models*, estimated emissions and fuel consumption on the basis of the number of stops, stopped delay, and link characteristics. In order to apply these indirect models in practice, it is necessary to first estimate the number of stops and the stopped delay using some other technique.

The development of the individual models within each of these two classes is described in the following sections.

4.3 Direct Estimation Models

For the direct estimation models, emissions were estimated directly on the basis of signal timing parameters, and thus the independent variables that were considered were degree of saturation (X), speed at capacity (S_c), free speed (S_f), cycle length (c) and the effective green to cycle length ratio (g/c).

On the basis of the step-wise regression results regression models were selected for each emission type. The regression coefficients and adjusted R^2 are provided in Table 3 for each selected model.

An examination of the residuals indicated 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.

Table 3: Regression Results: Direct Estimation Model

Dependent Variable (units)	Adjusted R^2	Independent Variable					
		Constant	S_f (km/h) ($\times 10^{-2}$)	X	S_c (km/h) ($\times 10^{-2}$)	c (sec) ($\times 10^{-3}$)	g/c ($\times 10^{-1}$)
CO (kg)	0.953	-5.687	5.29	1.506	2.82	-7.50	-2.06
HC (kg)	0.922	-8.703	6.37	1.877	2.66	-5.98	-1.70
NO_x (kg)	0.756	-6.307	263.0	0.0194	-0.436	375	0.0689
Fuel (litre)	0.787	-0.610	-5.81	3.919	1.714	1.146	2.47

4.4 Indirect Estimation Models

An indirect method of estimating emissions can be achieved by estimating emissions on the basis of the vehicle stops and delay that are caused by the signal. This indirect method of estimation may be desirable since well established methods exist for accurately estimating stops and delay (e.g. the methods described in the Canadian Capacity Guide) on the basis of traffic and signal characteristics. If the underlying causal factors that result in the production of vehicle tail-pipe emissions and fuel consumption are strongly related to vehicle stops and delay, then it should be possible to calibrate regression models with strong explanatory power relating emissions and fuel consumption to stops and delay.

A model calibration strategy, similar to that used in the development of the direct estimation models, was adopted for the development of indirect models. Two separate cases were considered. In each case, regression models were developed in which the independent variables were speed at capacity (S_c), free speed (S_f), number of stops (N_s) and stopped delay (D_s). In the first case, the actual number of stops and stopped

delay were obtained from INTEGRATION. It is expected that the explanatory power of these relationships represent an upper bound as in practice, the number of stops and stopped delay would be estimated using analytical techniques rather than the simulation. The results of these models are provided in Table 4a.

In the second case, estimates of the number of stops and stopped delay were obtained from application of the analytical expressions in the Canadian Capacity Guide. The explanatory power of these expressions are representative of that which would be expected to be obtained in practice. The results of these models are provided in Table 4b.

A comparison of the results provided in Tables 4a and 4b indicates that for all four environmental performance measures (i.e. fuel, NO_x, CO, HC), the use of N_s and D_s as estimated from the CCG, results in a reduction in the adjusted R^2 ranging from 2.7% to 10.3%. Furthermore, when the results in Table 4b are compared to those provided in Table 3 for the direct estimation models, it can be concluded that the direct estimation models provide adjusted R^2 values that range from 2% to 20% greater than those for the indirect estimation models. These results imply that the use of the direct estimation regression models is preferred over the indirect estimation models.

Table 4a: Regression Results: Indirect Estimation Models
(N_s and D_s from INTEGRATION)

Measure (units)	Adjusted R^2	Independent Variable				
		Constant	S_f (km/h) ($\times 10^{-2}$)	S_c (km/h) ($\times 10^{-2}$)	N_s ($\times 10^{-4}$)	D_s (sec) ($\times 10^{-6}$)
CO (g)	0.932	0.832	6.700	1.786	4.305	6.220
HC (g)	0.932	-2.014	8.246	1.293	5.666	8.611
NO_x (g)	0.695	1.191	3.002	0.2277	7.540	8.170
Fuel (litre)	0.829	0.641	3.061	-0.939	10.91	16.88

