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# **TOWARDS A REAL-TIME MICROSCOPIC EMISSIONS MODEL**

**Greg Marsden, Margaret Bell and Shirley Reynolds**

## **ABSTRACT**

This article presents a new approach to microscopic road traffic exhaust emission modelling. The model described uses data from the SCOOT demand-responsive traffic control system implemented in over 170 cities across the world. Estimates of vehicle speed and classification are made using data from inductive detector loops located on every SCOOT link. This data feeds into a microscopic traffic model to enable enhanced modelling of the driving modes of vehicles (acceleration, deceleration, idling and cruising). Estimates of carbon monoxide emissions are made by applying emission factors from an extensive literature review. A critical appraisal of the development and validation of the model is given before the model is applied to a study of the impact of high emitting vehicles. The article concludes with a discussion of the requirements for the future development and benefits of the application of such a model.

## **INTRODUCTION**

Air pollution is estimated to cost the European Union approximately 37 BECU (0.6% of Gross Domestic Product) every year (DGVII, 1995). As much as 90% of these costs are estimated to be attributable to road transport. In recent years serious pollution episodes have become more commonplace in major cities around the world. Traffic management policies and vehicular restrictions have been introduced to minimise the severity of such episodes (Henderson and Bull, 1996). Within the UK, the Environment Act of 1995 (HMSO, 1995) has placed a mandatory requirement on local authorities to establish Air Quality Management Areas (AQMA) where air quality standards, provided by the National Air Quality Strategy (NAQS) are exceeded or are likely to be exceeded (DoE, 1997).

Within the framework described above, it has been recognised that there is a need to establish air quality monitoring and management systems. One element of such systems is a long range forecasting model that will predict the onset of periods of poor air quality that are potentially hazardous to health. In the UK, a national forecasting service has been established (Stedman et al., 1998) using data from the National Atmospheric Emissions Inventory (Goodwin et al., 1999). In addition, more detailed local models of air quality are being developed, such as the Airviro model in Leicester (Hodges and Reynolds, 1999). Traffic emissions estimation can be performed on a number of different levels, from individual vehicle emission estimation through to city wide emission estimation (Lesort et al., 1996). The level of detail selected for the emissions estimation model should correspond to the corresponding transportation system effect that is being modelled (Sturm et al., 1996).

The model presented in this paper considers the potential use of real-time data, available as a by-product of a traffic signal control system, to provide realistic inputs

to a vehicle emissions model capable of operating in real-time over a city centre network. Such a model will enable on-line estimation of the exhaust emission impacts of incidents on the road network and the effectiveness of dynamic emission reduction strategies to be assessed by the network operator.

The paper begins with a discussion of the main factors to be considered in exhaust emission estimation. Next, the results and implications of a previous five-year investigation into estimating CO emissions from traffic data are discussed. The rationale for the approach taken is then presented, drawing the main issues from the previous two sections together. Then, the application of real-time inductive detector loop data as an input to the vehicle simulation model used is presented. Next, a description of the vehicle simulation and exhaust emissions model is provided. Results of a comparison of queue formation at a signalised intersection using the existing model and the enhanced model are presented. Vehicle emission factors are presented and discussed before the model is tested against road-side concentration measurements over a one week period in Leicester. A small-scale application of the model to examine the importance of high emitting vehicles is then reported. The conclusions discuss the methodological problems in the validation of emissions models through the use of pollutant concentration sensors and the wider implications of this work

## **VEHICLE EXHAUST EMISSION ESTIMATION**

The formation of vehicle exhaust emissions depends on a number of factors. Of particular importance, for a well maintained engine, is the fuel to air ratio. Modern petrol engine vehicles have electronically controlled fuel injection systems that optimise fuel flow rates to ensure stoichiometric combustion conditions (Heywood, 1988) where there is just enough oxygen available to completely oxidise the fuel. Under such conditions, Carbon Dioxide (CO<sub>2</sub>), water and Nitrogen are the main products of combustion.

Diesel engine emissions take a different profile to those from petrol engines due to the process of compression ignition that is used, rather than the spark ignition used in petrol engines. Diesel engines operate with a lower fuel to air ratio than petrol engines using lean burning fuel and air mixtures (Heywood, 1988). Principal pollutants from diesel engines are Nitrogen Oxide (NO), Particulates and Sulphur Dioxide (SO<sub>2</sub>). This paper presents a model to estimate carbon monoxide (CO) emissions, which are negligible from diesel engines, and so the process of diesel combustion is not considered further.

The petrol engine management system is also able to command extra fuel (enrichment) to provide peak demand power during periods of high engine load, to prevent engine knock during cold start and to operate accessories such as air conditioning during idle (LeBlanc et al., 1994). During enriched operation CO is emitted as insufficient oxygen is available to fully oxidise the fuel to CO<sub>2</sub>. In addition, greater quantities of hydrocarbon are emitted unburned every engine cycle as the cylinders are fuel rich. The impact of enrichment on NO<sub>2</sub> emissions is not as important as this is largely dependent on the engine temperature. Operating under

enriched conditions lowers the temperature of the engine slightly (through the presence of unburned hydrocarbons) to avoid damaging the catalyst and thus reduces NO<sub>2</sub> emissions. Exhaust emissions are significantly lower than engine out emissions due to the introduction of catalytic converters. Vlieger (1997), estimated that in real traffic conditions emissions for cars with three-way catalysts were 70% lower than for non catalyst cars. Cold start emissions, before the catalyst has warmed up, are therefore particularly elevated as there are enriched, non-catalyst exhaust out emissions.

Commanded enrichment occurs during a number of circumstances. Periods of hard acceleration from idle are particularly important in urban driving. Several studies (Kelly and Groblicki (1993), Vlieger (1997), Barth et al. (1996) and Lesort et al. (1996)) have highlighted the importance of enrichment emissions to the overall emission profile for a journey. In addition, these studies suggest that current fixed bed driving cycle testing in the US and Europe do not adequately represent typical driving conditions measured on the road today. Kelly and Groblicki (1993) measured exhaust emissions during a typical journey and found that enrichment events can increase CO emissions by a factor of 2500 while hydrocarbon (HC) emissions increased by a factor of 40 and NO emissions remained unchanged. Vlieger (1997) found overall emissions from aggressive driving were up to four times higher than those from normal driving. Ross et al. (1998) showed that a brief high power commanded enrichment event can produce more CO than 500 seconds of moderate driving.

The state of maintenance of an engine has also been found to be an important variable within the fleet relating to emissions. Bishop and Stedman (1996) and Muncaster et al. (1994) have used roadside remote sensing techniques and have estimated that 10% of the vehicle fleet could be responsible for 50% of vehicle emissions (for CO). An and Ross (1996) also estimated that 40% to 50% of vehicle emissions are due to deterioration of the vehicle emission control system.

In summary, harsh acceleration, poorly maintained vehicles and cold start can all have significant effects on vehicle exhaust emissions of CO and HC. The impact of these effects on NO<sub>x</sub> emissions is much less pronounced, with NO<sub>x</sub> emissions tending to increase with an increase in average speed. Optimisation of a traffic signal control network seeks to minimise overall vehicle delay which would therefore produce a reduction in CO and HC emissions through less stop-start behaviour and an increase in NO<sub>x</sub> through improved average speeds. Incident management strategies also seek to redistribute flows to improve network performance and, as a result, reduce CO and HC emissions produced through the congestion. The model proposed in this paper concentrates on CO emissions, although the future extension of the model to include NO<sub>x</sub> and HC is also seen as important to understand the total emissions effects of any traffic management strategy. However, CO and HC are most affected by urban management strategies and were deemed most appropriate. CO was chosen above HC as the exhaust emissions for the two pollutants follow a similar profile for petrol vehicles, but as this section has demonstrated, CO offers a more pronounced profile during enriched acceleration and with dirty vehicles than HC.

## PREVIOUS RESEARCH INTO PREDICTING CO LEVELS FROM SCOOT

Reynolds (1996) investigated the development of a semi-empirical model to predict carbon monoxide levels using data from the Split, Cycle and Offset Optimisation Technique (SCOOT) demand-responsive traffic signal control system (Hunt et al., 1981). The SCOOT system measures vehicle flow arriving on a link and uses a well established traffic model to estimate vehicle flows within the network and to optimise the traffic signals to minimise delays and vehicle stops. The research by Reynolds used data on collected directly from the SCOOT traffic model (FLOW, DELAY (average delay per vehicle), STOPS (vehicle stops), CONGESTION (when traffic is stopped over the detector) and CYCLE (cycle time)) and compared this directly with carbon monoxide data from roadside pollution monitors. The monitors were located five metres upstream of the stopline and were 1.5 metres above kerb level.

Initially, the distribution of the roadside carbon monoxide data was investigated and it was found to conform to a lognormal distribution. This finding meant that statistical tests that rely on assumptions of normality had to be used with care.

Several regression techniques were explored in an attempt to produce an empirical relationship between carbon monoxide levels and SCOOT traffic parameters. These were linear and multiple regression and ARIMA (AutoRegressive Integrated Moving Average). The most promising technique was the ARIMA which could produce an adequate model to fit historic data, but could not predict future levels at all.

