Cold Start Emission Modelling for the Australian Petrol Fleet

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ABSTRACT

Cold start vehicle emissions are excess emissions due to fuel-rich combustion in the engine, increased friction, and reduced emission control efficiency. Given the growing importance of cold start emissions with respect to motor vehicle emission inventories, it is essential to use accurate cold start emission factors for Australian conditions. This paper presents and discusses the approach that was taken to create cold start emission factor for COPERT Australia, a new software for Australian conditions. The method is based on an analysis of empirical Australian data, a literature review and a sensitivity analysis using four possible methods (phase detection functions). The method used in COPERT Australia combines empirical cold start emission profiles with a trip distance distribution to create technology specific cold start emission factors. Finally, these emission factors are used to create a first-order emissions inventory for South East Queensland using output data from a macroscopic transport model. It is estimated that cold start emissions make up a substantial part of air pollutant emissions with cold start to hot running emission ratios of about 0.10 (NOx), 0.50 (CO) and 0.80 (HC).

Keywords: cold start, emission, road traffic, motor vehicles, model testing, COPERT

GLOSSARY OF TERMS

ADR	Australian Design Rule
AFR	Air-to-fuel ratio
COPERT	COmputer Programme to calculate Emissions from Road Transport (http://www.emisia.com/copert/)
CUEDC-P	Composite Urban Emission Driving Cycle for petrol vehicles
Light-off	Point in time where the catalyst achieves 50% conversion efficiency for *e.g.* CO.
LCV	Light commercial vehicle
LD	Light duty vehicle
SEQ	South East Queensland

INTRODUCTION

Cold start vehicle emissions are defined as excess emissions (expressed as grams per vehicle start) at initial startup when the engine is cold due to fuel-rich combustion in the engine, increased friction, and reduced emission control efficiency, as compared with stabilised "hot running" conditions, where the vehicle engine, transmission and emission control technologies have reached their optimal operating temperatures (*e.g.* engine coolant ± 75-90 °C, three-way catalyst (TWC) > ± 250 °C).

Cold start emissions make a large contribution to total emissions from motor vehicles. For instance, cold start emissions of CO and HCs from modern (petrol) passenger cars typically make up 50-80% of total vehicle trip emissions (Smit 2011). Kirchstetter *et al.* (1996) reported that more than 50% of total regional CO and HC emissions in wintertime in the San Francisco Air Basin are cold start emissions.

Elevated fuel consumption and air pollutant emissions in cold start conditions are due to:

1. reduced catalyst efficiency;
2. fuel enrichment in the engine combustion process; and
3. lower fuel efficiency due to increased frictional losses in the engine and transmission systems.

These three aspects affect cold start emissions differently with respect to magnitude of their impacts, as well as their duration.

Closed-loop TWC technology is the main emission control for petrol engines. In hot running conditions, three-way catalysts reduce engine-out CO, HC, (organic) PM and NOx emissions substantially (> 90%). As a consequence, reduced catalyst efficiency due to cold starts has a large impact on vehicle emission levels.

After an engine start, a cold catalyst goes through two main stages. In stage 1 the converter gradually heats up by hot exhaust gases, but the reaction rate in the converter is generally low. After a short period of time, the temperature in the converter becomes sufficiently high for the reactions rate to increase and this generates additional heat (exothermic). The temperature and reactions rate then increase dramatically at this point and the converter "lights-off". Light off is typically defined as the point in time where the catalyst achieves a 50% conversion efficiency for *e.g.* CO. In stage 2, catalyst efficiency progressively improves after light-off conditions are reached as the so-called "light-off front" moves towards the converter outlet. Typically as the catalyst approaches optimal operating temperature, NOx is the first to reach a high conversion efficiency, followed by CO and then HC (Please *et al.* 1994).

Light-off times have improved substantially with the advent of improved engine and catalyst technology. In comparison with older vehicles, which could take several minutes to achieve light-off conditions, modern vehicles achieve light-off conditions quickly within one to a few minutes (Ntziachristos and Samaras 2001; Ashford and Matthews 2006). Tight control of the air-to-fuel ratio (AFR) in the exhaust gas enabled by the oxygen sensor (which itself requires light-off) is required for effective emission reduction. So the duration of fuel-rich combustion conditions during start also significantly impacts on catalyst efficiency and hence cold start emission levels. Adequate control of the AFR is particularly relevant for hot running conditions, where short periods of fuel-rich or fuel-lean operation result in short and sharp emission peaks. The time required for the vehicle engine and transmission system to reach its typical operating temperature (75-90°C) is longer as compared with the catalyst, and typically in the order of 5-15 minutes, but their impact on cold start emission is substantially lower as well (DTRS 2001; Hammerström 2002).