Table 4b: Regression Results: Indirect Estimation Models
(N_s and D_s estimated using CCG procedures)

Measure (units)	Adjusted R^2	Independent Variable				
		Constant	S_f (km/h) ($\times 10^{-2}$)	S_c (km/h) ($\times 10^{-2}$)	N_s ($\times 10^{-4}$)	D_s (sec) ($\times 10^{-6}$)
CO (g)	0.907	1.290	5.288	2.817	1.594	8.877
HC (g)	0.902	-1.398	6.365	2.662	1.705	12.60
NO_x (g)	0.634	1.760	0.6804	1.976	6.274	11.87
Fuel (litre)	0.744	1.686	-0.594	1.756	5.222	24.48

4.5 Comparison of Estimation Models

Figure 6 illustrates the characteristics of the Direct (Table 3) and Indirect (Table 4b) CO Estimation Models. Both modes were applied to a single lane intersection approach controlled by a two-phase signal. Each model was used to estimate the additional amount of CO that would be emitted as a result of the presence of the signal over a range of traffic demands. The approach was also simulated using INTEGRATION. Five repetitions, each with a different random number seed, were carried out for each degree of saturation both with and without the traffic signal. The additional CO emission produced by the presence of the signal was determined by subtracting the CO emission produced when no signal was present from the CO produced when the signal was present. The individual scenario results and the mean of the 5 repetitions are also illustrated in Figure 6.

The results in Figure 6 are consistent with the adjusted R^2 values provided in Tables 3 and 4b, which indicate that the Direct Estimation Models explain a larger portion of the variance in the observed data.

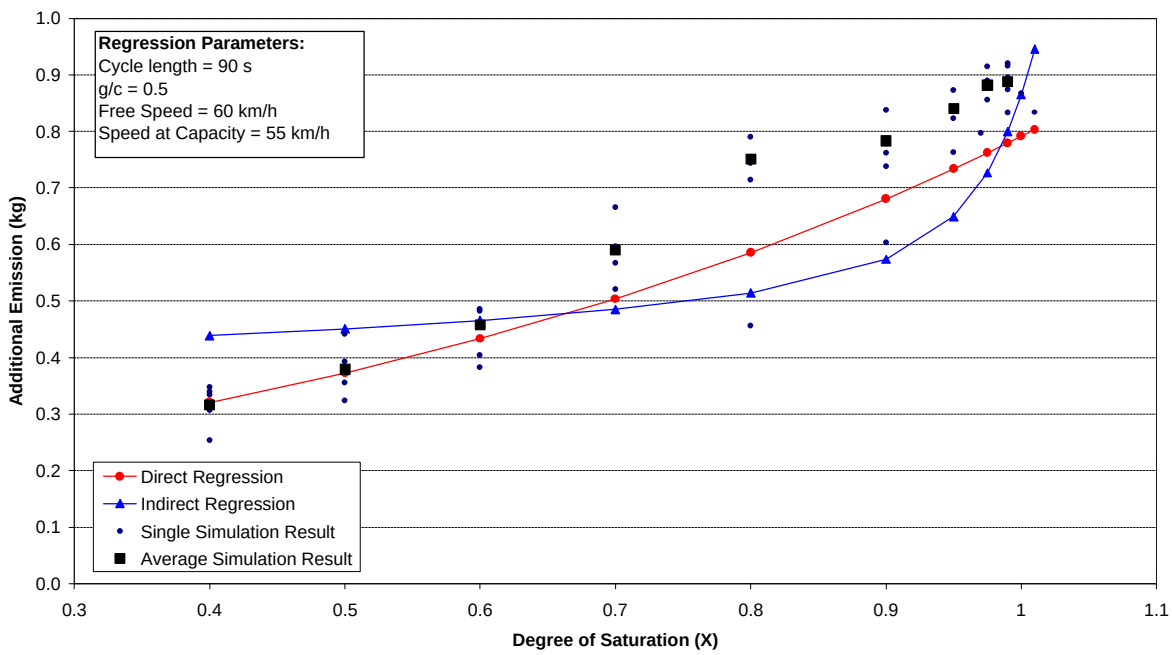

Figure 6: Estimates of CO as a Function of Degree of Saturation

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 NOx, 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 number 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 60 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 7 for emissions and Figure 8 for fuel consumption. From Figure 7, it is evident that the CCG emission 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 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.