At this point it was decided not to continue testing empirical relationships, but instead to take an alternative approach and develop a semi-empirical model. A linear model was proposed, which used SCOOT parameters to provide estimates of the vehicle operating mode, ie whether the vehicles passing a point were idling, accelerating, decelerating or cruising.

The definitions of the SCOOT parameters STOPS, DELAY, FLOW, CONGESTION and CYCLE were used to derive estimates for the number of vehicles passing the monitor in each operating mode. The model also took into account the operating mode of vehicles travelling on the opposite side of the road and the contribution of lingering pollution from previous time periods.

The proposed model was as follows:

$$y_t = \beta_0 + \beta_1 M_{i,t} + \beta_2 M_{c,t} + \beta_3 M_{a,t} + \beta_4 O_{i,t} + \beta_5 O_{c,t} + \beta_6 y_{t-1} + \beta_7 y_{t-2} + \epsilon_t$$

where

$y_t$  = predicted pollution level at time  $t$  (ppm)

$y_{t-1}$  = pollution level predicted in the previous time interval,  $t - 1$  (ppm)

$y_{t-2}$  = pollution level predicted at time  $t - 2$  (ppm)

$M_{i,t}$  = number of vehicles idling on the monitoring side of the road

$M_{c,t}$  = number of vehicles cruising on the monitoring side of the road

$M_{a,t}$  = number of vehicles accelerating on the monitoring side of the road

$O_{i,t}$  = number of vehicles idling on the opposite side of the road

$O_{c,t}$  = number of vehicles cruising on the opposite side of the road

$\beta_n$  = constants

$\epsilon_t$  = error term.

Data collected over the course of one month in Nottingham was used to derive coefficients for the model using least squares regression analysis. However, further investigation showed that some variables were collinear and the residuals were significantly autocorrelated.

Several possibilities were considered for the unexplained variance in the model. These included (urban) background levels of carbon monoxide and meteorological variables. Only the temperature was found to improve the model accuracy. The other factor that could have an effect is the emissions of the individual vehicles, and particularly the contribution of dirty vehicles. However, it was not possible to investigate this further as the SCOOT data, by its nature, does not give any information about vehicle type.

The work carried out by Reynolds left many questions unanswered. No meaningful relationships were established between the traffic model summary parameters (e.g. average delay per vehicle per cycle) and the CO levels. Had such a relationship been established, the data collection and regression procedure would have been required for every link in the network. The research described in this paper builds on the experience gained by Reynolds and addresses these issues through a different approach.

## **MODEL PARAMETERS**

The model proposed within this paper incorporates the key findings from the studies into real-world vehicle emissions and the work performed by Reynolds. The proposed model for estimating CO emissions therefore includes factors to take account of:

- Vehicle operating mode (acceleration, cruise, idle, deceleration);
- Enriched acceleration;
- State of repair of the vehicle emission control system; and
- Type of engine (petrol or diesel)

The effects of cold start have not been considered as the model validation site was located on an in-bound link in a city centre where it was assumed that there would be very few vehicles operating with a cold catalyst. Typical light off times for catalysts are in the order of two minutes (Ross et al., 1998). The absence of a significant number of cold start vehicles has removed a potentially significant variable in this preliminary modelling assessment and this will need to be incorporated as the model is extended. Work is currently underway in the UK to improve the emissions factors for cold start vehicles (Cloke et al., 1998) which will support this process.

A number of traffic models have been adapted to include estimates of exhaust emissions. Comprehensive reviews of existing models can be found in Algers et al., (1997), Shearn et al., (1997) and Joumard et al. (1999). Whilst traffic models have been well validated to assess the impacts of signal optimisation or geometric design on traffic flow the internal algorithms have not been validated for predicting vehicle activity (Hallmark and Guensler, 1999). The accurate representation of acceleration profiles of vehicles has been shown above to be particularly important in accurately determining vehicle emissions. In addition, alternative traffic control and management

strategies may change the pattern of activity in a network and thus the instantaneous speed and acceleration profiles (Hallmark and Guensler, 1999).

The model proposed here overcomes the potential problem of inadequately representing flows within a network by using data from inductive loop detectors (rather than from the traffic model as in Reynolds (1996)), which is available in real-time from the SCOOT demand-responsive traffic signal control system. SCOOT has been installed in over 170 cities around the world (Bretherton and Bowen, 1998) and therefore, this model could see widespread application.

## **TRAFFIC INPUT DATA**

The SCOOT traffic control system uses data on vehicle occupancy produced by inductive detector loops located at the upstream end of every link within a SCOOT network. The inductive detector loops sample for occupancy (whether a vehicle is over the loop or not) every quarter of a second registering a 1 for vehicular presence, otherwise a 0. Inductive detector loops are often used for counting vehicles on inter-urban roads where speeds are high. One study in America by Klein (1993) stated that “*The accuracy of the inductive loop with respect to count was 99.4%*”. This result was consistent with that of Cherrett et al. (1996).

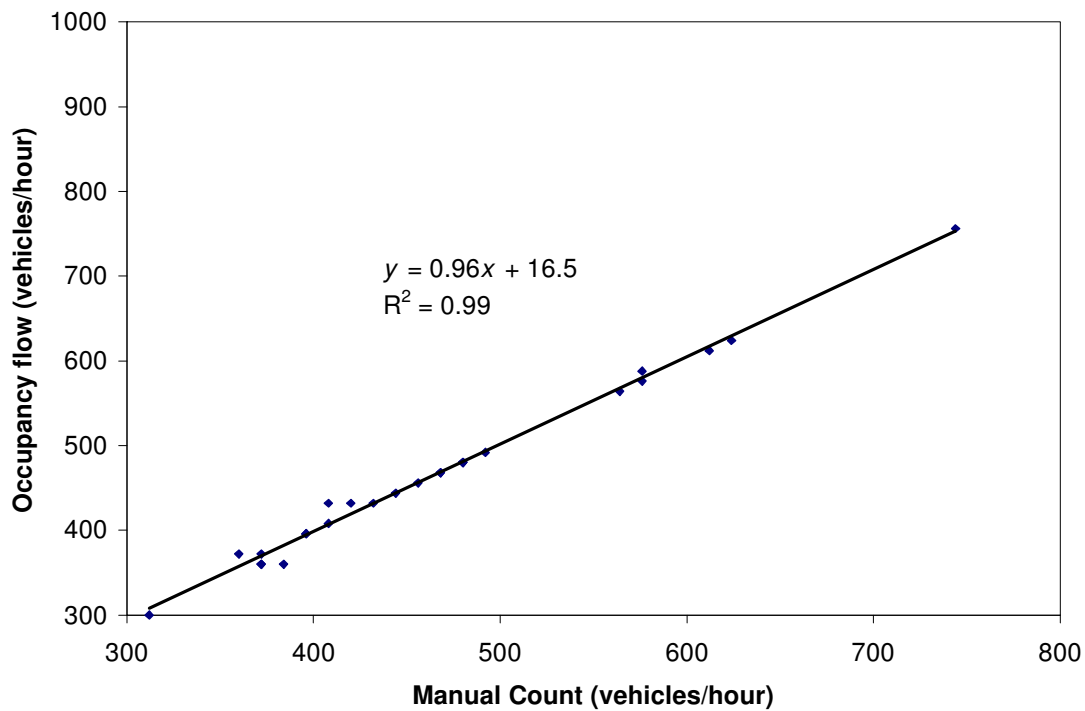
If vehicle arrival time is provided to a traffic simulation model then the estimation of queue formation should be enhanced. This could be improved further by estimating vehicle arrival speed and classification. The potential application of inductive loop data in providing these estimates was investigated.

### ***Vehicle Counts from SCOOT Occupancy***

Traffic travelling across SCOOT loops was monitored using video recordings made using a roadside video camera whilst collecting the raw quarter second occupancy data (Marsden, 1998). Using specially designed software, automatic data capture into computer memory directly from visual surveillance of the videos was made possible. Various detector loop configurations were studied over a range of traffic flow and on-street conditions. The real-time visually observed data were then matched with the SCOOT occupancy data and a comprehensive statistical analysis performed.

Figure 1 shows the measure of flow obtained from the occupancy data plotted as a function of the observed manual count for two surveys on 6th November and 7th December 1995. The survey site is a single lane carriageway in a built up urban area of Leicester. The occupancy data from SCOOT was collected through the Instrumented City Facility (Bell et al., 1996a). Counts were made during every traffic signal cycle (green start to green start) and scaled up to an hourly flow equivalent.