So in conclusion, there are different factors that contribute to cold start emissions and they differ in magnitude as well as duration of impact. The literature suggests that, at an ambient temperature of about 20°C, hot running conditions should generally be achieved for all relevant vehicle components (engine, transmission, catalyst) within 15 minutes of driving. However, "light-off" conditions for the catalyst and tight control of the air-to-fuel ratio, which together largely determine the magnitude of cold start emissions, will be achieved much faster than this, *i.e.* typically within a minute of engine start for modern vehicles and a maximum of a few minutes for older technology vehicles.

Given the growing relative importance of cold start emissions, it is essential to use accurate cold start emission factors for Australian conditions. Empirical Australian vehicle emissions data have therefore been analysed and used in this research to develop appropriate cold start emission factors. These emission factors have been incorporated in the COPERT Australia software (Emisia 2013).

EMPERICAL DATA

Australian Test Data

The Second National In-Service Emissions (NISE2) studies (DEWHA 2005; RTA 2009) provide vehicle emissions test data measured in a certification-grade laboratory in both cold start (12 hour "overnight soak" at 20-30 °C) and hot running conditions for 170 Australian petrol light-duty vehicles (Table 1), which includes PCs (passenger cars), SUVs (sport utility vehicles) and LCVs (light-commercial vehicles), and a range of model years (1986-2008).

Test Data Verification and Preparation

All hot and cold modal test data were subjected to a verification and correction protocol. This included:

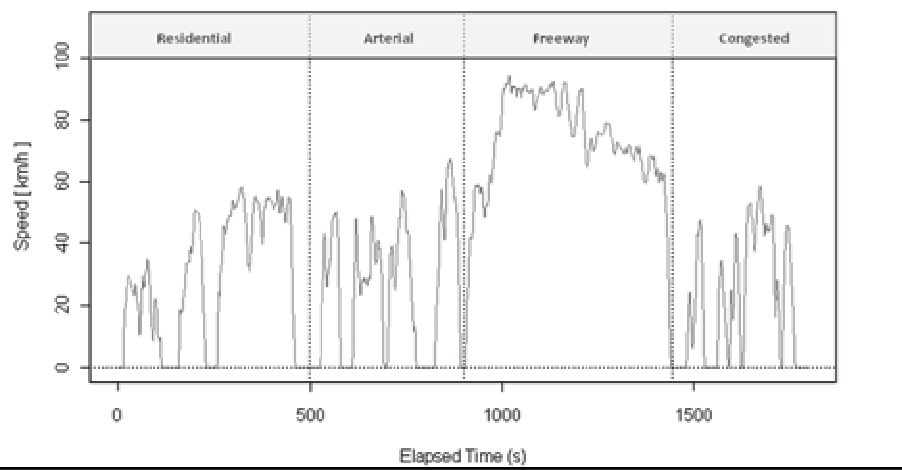

Figure 1. CUEDC-P Real-World Driving Cycle

Table 1 – Test Matrix (Petrol Light-Duty Vehicles)

Vehicle Class	Emission Standard		Carbureted No catalyst		Fuel-injected No catalyst		Fuel-injected Three-way catalyst	
	Australia	Equivalent	Manual	automatic	manual	automatic	manual	automatic
Small Passenger Car	ADR37-00	US 1975	-	-	-	-	5	4
	ADR37-01	US Tier 0	-	-	-	-	4	6
	ADR79-00	Euro 2	-	-	-	-	1	4
	ADR79-01	Euro 3	-	-	-	-	3	5
Medium Passenger Car	ADR37-00	US 1975	-	-	-	-	3	6
	ADR37-01	US Tier 0	-	-	-	-	-	7
	ADR79-00	Euro 2	-	-	-	-	3	7
	ADR79-01	Euro 3	-	-	-	-	2	7
Large Passenger Car	ADR37-00	US 1975	-	-	-	-	2	7
	ADR37-01	US Tier 0	-	-	-	-	-	9
	ADR79-00	Euro 2	-	-	-	-	-	7
	ADR79-01	Euro 3	-	-	-	-	-	11
Light-Commercial Vehicle	ADR36	-	-	1	-	1	3	-
	ADR37-00	US 1975	1	-	-	-	2	-
	ADR37-01	US Tier 0	-	-	-	-	2	2
	ADR79-00	Euro 2	-	-	-	-	3	3
	ADR79-01	Euro 3	-	-	-	-	2	4
SUV Compact	ADR37-00	US 1975	-	-	-	-	2	3
	ADR37-01	US Tier 0	-	-	-	-	1	5
	ADR79-00	Euro 2	-	-	-	-	1	4
	ADR79-01	Euro 3	-	-	-	-	1	5
SUV Large	ADR36	-	-	-	3	2	1	-
	ADR37-01	US Tier 0	-	-	-	-	-	4
	ADR79-00	Euro 2	-	-	-	-	-	6
	ADR79-01	Euro 3	-	-	-	-	-	5

1. smoothing of 1 Hz speed-time data with a T4253H smoothing algorithm;
2. (constant) time re-alignment maximizing the Pearson correlation between fuel rates and instantaneous positive drive power;
3. verification of emission traces (analyser drift, clipping); and
4. computation of verification statistics (*e.g.* BSFC, mean thermal efficiency, mean measured and computed cycle power).