Figure 7 also indicates that the Direct and Indirect Estimation Models developed in this research produce similar emission trends. This seems to imply that the observed differences between the emissions estimated from the CCG and from the proposed models result from a difference in the emission rate (e.g. mass of emission per stop and per second of stopped delay). A direct comparison of the emission rates is not possible

because the regression models include the independent variables S_f and S_c along with D_s and N_s.

The validity of the CCG models can not be independently determined because 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.

The comparison of the fuel consumption models in Figure 8 indicates that the proposed models estimate greater fuel consumption than does the CCG model, especially when the degree of saturation is greater than 0.95. The level of confidence that can be placed in the proposed fuel consumption models is much lower than that which can be placed in the proposed emission models. This lower level of confidence is largely a result of the uncertainty associated with the validity of the fuel consumption sub-model incorporated within the INTEGRATION model. This sub-model does not appear to have been as rigorously validated as the emission sub-models, and therefore, the proposed fuel consumption model provided in this paper should be considered preliminary and used with caution.

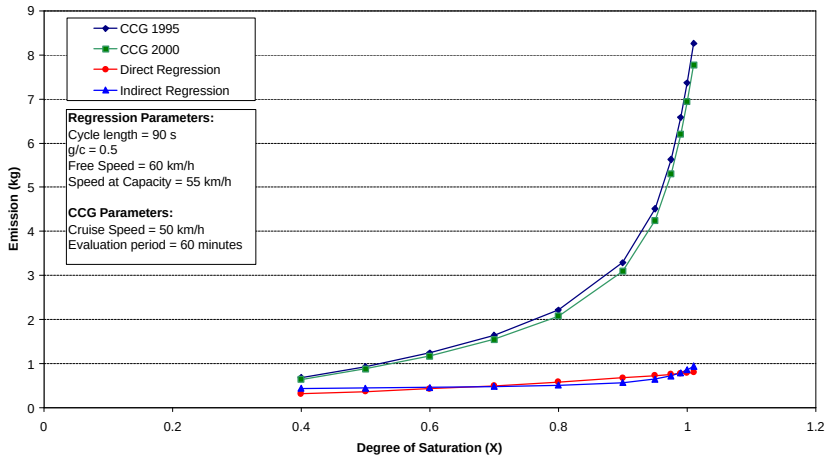

Figure 7a: Carbon Monoxide (CO)

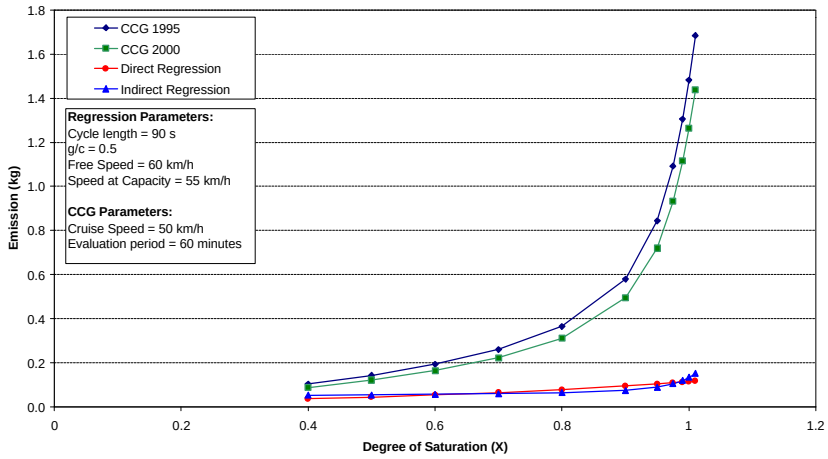

Figure 7b: Hydrocarbons (HC)