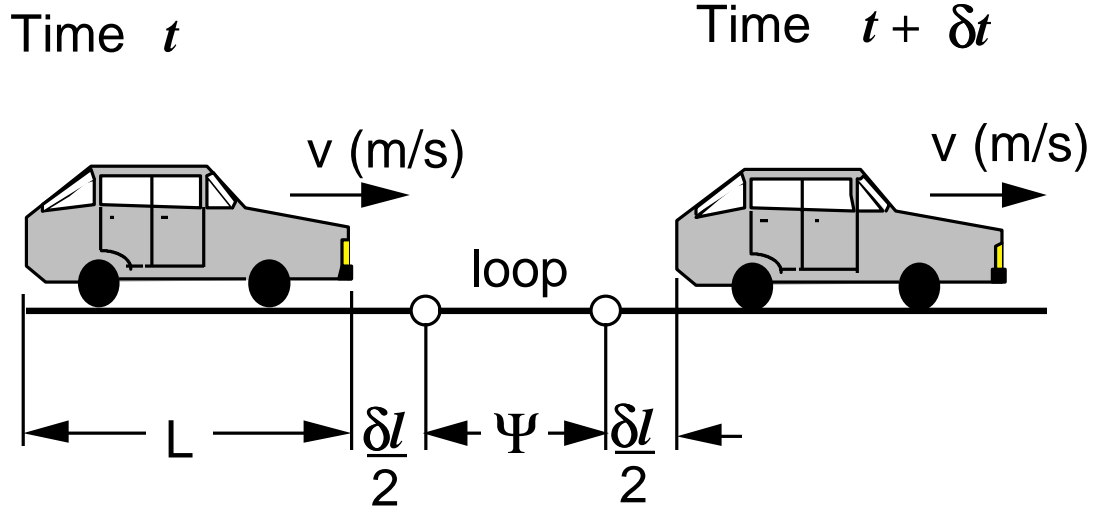


**Figure 1: Inductive detector loop flow against manual count flow**

Inductive detector loops that span one lane of traffic produced good quality estimates of flow over a wide range of flow conditions. These were estimated to represent 70% of loops within a network. Investigations at three other sites found similar high correlation between the occupancy based and the manual count.

### *Vehicle Classification from SCOOT occupancy*

Occupancy is measured using an electromagnetic field generated by the inductive detector loop. Occupancy is a measurement made over a specific area at a specific time and is only registered as positive if enough of the lines of magnetic flux are cut to cause a voltage pulse, above a minimum threshold value. The number of occupancy bits that will be registered for a vehicle travelling over a SCOOT loop can be estimated. Consider a vehicle of length  $L$  (m) travelling over an inductive loop of length  $\Psi$  (m) with a constant speed  $v$  (m/s) as shown in Figure 2.



**Figure 2: Vehicle crossing an inductive detector loop**

The zone of detection for the loop is equal to  $\Psi + \delta l$ , where  $\delta l$  is the total length beyond the physical dimensions of the loop which has a magnetic field of sufficient magnitude to measure vehicular presence. The value of  $\psi$  for all SCOOT loops is 2m.

The time  $\delta t$  (seconds) which the vehicle spends over the zone of influence of the inductive detector loop ( $\Psi + \delta l$ ) is given by:

$$\delta t = \frac{(\Psi + \delta l + L)}{v} \quad (1)$$

As sampling of the inductive loop occurs every quarter of a second, the number of occupancy bits registered by a vehicle ( $\Theta$ ) is therefore given by:

$$\Theta = \frac{4(\Psi + \delta l + L)}{v} \quad (2)$$

Clearly, the number of occupancy bits registered per vehicle is inversely proportional to its speed and directly proportional to the combined length of the vehicle and loop measurement zone. The theory above demonstrates that vehicles of significantly different lengths, travelling at a constant speed, will register different values of  $\Theta$ .

Previous studies have used detector signal strength (Davies, 1986) and comparison of profiles of strength based on much faster sampling rates (Pye, 1984). The quarter second resolution of the 0 or 1 output from SCOOT meant classification decisions were based on different types of vehicle having significantly different lengths. Vehicle classification was based on the three groups defined as follows:

CAR                    all cars, three wheelers, transit vans (inc. small box vans);

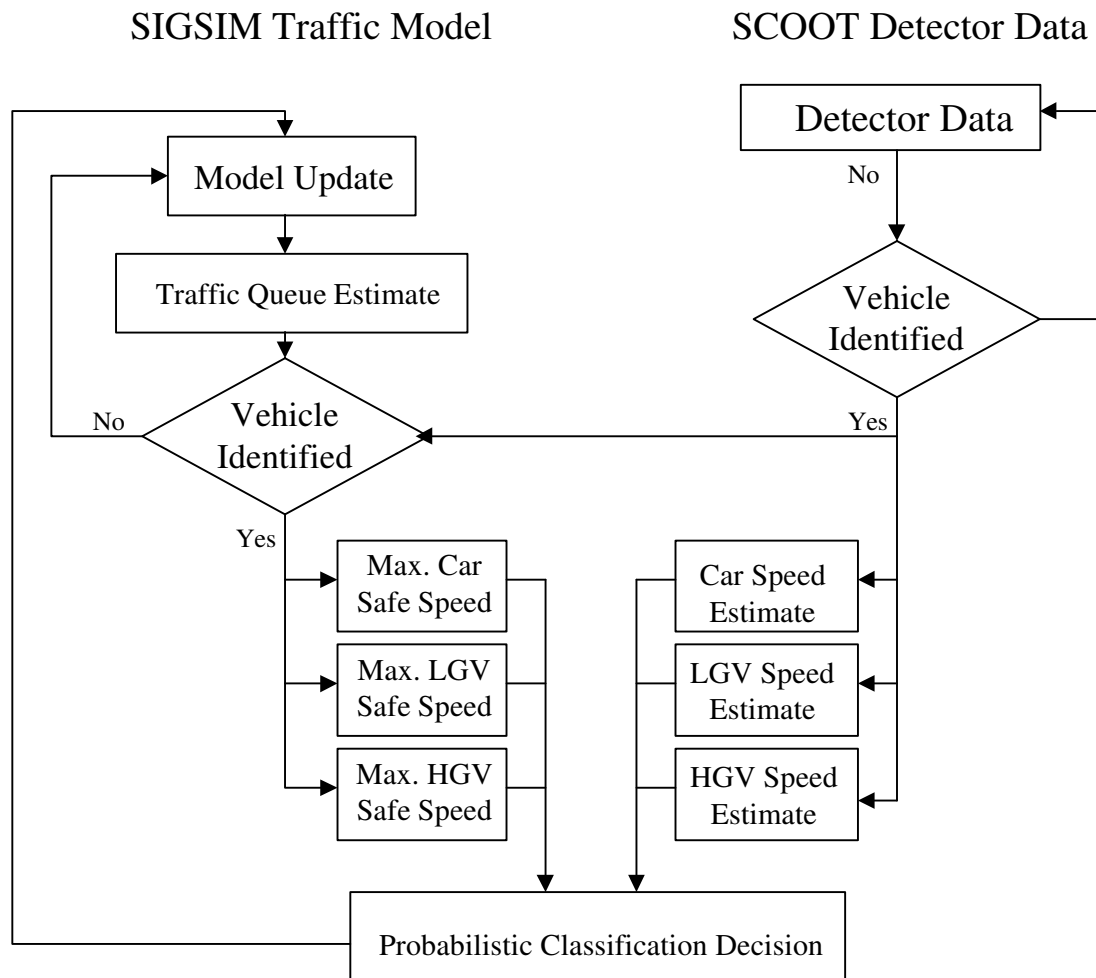
- LGV commercial minibuses, 2 axle goods vehicles, short, multiple axle goods vehicles (e.g. refuse collectors); and
- HGV single and double deck buses, articulated goods vehicles, long multiple axle goods vehicles.

The distribution of the length of the UK fleet according to the three groups was obtained from vehicle manufacturer specifications and measurements of light and heavy goods vehicles made at a Post Office depot, a commercial vehicle rental company and a local chemical factory. The statistics for the resulting distributions are shown in Table 1 along with those presented by (Bell, 1977).

**Table 1: Vehicle Length Information**

<b>Vehicle Classification</b>	<b>Mean Length (m) (1997)</b>	<b><math>\sigma</math> length (1997)</b>	<b>Mean Length (m) Bell (1977)</b>	<b><math>\sigma</math> length Bell (1977)</b>
CAR	4.21	0.39	4.20	0.40
LGV	7.05	1.15	7.68	1.08
HGV	15.71	2.52	13.35	1.36

The detector data was used as input to the SIGSIM microscopic traffic simulation model (Silcock, 1993) where information on queue length was fed back to the vehicle classification and speed prediction model. This enabled enhanced speed estimation and classification decisions to be made when the back of queue was close enough to the SCOOT loop to affect the speed of the vehicle at the loop (Marsden, 1998). A flow diagram of the integration of the detector data and SIGSIM is shown in Figure 3.



**Figure 3: Flow Diagram of Vehicle Classification from Occupancy Data**

99% of the traffic at the validation site was cars of which 98% were estimated correctly. Some incorrect classification of cars as LGVs resulted in a 39% overestimate in the number of LGV. There was also an 11% overestimate of HGV. However, as less than 2% of vehicles at the site were HGV and LGV these errors were not significant enough to affect the emission estimates. The observed mean and modelled mean speeds for vehicles travelling over the loop with  $\Theta$  less than or equal to six was not statistically significantly different at a 95% confidence level except for  $\Theta$  equal to three where there was no statistically significant difference at a 99% confidence level.

Detailed statistical analysis of speed-occupancy relationships at two other sites (Marsden, 1998) revealed that a three type vehicle classification system should be possible to speeds of 8.3 km/hr and above. The errors in LGV classification are predominantly caused by the similar performance of commercial minibuses to some cars and the classification system may benefit from further refinement. However, overall, it was felt that the results demonstrated that the data obtained from SCOOT inductive detector loops can successfully be used to estimate vehicle classification and speed as an enhanced input to the SIGSIM model.