Mean cycle emission values (g km^{-1}) were compared for both modal and bag tests and a maximum error of ±5% for CO_2 and fuel consumption and ±20% for the air pollutants was accepted. Such differences originate from the fact that different analyser units are used for the bag and modal tests and due to signal synchronization limitations in the modal results. A verified modal dataset for 166 Australian vehicles (417 emission tests) was prepared for subsequent analysis and modelling.

The similarity of the speed-time data was verified for each pair of cold start and hot running emission tests and as compared with the official cycle (CUEDC-P). The mean absolute error (MAE) in instantaneous speeds as compared with the official CUEDC-P cycle for each vehicle was less than ±2.0 km h^{-1} (as specified in the ADR79/00 legislation), with a maximum value of 1.0 km h^{-1} and an average MAE of 0.8 km h^{-1}. The mean absolute error (MAE) in instantaneous speeds between the cold and hot running speed traces had a maximum value of 1.1 km h^{-1} and an average MAE of 0.6 km h^{-1}. This indicates that the selected 166 vehicles have all been driven in a similar fashion, which in turn allows for aggregation of the emissions tests for cold start analysis.

An automated procedure was coded to extract driving cycle segments and their associated modal emissions data from the verified modal database for each pair of cold start and hot running emission tests. Similar to average speed algorithm development (Smit and Ntziachristos 2012), the spatial resolution was set to 100 m. The segmented database includes 1) relevant vehicle information, and 2) for each pollutant and 100 m segment, the (cumulative) difference between cold start and hot running emissions (g), as will be discussed in section 4.

A REVIEW OF COLD START MODELS

The theoretical basis of cold start emissions modelling around the world is to consider cold start emissions as separate and additional emissions to hot running emissions (*e.g.* Joumard and Sérié 1999; Joumard *et al.* 2000; Keller 2004; André and Joumard 2005; EEA 2007; Favez *et al.* 2009; US EPA, 2011). Cold start emission factors (grams per engine start) for a particular vehicle class are then multiplied with the number of engine starts to compute total cold start emissions in a road network.

The cold start emission factors are typically computed by modification of a 'base' cold start emission factor using correction algorithms for travel or trip distance, parking time, ambient temperature and average (cycle) speed. The base emission factors are usually derived from empirical emissions testing data with ambient temperatures and parking or "soak" periods that are similar around the world (*i.e.* 20-30 °C and 12 hour soak period). However, the base emission factors can be based on different driving cycles, test methods (bag, modal) and phase detection functions, as will be discussed later. For the determination of cold start emission factor, the concept of "cold start distance" (d_{cold}) or "cold start time period" (t_{cold}) is used, which represent either the (pollutant dependant) distance or the time period for emission levels to stabilize around its hot running value, *i.e.* where hot and cold emissions profiles converge and the cold start period ends (Figure 2).

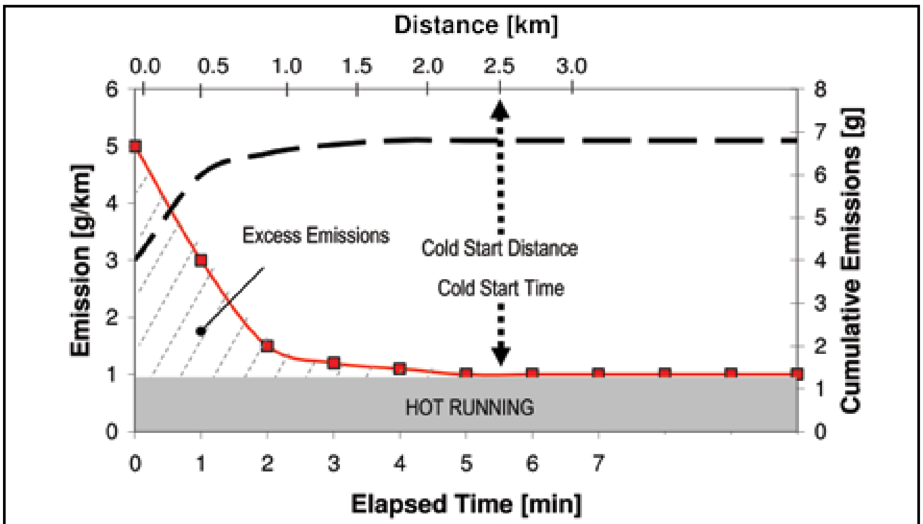

Figure 2. Schematic of Theoretical Cold Start Excess Emissions (Cold Start Emissions Profile = Red Line with Squared markers, Cumulative Emissions = Dashed Black Line).