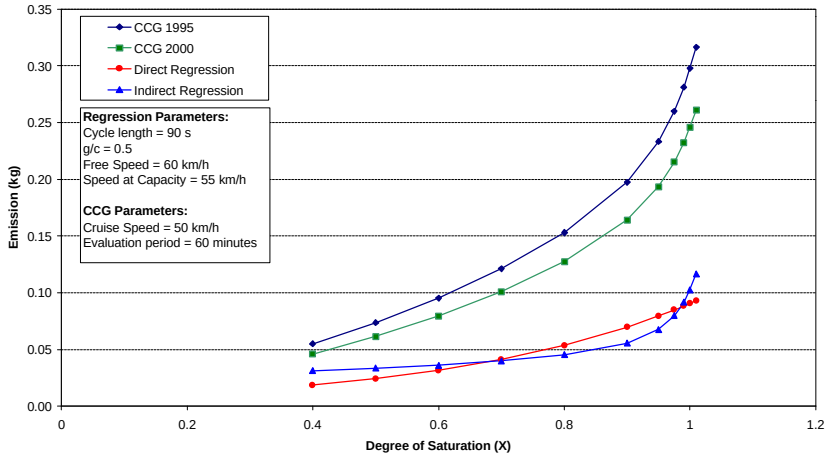

Figure 7c: Nitrogen Oxides (NO_x)

Figure 7: Comparison of proposed emission models with the models proposed by the Canadian Capacity Guide

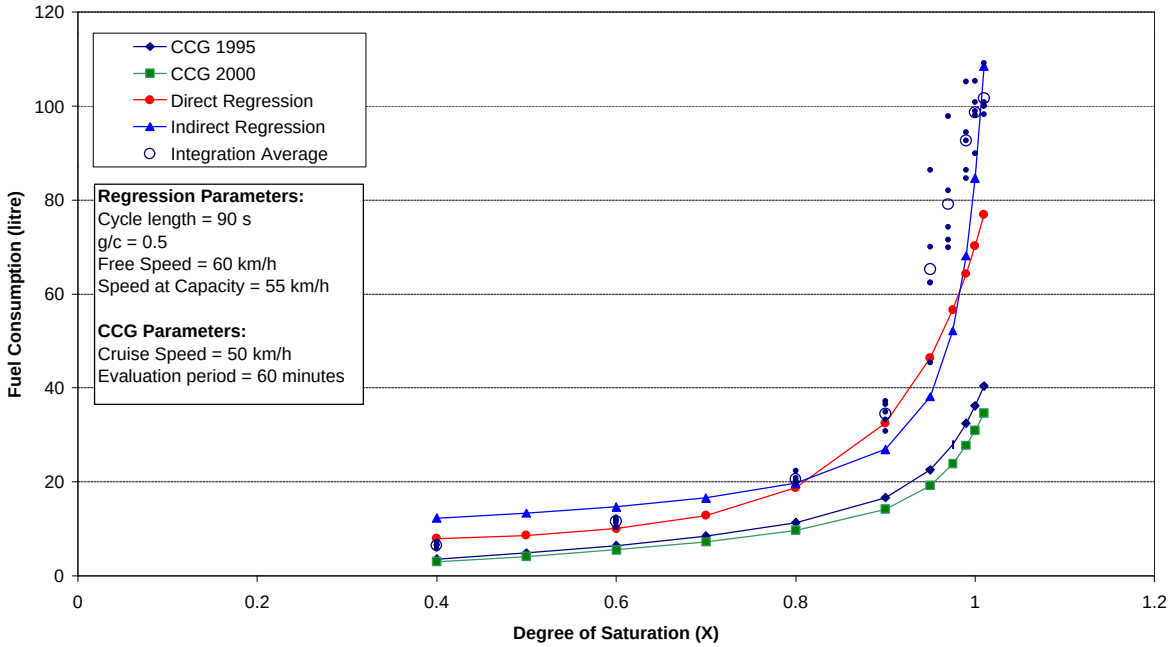

Figure 8: Comparison of proposed fuel consumption model with the CCG fuel consumption model

6. CONCLUSIONS AND RECOMMENDATIONS

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 Canadian Capacity Guide (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 (in terms of reliability) 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.

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