## QUEUEING MODEL IMPROVEMENTS

Following the adaptation of SIGSIM to generate speed, classification and arrival time information (available from the time stamped SCOOT message) from the inductive loop detector data an assessment of the improvements to the traffic modelling was made. The car following model within SIGSIM produces estimates of the vehicle speed and acceleration every two-thirds of a second and is based on the Gipps car following algorithm (Gipps, 1981).

An assessment was made of the changes to the queue length at the start of the green traffic phase that resulted from using traffic characteristics from actual vehicles using the SCOOT occupancy data rather than the generic shifted negative exponential function normally used within the SIGSIM model to generate arrival rates. The assessment was performed on a single lane link. The traffic signal timings were obtained from the SCOOT system and were therefore synchronised with the vehicle occupancy data. The results of this comparison are shown in Figure 4 and Figure 5.

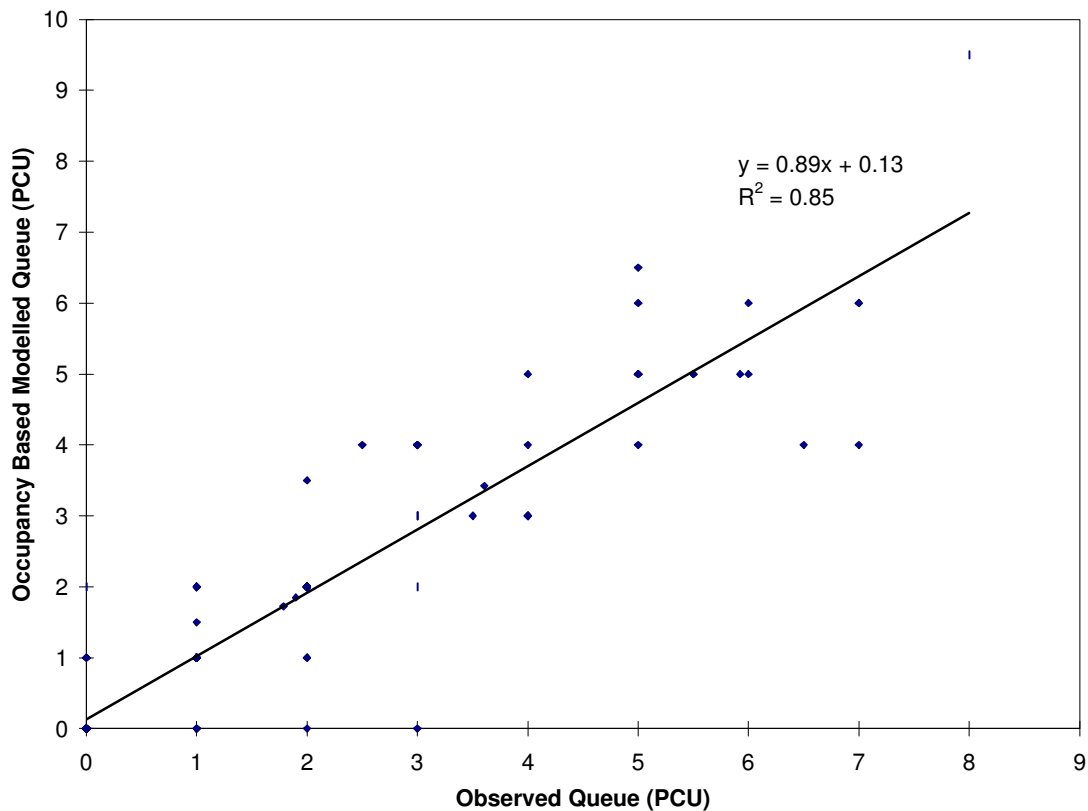
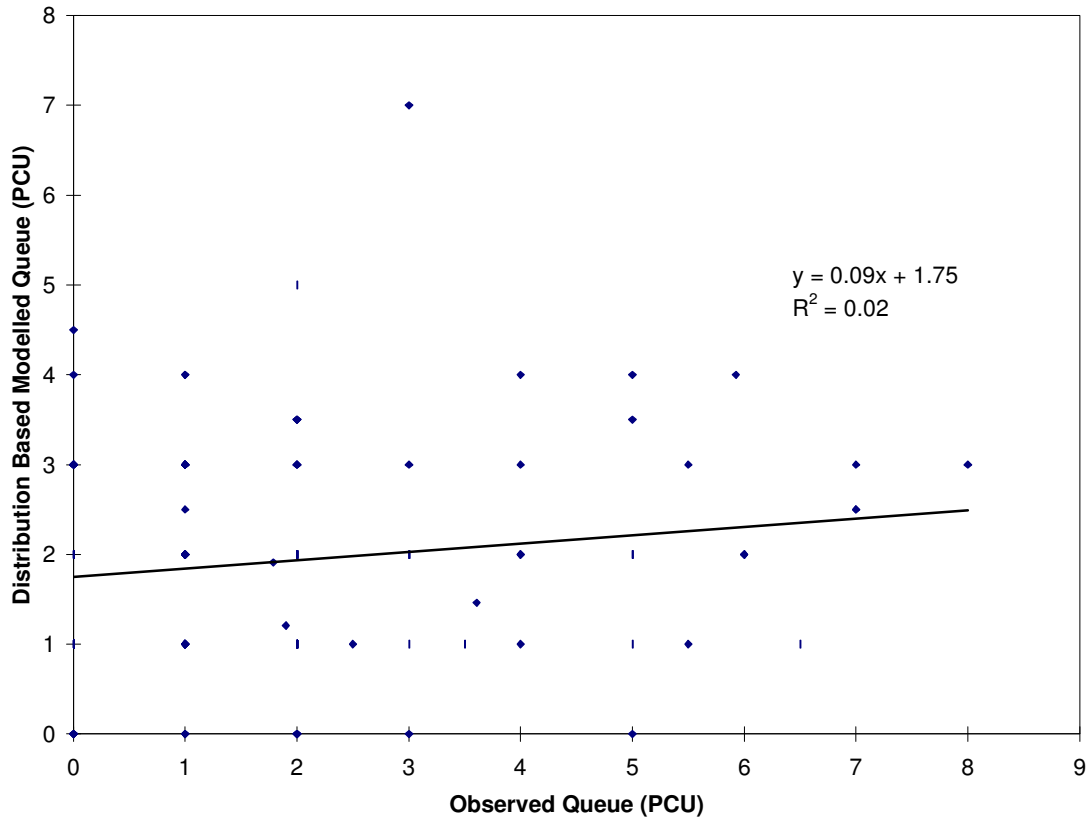


Figure 4: Occupancy derived queue measure against observed queue



**Figure 5: Shifted Negative Exponential derived queue measure against observed queue**

In modelling traffic at an intersection, SCOOT produces an estimate of the queue on each link. However, this measure uses the combined link profile units (thus losing the individual vehicle definition required for this work) but, more importantly, models the queue as a vertical queue at the stop-line. An assessment of SCOOT modelled queue against observed queue showed the SCOOT model to estimate just over half of the modelled queue ( $y = 0.50x + 0.26$ ,  $R^2 = 0.62$ ). Estimates of vertical queue can be converted to a horizontal queue if the arrival flow rate is known (Bell, 1997). However, the presence of a greater degree of variation of modelled SCOOT queue at the lower levels of observed queue (where vertical and horizontal queue are closest) precluded the measure from further study.

The occupancy derived flow and speed measure provides a high quality input which, in combination with the microscopic car following model produces a good estimate of queue length. This lends confidence to the model providing good estimates of the distance-time trajectories of vehicles along the link. It is likely therefore, that the model will provide good estimates of the amount of time vehicles spend accelerating, decelerating, cruising and idling on a link. Statistical testing showed a slight systematic underestimate of the queue length probably due to extra delay from turning traffic and start-up delays that were not accounted for by the model. However, despite this the algorithms were shown to offer significant advantages over using probabilistic arrival patterns.

## EMISSION FACTORS

Within Europe, the COST 319 initiative (Joumard et al., 1999) has gathered together the state-of-art of vehicle emission measurement. The most significant databases that exist (e.g. Jost et al., 1992) relate to flat bed dynamometer testing where specific urban driving cycles were specified. However, despite increasing co-operation and development of databases, no suitable European database was available at the time, that took account of driving mode, enriched driving and vehicle maintenance. Much of the pioneering work in this area has been carried out in the USA.

Stephens et al. (1996) analysed second-by-second emission data from 73 light duty cars and trucks in the USA. The results were obtained using the laboratory FTP test. Pollutant levels were given for the driving cycles split by the driving modes accelerating, decelerating, idling and cruising. The average emission concentrations at the exhaust were estimated and these are shown in Table 2.

**Table 2: Modal average concentrations during warm running (Stephens et al., 1996)**

<b>Pollutant</b>	<b>Acceleration</b> %	<b>Deceleration</b> %	<b>Cruise</b> %	<b>Idle</b> %
CO	0.17	0.12	0.10	0.07

It is now widely acknowledged that the FTP driving cycle does not adequately represent enrichment events commonly found on street (EPA, 1993). The maximum acceleration in the test cycle was 3.3 mph/s (1.48m/s<sup>2</sup>). The US Environmental Protection Agency has since commissioned a review of the procedure.