Phase detection functions are often used to determine the travel time or travelled distance where the cold start period ends. The cold start emission factor is then computed by subtracting the sum of the hot emissions over t = 0 to t = t_{cold} seconds or d = 0 to d = d_{cold} meters from the cold emissions for the same period or distance and measured under same test conditions (vehicle, driving cycle(s), laboratory). Theoretically, the cold start emission factor should be time-independent after the point where cold start and hot running emission profiles converge. It is assumed that the hot running emissions (g km^{-1}) are (more or less) constant throughout the test cycle. This results in a typical log-shaped cumulative emissions profile with a strong initial increase at the beginning of the test, after which the rate of increase becomes less until it reaches zero at the cold start distance (Figure 2).

EXAMINATION OF AUSTRALIAN DATA

For vehicle emission and subsequent air quality modelling, the interest is not so much in the cold start behaviour of individual vehicles, but rather in the sum of those behaviours (*i.e.* at "traffic stream" level). Therefore, cold start emission factors are required for each vehicle class used in COPERT Australia, which are defined as a combination of vehicle type, fuel type and emission standard. Modal hot and cold emissions data were used to compute cold start emission values as a function of trip distance, for 25 light-duty (LD) petrol vehicle categories (j), which are:

- small petrol passenger cars (ADR37/00, ADR37/01, ADR79/00, ADR79/01);
- medium petrol passenger cars (ADR37/00, ADR37/01, ADR79/00, ADR79/01);
- large petrol passenger cars (ADR37/00, ADR37/01, ADR79/00, ADR79/01);
- petrol compact SUVs (ADR37/00, ADR37/01, ADR79/00, ADR79/01);
- petrol large SUVs (ADR36, ADR37/01, ADR79/00, ADR79/01);
- petrol LCVs (ADR36, ADR37/00, ADR37/01, ADR79/00, ADR79/01).

The cold start emission values effectively represent the cumulative empirical differences between cold start and hot start emissions for 195 trip distance segments (i) at 100 m resolution, reflecting the total cycle length of 19.5 km, *i.e.*

$$E(i)_j = \sum_{1}^{i} \left(\sum_{1}^{m} \left(e_{cold,i,k} - e_{hot,i,k} \right) \div m_j \right) \quad (1)$$

$E(i)_j$ represents the series of cumulative cold start emission values (g $start^{-1}$) for vehicle class j and trip segments i = 1 to i = n, where each segment is 100 m long. It is computed as a function of the total cold start ($e_{cold,i,k}$) and hot running ($e_{hot,i,k}$) emissions (g) for segment i and vehicle k and the total number of vehicles in vehicle class

j (m_j). Normalised 'cold start profiles' are then computed as follows:

$$E(i)_j^N = E(i)_j \; / \; MAX\,(E(i)_j) \quad (2)$$

Figure 3 shows the normalised cold start profiles as a function of distance for 25 petrol LDV categories used in COPERT Australia. The grey areas in the polygon plots reflect the observed range of normalised emission values at each 100m segment (travel distance bin), whereas the lines within the areas represent the normalised emission profiles for a particular vehicle category.

A distinction can be made between fuel consumption (and thus CO_2) and the air pollutants CO, HC and NOx. For fuel consumption the cold start profiles show a consistent log-shaped profile, in line with the expected theoretical shape, although there is some variation among vehicle classes. For instance, the bulk (80%) of the cold start emissions are emitted anywhere between 3 km and 14 km depending on the vehicle class. With respect to the air pollutants, HC aligns generally best with the theoretical log-shape, but there is some variation (particularly at the end of the driving cycle), where the cumulative profile is reduced. The bulk (80%) of the cold start emissions are emitted anywhere between 300 m and 3 km, depending on the vehicle class. For CO and NOx, there can be significant deviations from the theoretical log-shape, with some vehicle classes having final cold start emission values varying between +50% and -150% of the peak value that is typically achieved early in the cycle. The bulk (80%) of the cold start emissions are emitted anywhere between 200 m and 6 km for CO and between 200 m and 18 km for NOx, depending on the vehicle class.

An examination of the cold start profiles, and underlying cold and hot segmented (100m) emissions, revealed that there are a few factors that can cause deviations from the theoretical logarithmic shape.

1. The absence of a significant cold start 'hump' at the start of the test, which makes the cumulative cold start profile sensitive to small differences between the hot and cold start profiles. Small cold start humps can occur with vehicles that achieve fast light-off conditions and employ specific control strategies that will minimize cold start emissions such as close-coupled catalysts, electrically heated catalysts, secondary air injection and hydrocarbon traps.
2. Elevated hot or cold start emissions for a limited time period or specific time periods during the test (*e.g.* the onset of high speed freeway driving), which can result in 'inversions' (*i.e.* negative cumulative cold start emission values) and/or generate a randomly fluctuating appearance of the cumulative cold start profile. These systematic differences between the hot and cold profiles appear to be related to the engine management system and engine calibration.
3. The occurrence of a single or a few high emission spikes in either the hot or the cold start emission profiles, sometimes substantially larger than the cold start peak at the start of the test. These peaks can occur anywhere during the test, causing sudden step changes to the cumulative cold start profile, which may cause 'inversions'. Spikes can either be consistently or randomly observed in repeat tests. The random peaks appear to be caused by temporary deviations from the optimum air-to-fuel ratio or intermittent emission control defects. Consistent spikes (*i.e* observed over multiple repeat tests) appear to be related to the engine management system.