A study carried out to determine a more suitable driving cycle for Los Angeles and to sample vehicle emissions for the current fleet in California is described by An et al. (1995). 165 vehicles were tested covering a wide range of models with a mileage of between 3 200 and over 200 000 miles. 41 of the vehicles tested did not have a catalytic converter. An et al. (1995) split the vehicles tested into five categories:

1. “*P-cars*’, representing the properly functioning cars whose tailpipe emissions are less than the 1983-1992 FTP standards, corresponding to 7.0g/mile for CO. A *P-car* is most likely to be a well-maintained new car with mileage less than 50 000 miles, typically the manufacturers guarantee mileage;
2. *M-cars*’, representing cars with malfunctioning emission controls, resulted in severe tailpipe emission levels;
3. *D-cars*’, representing cars whose emission control devices are naturally deteriorated. A *D-car* is most likely to be an older car with an odometer reading above 50 000 miles and its emission system not severely damaged;
4. *R-cars*’, imaginary cars to represent the real-world average fleet emissions, composed of a mixture of the *P-*, *M-*, and *D-* cars characteristics;
5. *N-cars*’, representing cars without catalytic converters. All cars in the previous categories are catalyst equipped.”

Rather than approaching the modal emission definition in terms of acceleration, deceleration, cruise and idle, An et al. (1995) define the four main driving modes as:

1. stoichiometric emissions;
2. cold/warm-start emissions;
3. high-power enrichment emissions; and
4. lean-burn emissions

The stoichiometric operating condition represents the behaviour of the vehicle throughout the drive cycle with the exception of start-up events and brief enrichment periods. Table 3 shows the correlation between the four driving states defined above for the traditional engine driving modes.

**Table 3: Correlation between emission modules and driving modes (An et al., 1995)**

	<b>idle</b>	<b>start</b>	<b>cruise</b>	<b>acceleration</b>	<b>deceleration</b>
stoichiometric	++		++	++	+
cold/warm start		+++			
enrichment		+++	+	++	+
lean-burn	++		++		+++

Where:

- +++ represents strong correlation;
- ++ represents moderate correlation; and
- + represents weak correlation.

Estimated emissions factors for each of the five vehicle types listed above were developed for CO, HC and NO<sub>x</sub>. The CO emissions factors for each of the five vehicle types are shown below in Table 4. Stoichiometric and stabilised operation and enrichment and high power operation are analogous.

**Table 4: Vehicle emission factors from An et al. (1995)**

<b>CO Emission Factors (g/mile)</b>	<b>P-Cars</b>	<b>M-Cars</b>	<b>D-Cars</b>	<b>R-Cars</b>	<b>N-Cars</b>
Stabilised	1.12	25.6	4.21	5.33	8.45
Cold Start	2.34	8.5	3.63	3.69	5.97
Hot Start	0.55	4.0	0.94	1.12	2.88
High Power	3.5	20.5	4.73	5.90	20.9
Total	7.5	58.6	13.5	16.0	38.2

For this work, a combination of the emission factors from Stephens et al. (1996) and An et al. (1995) was used to derive emissions for five driving modes (harsh acceleration, acceleration, idle, cruise and deceleration) for four different vehicle types (P-cars, M-Cars, D-cars and N-cars). The values obtained from the Stephens study were assumed to be equivalent to those obtained from R-type cars (the average vehicle). The factors for acceleration, deceleration, cruise and idle for the four vehicle



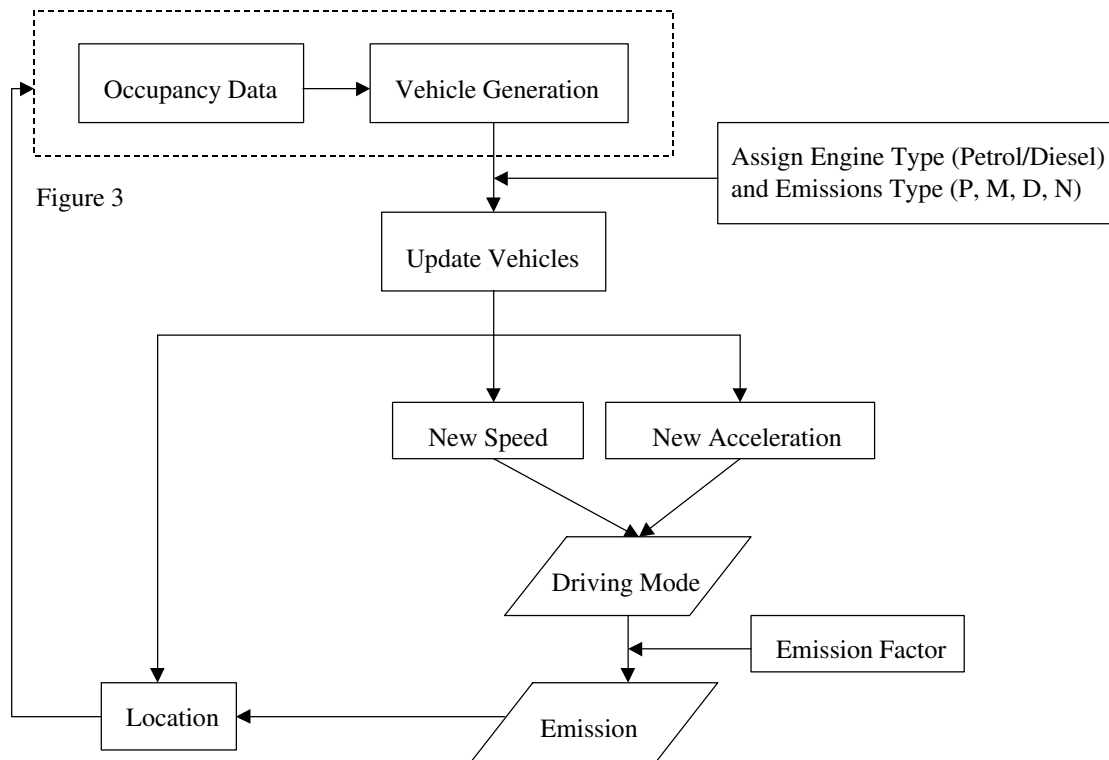
types to be considered were obtained from the Stephens factors by multiplying the ratio of the average vehicle to the vehicle type considered as follows:

$$E_{m(PCar)} = E_{m(Stephens)} \times \frac{P_{carStabilised}}{R_{carStabilised}} \quad (3)$$

A further extension to this was the introduction of a harsh acceleration mode. The value for harsh acceleration was obtained by multiplying the acceleration figure for the vehicle engine type by the ratio of high power emissions to the stabilised emissions from Table 4.

The definitions of the boundaries between driving modes were taken from Stephens et al. (1996) for acceleration, deceleration, cruise and idle. The definition of enriched driving was found to vary between studies. An et al. (1995) estimated that enriched engine performance occurs 2.4% of the time, Kelly and Groblicki (1993) estimated that such conditions exist for 1.2% of a typical urban journey whilst Ross et al. (1998) estimate commanded enrichment for 3.6% of the time. The acceleration distributions within SIGSIM are specified by parameter values provided by the user. Although they may not be truly representative of 1999 traffic behaviour, we adopted Gipps' original values for the model. An examination of the acceleration rates produced by the SIGSIM traffic model for a sample data run was used to estimate the 98th percentile of acceleration levels. Accelerations above this value (2.24m/s<sup>2</sup>) were taken to result in enriched operation. This compares to a threshold value of 2.69m/s<sup>2</sup> estimated by Hallmark and Guensler (1999).

A schematic diagram of the SIGSIM with Pollution Level Estimation (SIGSIMPLE) model is shown in Figure 6.



**Figure 6: SIGSIMPLE Schematic Diagram**

## **METHODOLOGICAL APPROACH FOR THE EMISSIONS MODEL VALIDATION**

The limitations of using USA based emission factors in a UK study are acknowledged. Perhaps it is reasonable to assume that the relative levels of pollutant emission for the different vehicle modes are similar. Although the absolute emission levels may be incorrect, the shape of the distribution of emissions will be the same. Another complication in validating the emissions estimated by the model is that due to chemical reactions and dispersion, pollutant concentrations measured at the roadside are not the same as emissions.

A further complication occurs if any attempt is made to compare the level of emissions predicted for a period of time with that measured simultaneously in the same period of time. This is created by the contribution to emissions of gross emitting vehicles. Whilst 10% of vehicles can be labeled as gross polluters (Bishop and Stedman, 1996), the actual labeling of vehicles is random (and this is unlikely to correspond to actual passing gross emitting vehicles). The same will apply to cold start vehicles when they are incorporated.

The problems of comparison of emissions with pollutant concentrations were side stepped to some extent by aggregating measurement and prediction over five minute periods and comparing the distributions of estimated emissions with measured pollutant concentrations.