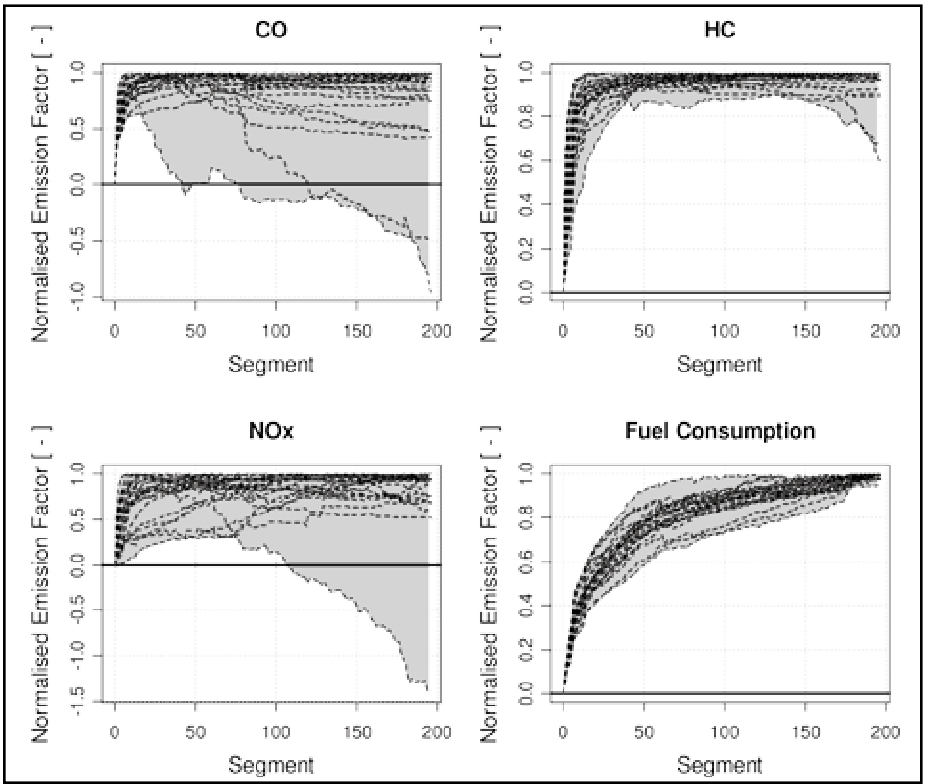

Figure 3. Range of Normalised Cold Start Emission Factors as a Function of Travel Distance for 25 Petrol Vehicle Classes

Importantly, the deviations from the theoretical shape of cold start profiles appear to be valid measurements. This means they should not be discarded and should be used in the development of cold start algorithms. The only exception could be the occurrence of random spikes in the modal profiles. However, these random spikes are likely to occur in the real-world, so the best way to deal with tests with random spikes is to use the results from repeat tests (as is done in this research) and use these averaged values in subsequent modelling. It is noted that retaining these "unusual" emissions data is in line with overseas practice (*e.g.* US EPA, 2001).

COMPUTING BASE COLD START EMISSIONS FACTORS USING PHASE DETECTION FUNCTIONS

Different methods have been used to compute where the cold start period and the hot running period begins in a test. They vary in level of complexity. Four approaches are used in this paper as a sensitivity analysis.

1. The simplest method, called the 'bag method', assumes that the cold start period ends at a fixed point in time, such as at the end of a driving cycle or at the end of a particular part of the driving cycle ('sub-cycle'). This approach is commonly used when cold start emission factors are developed from 'bag' data where only aggregated emission results are available for either the driving cycle or parts thereof (Schifter et al., 2010; US EPA, 2011; 2012). In this paper the 'bag' method is applied by simply assuming two cold start times:
   a. the end of the CUEDC-P (t_{cold} = 1797 seconds, d_{cold} = 19.4 km); and
   b. the end of the 'Residential' sub-cycle in the CUEDC-P (t_{cold} = 498 seconds, dcold = 3.8 km)
2. The 'regression method' uses a time-series of differences in segmented emissions (g start^{-1}) between hot running and cold start conditions and fits a simple regression equation using robust (linear) least-squares regression (IWLS). The regression coefficients are used in the phase detection function to compute the cold start distance (Smit, 2011).

Refer to Appendix A for the algorithms used in this approach.

3. The 'standard deviation method' was developed for emission testing where a particular short drive cycle (< 200 seconds) was repeated several times with the test vehicle starting in cold start conditions (André and Joumard, 2005; Favez et al., 2009). The standard deviation method progressively computes the standard deviation backwards, *i.e.* first for the last two cycles, then the last three cycles, etc. The minimum computed standard deviation is used to assign which cycles represent hot running or cold start conditions. The phase detection computation method used by Favez *et al.* (2009) was modified for application to data from a single driving cycle. To control for driving behaviour impacts the difference between the hot running and cold start emissions for each cycle segment was used as input to the computation. Refer to Appendix A for the algorithms used in this approach.