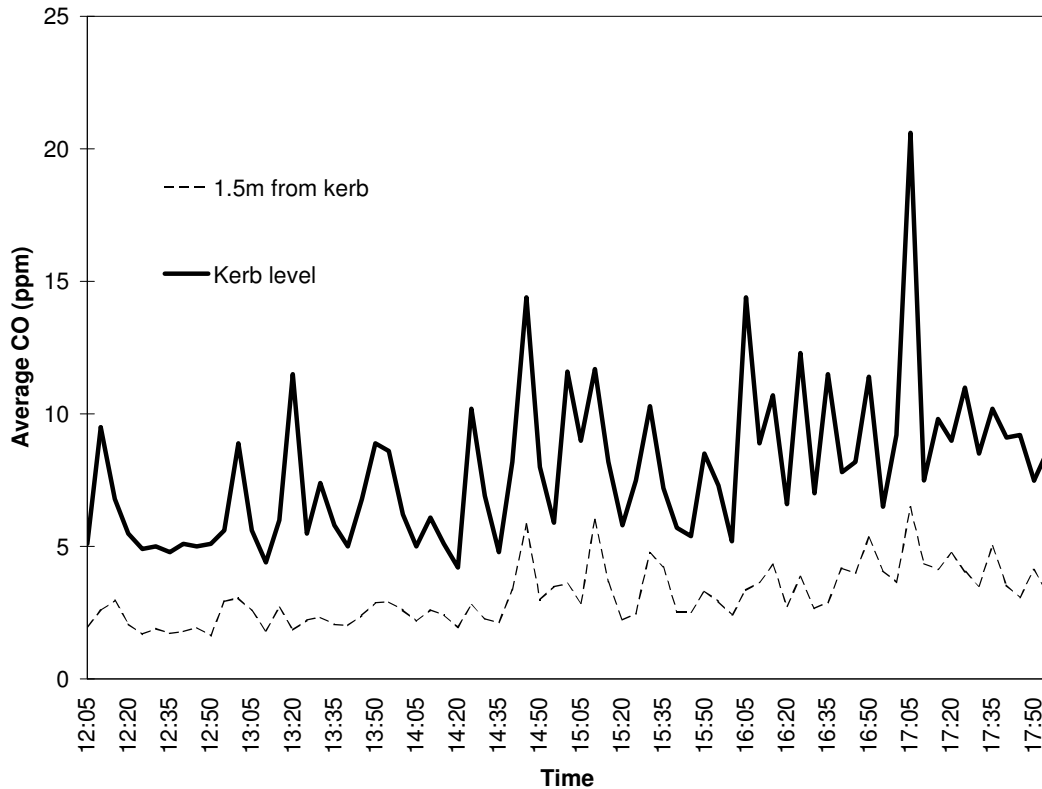
This study was also restricted to the estimation of CO emissions for the reasons described in the section on vehicle exhaust emissions estimation. An assumption was made that all light and heavy goods vehicles were diesel and therefore contributed a negligible amount of CO. A manual traffic count of the proportion of diesel cars found in the validation site was undertaken. Observations of over 3500 vehicles showed 17% of passenger cars to be diesel vehicles.

The vehicle split between car and light and heavy goods vehicles was determined using the SCOOT occupancy data. Assumptions about the state of repair of the engines for cars within the catalyst classification were taken to be those from An et al. (1995). The proportion of non-catalyst cars was estimated from observations of the vehicle fleet age and knowledge of the rate of introduction of catalytic converters. For the research described within this paper, the split between engine types within the car category was therefore estimated to be:

- 36% non-catalyst petrol-engine cars
- 14% P-type cars;
- 8% M-type cars;
- 25% D-type cars; and
- 17% diesel cars.

## **MODEL ASSESSMENT**

Marsden and Bell (1999) showed that pollutant concentration measurements at floor level at the kerbside consistently measured local peaks in pollutant levels. An example of this phenomenon is shown below in Figure 7 where equipment at kerb level (Golden River Marksman M660 monitor) and situated at 1.5m from floor level (SIEMENS Roadside Pollution Monitor (Bell et al., 1996b)) are compared. Automatic monitoring equipment situated at 1.5m from floor level (to measure personal exposure levels) exhibit less clear profiles of pollutant concentrations, probably due to dispersion effects.



**Figure 7: Comparison of ground level and 1.5m above ground CO concentration measurements**

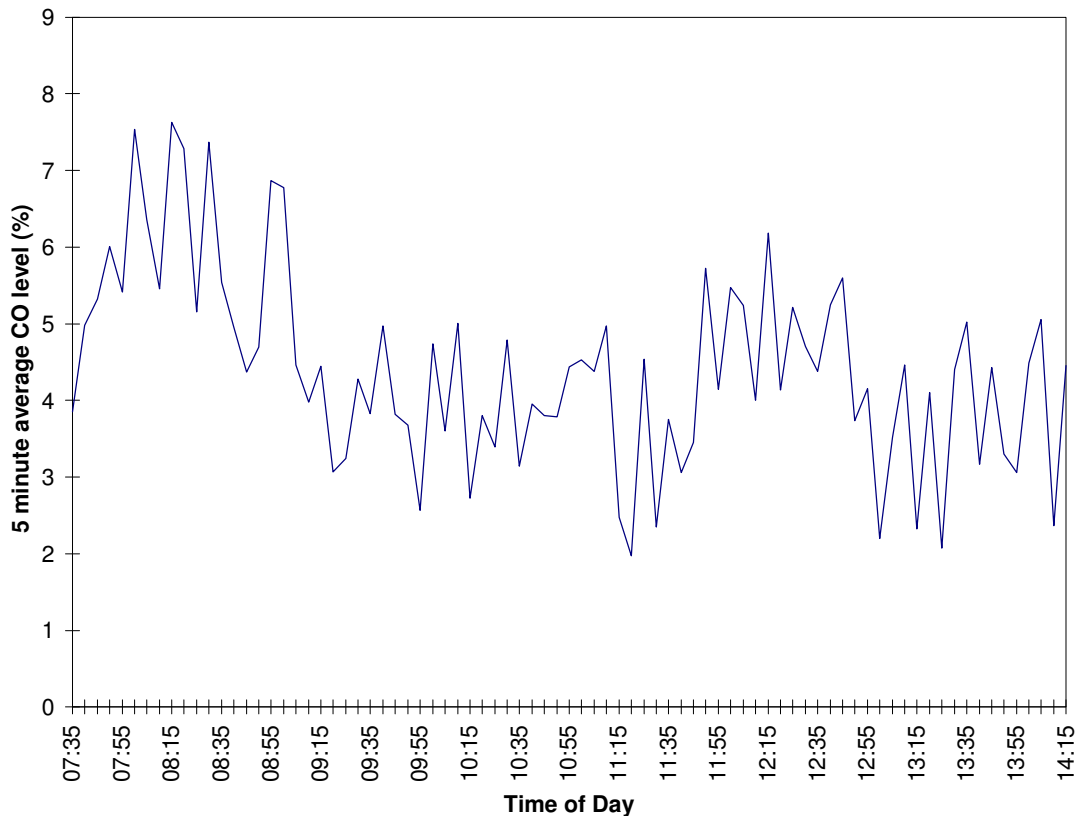
Other analysis from Marsden (1998) did not show any evidence of significant re-circulation of pollutants at the site (the site is not a narrow canyon). It was also found that the wind had a significant effect on pollutant concentration readings at 1.5m that was not evident at ground level. Whilst the future development of the model would incorporate a dispersion model to provide estimates of pollutant concentrations, as well as emissions, a limited validation of the model was attempted using the ground level CO monitors. The CO sensors were used to measure pollutant concentrations at floor level over a period of one week. SCOOT occupancy data was collected simultaneously. Details of the survey periods and sensor locations are shown in Table 5.

**Table 5: Validation survey details**

Date	Monitor Location	Survey Period	Duration (hours:mins)
28 <sup>th</sup> July 1997	5m from stop-line	13:10 – 16:00	2:50
29 <sup>th</sup> July 1997	5m from stop-line	12:00 – 18:00	4:00
30 <sup>th</sup> July 1997	5m from stop-line	11:40 – 14:00	2:20
	25m from stop-line	11:40 – 13:45	2:05
31 <sup>st</sup> July 1997	5m from stop-line	12:00 – 18:00	6:00
1 <sup>st</sup> August 1997	5m from stop-line	11:00 – 17:00	6:00

The Marksman M660 units produce an average CO concentration for a five minute period, based on the average of readings taken every second over that period. Results of an analysis of three roadside pollutant monitors at 1.5m from floor level on a

minute by minute basis showed that on average, consecutive minute readings differ by between 12.9% and 19.6% with maximum differences of between 66.7% and 126%. This shows the importance of modelling exhaust emissions every traffic signal cycle. However, given the limitation of the time resolution of the pollutant sensor, the predicted exhaust emissions (estimated every 0.67 seconds) were also summed up and aggregated to a five-minute average. The five-minute averages were calculated for each 10 metre section of road. A sample output from the SIGSIMPLE is shown in Figure 8.



**Figure 8: Sample output of the exhaust emissions estimation model**

The distributions of estimated emissions were compared directly to the pollutant concentration measurements taking no account of dispersion of the emissions. The hypothesis was made, in the light of the comparative study of monitor types and locations, that monitoring readings at kerb level would be related to exhaust out emissions. The units of estimated emissions and pollutant concentrations are different so the distributions were standardised before comparison. Spiegel (1992) states that “*These (standardised variables) are of great value in the comparison of distributions.*” Standardising two samples (such as observed and modelled CO) gives both samples the same x-axis scale and the same mean (zero). Spiegel (1992) defines a standardised variable as:

$$z = \frac{X - \bar{X}}{s} \quad (4)$$

where:

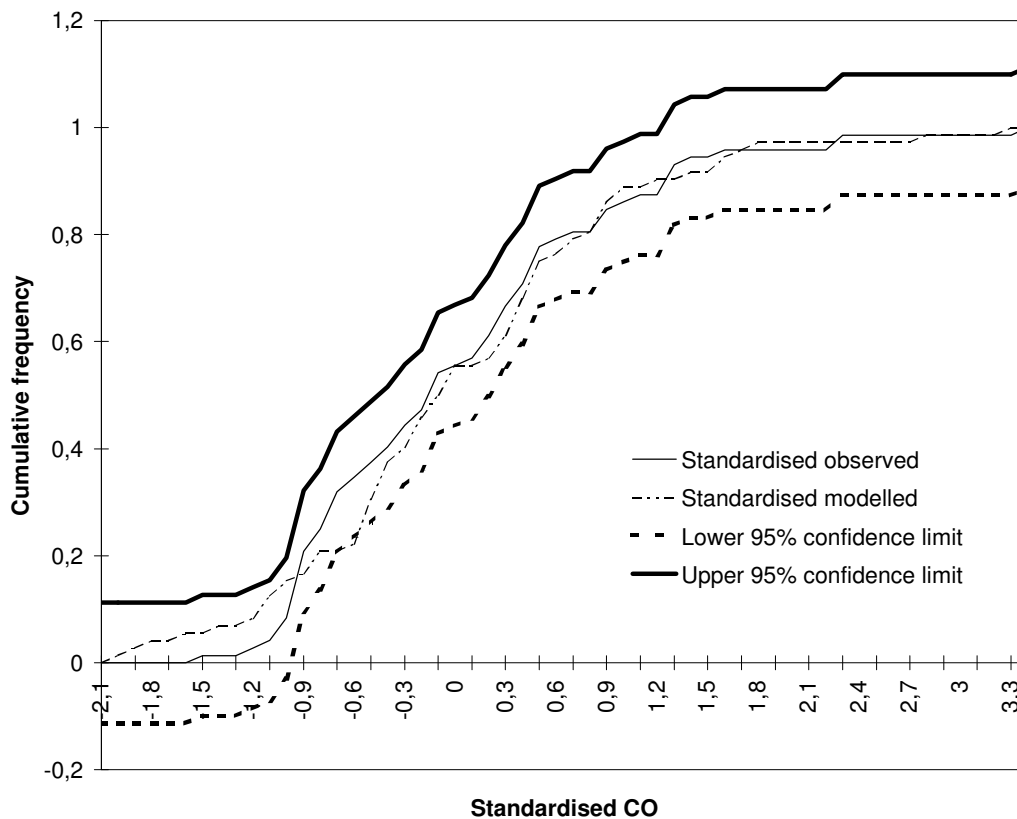
$X$  is the variable (in this case CO);

$\bar{X}$  is the sample mean; and

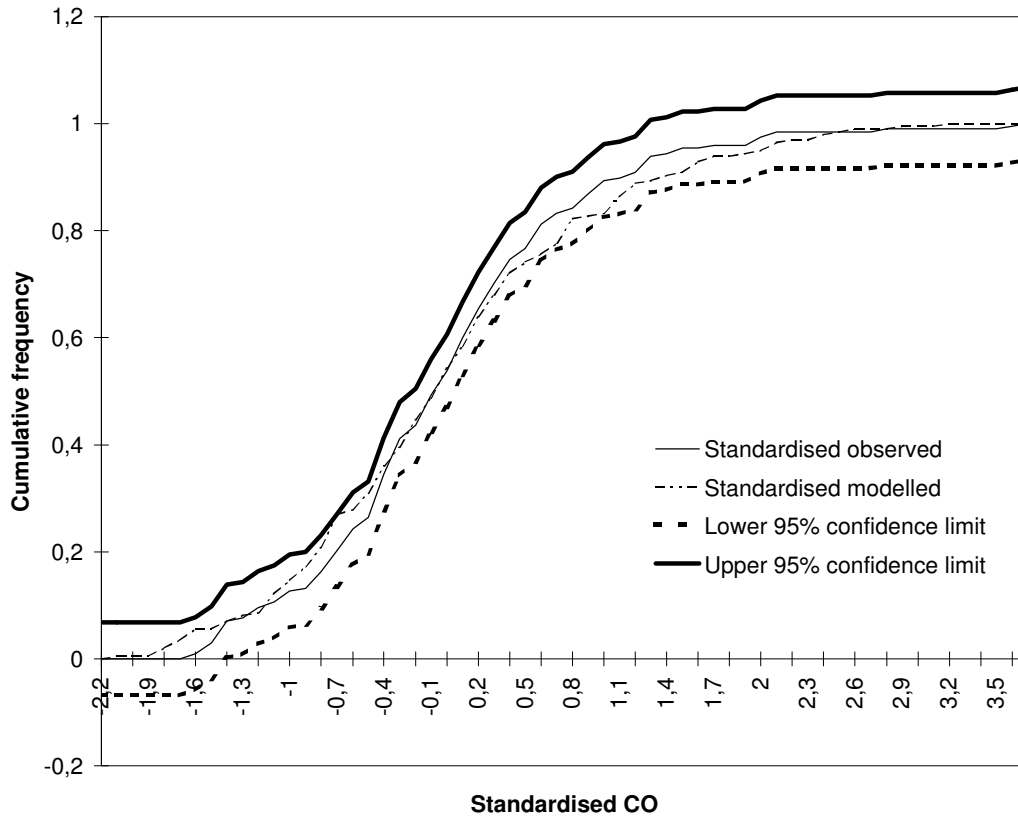
$s$  is the sample standard deviation.

The maximum number of observations available to compare the measured with the modelled results was 72 (all day 31st July). This sample size makes the  $\chi^2$  test unsuitable for comparing the shape of the distributions. The Kolmogorov-Smirnov test is more appropriate for testing discrete or finely aggregated distributions. This test is employed for all further comparisons. The Kolmogorov-Smirnov test assesses the differences in cumulative distribution functions. The critical value for the Kolmogorov-Smirnov test is obtained from look-up tables (e.g. Kanji, 1993) where the number of degrees of freedom equals the combined measured and modelled sample size. The null hypothesis that the modelled standardised distribution is not different from the measured standardised distribution was tested. The 95% confidence limits were calculated by adding to and subtracting from the standardised distribution line, the 95% confidence measure.

Figure 9 shows a typical plot of the standardised distributions for 31<sup>st</sup> July at the measurement point 5m and the modelling section 0 to 10m. Figure 10 shows the plot for the whole week of surveys combined. Table 6 shows the results for the whole week of surveys.



**Figure 9: Standardised Observed (5m) and Modelled (0 to 10m) CO levels 310797**

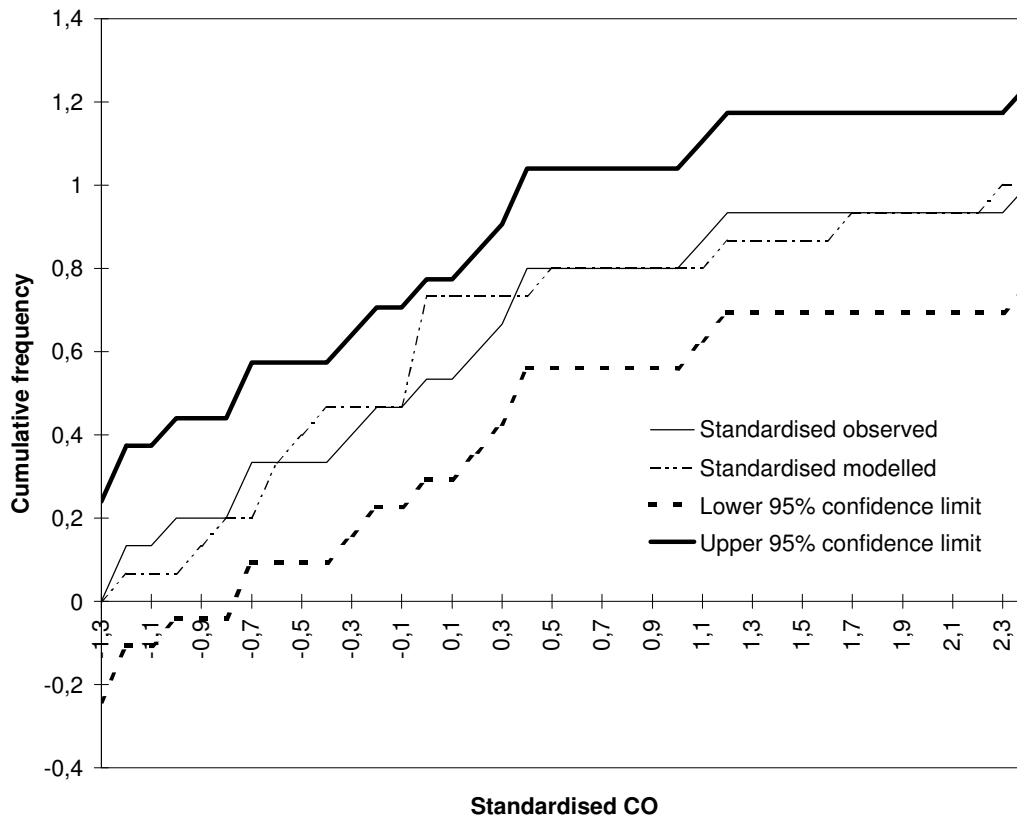


**Figure 10: Standardised Observed (5m) and Modelled (0 to 10m) CO levels – whole week combined**

**Table 6: Minimum and maximum differences between observed and modelled standardised CO distributions**

Date	Kolmogorov-Smirnov test 95% critical value	Standardised (observed - modelled)	
		min.	Max.
28 <sup>th</sup> July 1997	±0.26	-0.21	0.29
29 <sup>th</sup> July 1997	±0.19	-0.31	0.31
30 <sup>th</sup> July 1997	±0.24	-0.13	0.13
31 <sup>st</sup> July 1997	±0.11	-0.08	0.13
1 <sup>st</sup> August 1997	±0.12	-0.06	0.11
All	±0.07	-0.07	0.06

Figure 11 shows the plot for the standardised modelled section 20 to 30m for 30<sup>th</sup> July compared to the standardised measured distribution obtained from the second M660 unit located 25m upstream of the stop-line.