The cold start distances were computed for each vehicle class and pollutant, using the four detection methods ("Cycle", "Subcycle", "IWLS", "Standard Deviation"). Computation of the cold start (excess) emission factors for vehicle class *j* (EF_j), expressed as g start^{-1}, are determined by looking up the cumulative cold start emission value for vehicle class j for the segment that corresponds with the cold start distance as computed with each detection method.

This process is illustrated in Figure 4. It shows the NOx emission factors as a function of trip distance (*i.e.* cumulative difference between cold and hot start profile for each 100 m segment) and the phase detection points as determined with the four methods, for 25 light-duty vehicle categories. The standard deviation method consistently shows the smallest cold start distance values and on average produces the lowest cold start emission factors. The cycle method is mostly influenced by the non typical profiles. The IWLS method is generally less influenced

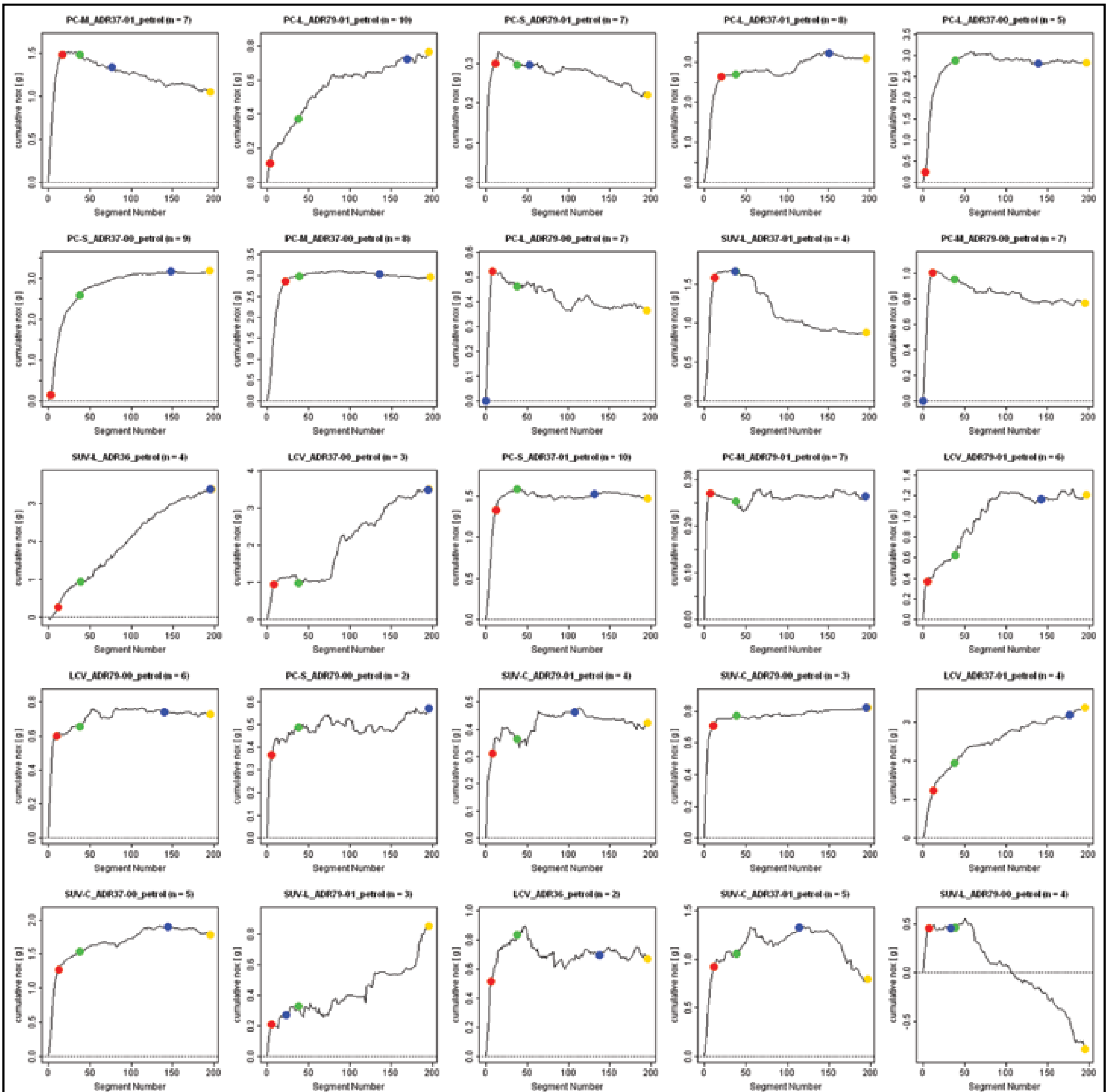

Figure 4. Travel Distance Based Cold Start NOx Emission Factors for 25 Light-Duty Vehicle Categories (Cycle = Yellow, Subcycle = Green, IWLS = Blue, Standard Deviation = Red).

and is robust for NOx, with on average computing the highest NOx emission factors, but does have a zero emission factor in cases where a negative regression line is predicted. Figure 5 shows the results for all pollutants and fuel consumption.