**Figure 11: Standardised Observed (25m) and Modelled (20 to 30m) CO levels 300797**

The results show that the distributions of modelled standardised emissions are not statistically significantly different from the measured standardised pollution distribution to the level of 95% confidence on two of the five survey periods. The differences on two of the other survey periods are small and the combined distributions for the five survey periods are not statistically significantly different. Whilst this does not validate the model, it lends confidence to the approach taken to assess exhaust emissions against measured kerbside, ground level measurements and of determining emissions according to driving mode.

The approach taken in attempting to validate the model requires further investigation, particularly with regard to the application of this model at a site independent of any of the calibration procedures. However, whilst the majority of the monitoring comparisons were performed at the 5m measurement point, it was encouraging that the mid-link standardised modelled and measured distributions were also not statistically significantly different at a 95% level of confidence. The approach described to assess the quality of the emissions estimates using kerb level monitors could also be applied to a number of other in-use emissions estimation models which have yet to undergo such a validation, due mainly to the methodological difficulties that this study has attempted to overcome.

In addition to validating the emissions estimation aspect of the model at an independent site, the inclusion of European emission factors, whilst continuing to use the approach of An et al. (1995), is a priority. This would include a wider range of pollutants and also the effects of cold start vehicles.



The approach described in this paper has significant advantages over that currently being proposed for use within SCOOT (Bretherton and Bowen, 1998) which relies on average speed estimates over the link. To fully understand the benefits of introducing new technologies such as electric vehicles or semi-automatic driving, where changes to the driving profile and in particular acceleration of vehicles are significant, it is essential to have a model capable of modelling the impacts of such changes. The model evaluation presented here would benefit from a further independent validation of the traffic model with data from an Instrumented Vehicle (Brackstone et al., 1999).

Further development of the vehicle prediction model could also be undertaken. However, video image technology or new intelligent loop classification systems may offer a better long-term alternative identification methodology for emissions estimation. Number plate recognition could also be linked to the vehicle licensing database to provide further information about the vehicle.

## **APPLICATION OF THE MODEL**

The SCOOT traffic control system operates in real-time over large parts of an urban centre network. The model proposed in this paper could operate in a number of ways with the SCOOT system:

1. As a real-time emissions estimator which could feed directly in to air quality models or as a permanent monitor of the evolution of levels of emissions over time as new strategies are introduced on the network;
2. as a strategic assessment tool. University College London has developed the SIGSIM model to run using parallel computing techniques. A virtual SCOOT network could be operated in conjunction with SIGSIMPLE such that different traffic control scenarios could be modelled in response to traffic incidents or forecast air quality episodes to minimise a particular target pollutant;
3. as a wider policy assessment tool to examine the emissions effects of the introduction of new engine technology or new vehicle-control algorithms.

A trial application of the model to examine the comparative benefits of the gradual reduction of the number of non-catalytic converter equipped vehicles and the removal of the 10% of high emitting vehicles from the fleet was undertaken. The modelling required an alteration of the vehicle fleet composition.

The base case scenario was that used for the validation study with 36% non-catalyst vehicles and 8% dirty vehicles. Three alternative scenarios were examined. In the first scenario, all of the non-catalyst equipped vehicles were assumed to be replaced by properly functioning (P-type) cars. In the second scenario, the non-catalyst fleet proportion was held constant and the high emitting vehicles were replaced with P-type cars. In the third scenario, both the non-catalyst and the high emitters were replaced with P-type cars. Table 7 shows the changes in mean, standard deviation and maximum observed values for each 10 metre section of road for the whole week's data.

**Table 7: Reductions in emissions estimated from strategies 1 to 3 over base case**

Location	Scenario 1			Scenario 2			Scenario 3		
	Change over base (%)			Change over base (%)			Change over base (%)		
	$\mu$	$\sigma$	max	$\mu$	$\sigma$	max	$\mu$	$\sigma$	max
0-10m	35.5	13.6	10.3	35.1	42.1	43.4	67.2	69.0	65.8
10-20m	30.9	6.5	7.1	33.3	40.0	49.9	65.3	66.9	67.7
20-30m	40.3	36.7	35.4	36.9	44.9	51.4	66.3	68.7	69.9
30-40m	36.6	29.6	32.7	34.8	38.0	46.6	65.1	65.3	68.2
40-50m	36.2	22.9	28.6	35.7	43.4	44.4	66.4	69.5	72.3

The results from Table 7 show that the magnitude of the change in the mean value of emissions brought about by scenarios one and two is similar, ranging between 30.9% and 40.3%. It has been estimated that 10% of vehicles produce 50% of CO emissions (Bishop and Stedman, 1996). The results show that a reduction in emissions of 33.3% to 36.9% could be achieved if these vehicles were all identified and replaced by clean vehicles (scenario two). A reduction of 40% would perhaps be expected if the 10% of P-type vehicles were to represent 10% of the emissions for the fleet. However, it is intuitively reasonable that a 40% reduction is not achieved because the data to determine the relative contribution of clean and dirty vehicles has been measured using remote sensing techniques. Such techniques require vehicles to drive by whilst cruising at a constant velocity. This underestimates the contribution of enriched emissions from properly functioning vehicles during acceleration, (which are almost three times as high as stabilised emissions as shown in Table 4) and overestimates the contribution of dirty vehicles as cruising emissions for high emitters are higher than the corresponding acceleration emissions (Table 4). This finding is supported by a previous review carried out by the Sierra Research Foundation (Austin et al., 1994).

The comparison of maximum values and standard deviations shows a more clear difference between the strategies, particularly in the areas closest to the stop-line. Removing the high emitters from the fleet reduces the standard deviation of the emissions estimated by between 38% and 44.9% and reduces the maximum emissions levels estimated by between 43.4% and 51.4%. Removing only non-catalyst vehicles from the fleet alone provides reductions in standard deviation of the emissions of between 6.5% and 36.7% and reductions of the maximum value of between 7.1% and 35.4%. The role of dirty vehicles is clearly important in determining the maximum emissions on a road section, particularly when idling, which is most likely to occur near the stop-line, supported by the scenario one results for 0 to 10m and 10 to 20m.

The results for scenario three suggest that the benefits of the two measures for fleet improvement can bring about a reduction in CO emissions of between 65.1% and 67.2% and that the reductions in maximum values observed and standard deviations are of a similar order of magnitude. Whilst the results show that the reduction in mean values is relatively constant along the link, this implies a greater absolute reduction in emissions nearer the stop-line as this is where the majority of idling and acceleration events occur (average levels at 0 to 10m are between 2 to 2.5 times higher than at 20 to 30m for the link studied). The benefits for personal exposure to pollution should therefore also be important, as pedestrian crossing facilities are often located at the stop-line.

## **CONCLUSIONS**

A microscopic emissions model for estimation of CO exhaust emissions has been developed that could operate on-line in real-time and off-line, as a strategy assessment tool. The model can use input from the SCOOT demand-responsive traffic control system to identify vehicle type and estimate speed of vehicles as they pass over the inductive detector loops located toward the upstream end of each link within a SCOOT network.

The exhaust emissions estimates have been compared with floor level kerbside CO concentration measurements. No statistically significant differences were found between the standardised distributions of measured concentrations and modelled emissions over five days of surveys. Further testing of the methodology at independent sites is required to prove the validity of the model. However, this study has attempted to develop a methodology for validating microscopic emissions models without the incorporation of dispersion modelling techniques. Kerbside, ground-level pollution sensors were found to be less affected by dispersion and local weather conditions than those at face height.

Microscopic modelling of traffic flow and driving mode plays an essential part in the assessment of the potential of and implementation of new traffic demand management measures that will significantly alter the driving profile over an area. Macroscopic traffic models based simply on average speed and flow levels will not adequately model the detail of the effects of new technologies on driving patterns. Several studies have highlighted the importance of driving modes and acceleration to exhaust emissions and this paper has demonstrated the feasibility of modelling these factors.

An exploratory application of the model has reinforced the need to improve the detection and maintenance of high emitting vehicles which were shown to be responsible for significantly elevating overall CO emissions, particularly during idling and acceleration periods which predominate near the stop-line, where pedestrian exposure may be highest. Further application of the model using parallel-computing techniques has been proposed to enable on-line emissions control strategies to be implemented.

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