For the air pollutants CO, HC and NOx, the detection methods can predict widely varying cold start distances and thus cold start emission factors. This is caused by the variability in empirical cold start emission profiles (*e.g.* Figure 4). Since the empirical cold start profiles are based on valid measurements, these results indicate that no single phase detection method can provide an accurate computation of cold start emission factors for COPERT Australia. In comparison with the air pollutants, the results for fuel consumption are consistent. The cycle and IWLS methods predicts the maximum cold start excess consumption values, whereas the standard deviation are substantially and consistently lower, up to 60%. The consistency in the cold start profiles for fuel consumption translates into a consistent prediction of cold start emission factors, but the results are still quite different for the different phase detection method.

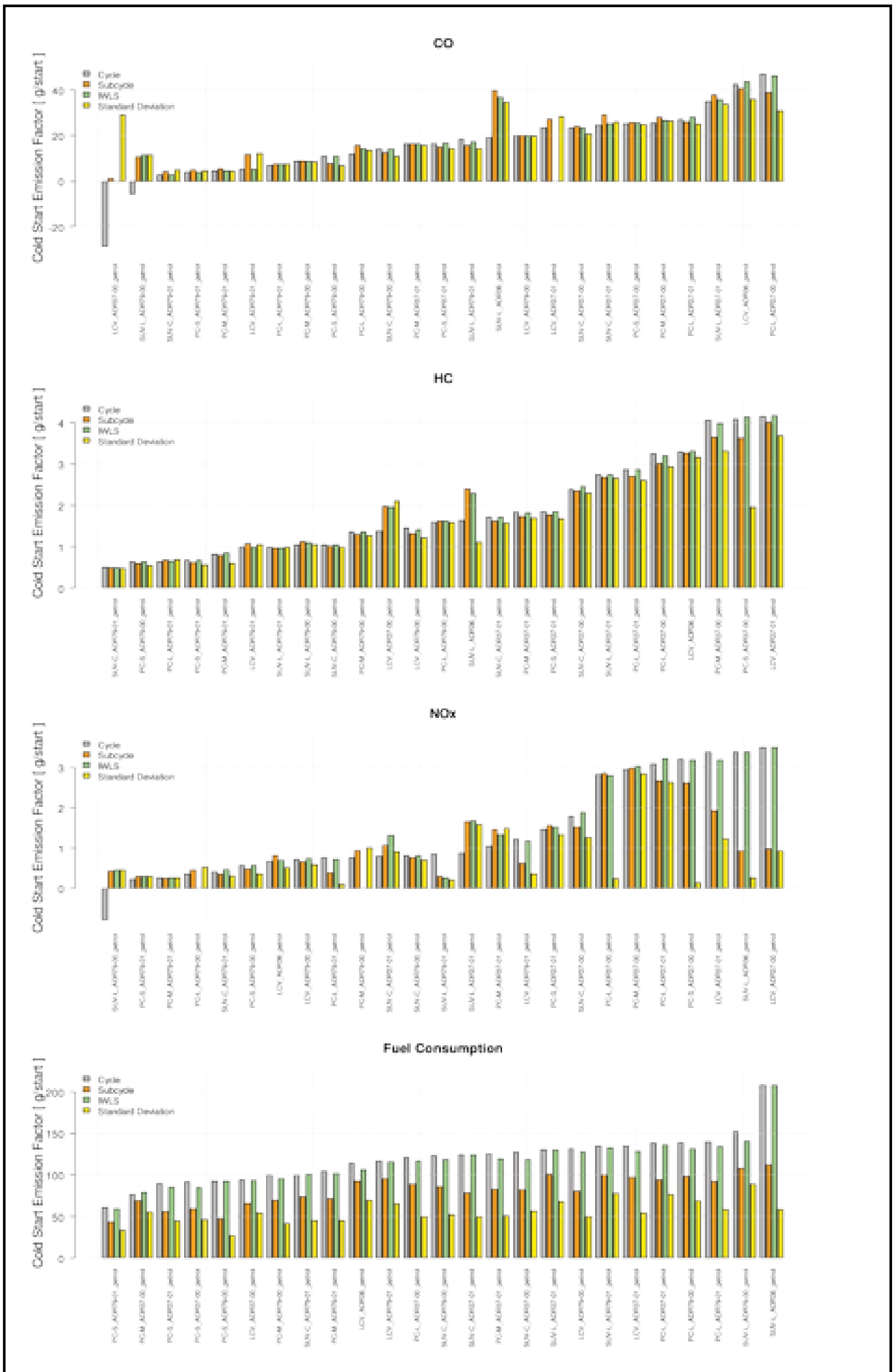

Figure 5. Cold Start Emission Factors Computed with Four Phase Detection Methods for 25 Petrol Vehicle Classes.

TRIP AVERAGED COLD START EMISSION FACTORS

All phase detection methods reflect certain assumptions regarding expected cold start behaviour and none of the methods have been adequately validated for accurately detecting the end of the cold start period. Examination of empirical data shows that several vehicles do not exhibit the expected log-shaped theoretical behaviour (Figure 3, discussed before) and that 'cold start' effects may, or may not, occur in different parts of the cycle as a result of vehicle specific factors such as the engine management system, engine calibration, the use of fast light-off strategies and sensitivity to deviation from the optimum air-to-fuel ratio. So accurate determination of cold start periods and cold start distances may, in fact, be an elusive goal.

Empirical Cold Start Emission profiles

The cold start emission factors for COPERT Australia is based on empirical cold start emission factor profiles (*e.g.* Figure 4), in combination with information on trip distance distributions. Instead of computing a single base cold start emission factor using detection functions, and then correcting for travel distance with a generic function (André and Joumard, 2005), the segmented (100 m) modal hot and cold start data are used to compute a set of 'reference' (*i.e.* soak time is 12 hours, 20-30 °C) empirical cold start emission factors for a range of travel distances for 25 petrol vehicles classes. These emission factors are then combined with information on the trip length distribution for one Australian city (Brisbane) to compute the final (distance weighted) cold start emission factors.

Daily Trip Distance Distribution

Trip matrices from the South East Queensland (SEQ) Strategic Transport Model (DTMR, 2012a) and information from the SEQ Household Travel Survey (DTMR, 2012b) were used to compute a daily trip length distribution (100 m resolution) as is shown in Figure 6. Note that for the purpose of readability, the chart shows an aggregated histogram with 1km bins and excludes trip distances ≥ 20km (16% of the total number of trips). The average trip distance is computed to be 11.3 km per trip. This value is slightly higher than the mean "private vehicle trip" distance of 10.5 km per trip reported in the SEQ Household Travel Survey (DTMR, 2012b).

RESULTS AND DISCUSSION

Table 2 shows the computed emission factors for COPERT Australia for each pollutant and vehicle class. There is a generic downward trend of cold start emission factor with ADR class, as would be expected (Figure 7). However, certain vehicle classes deviate from the trend. For instance, a negative CO cold start emission factor is computed for ADR37/00 LCVs. This is caused by the

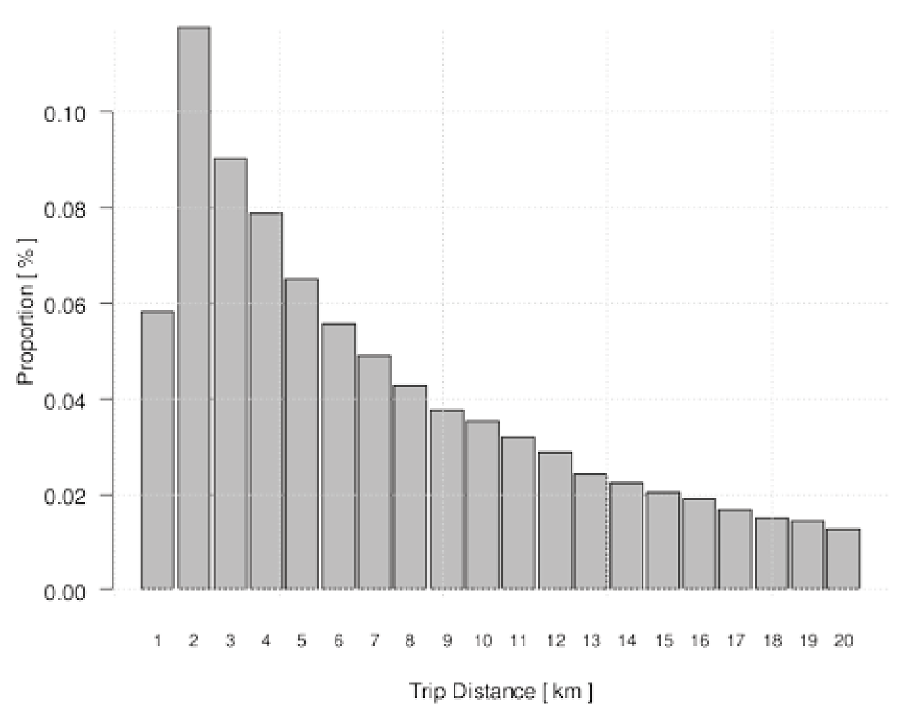

Figure 6. LDV Trip Distance Distribution for the SEQ Network

Table 2 – Cold Start Emission Factors (g start^{-1}) for COPERT Australia (Petrol Light-Duty Vehicles)

Vehicle Class	CO	HC	NOx	FC
LCV ADR36 petrol	38.4	3.0	0.7	88
SUV-L ADR36 petrol	28.9	1.9	1.6	129
PC-S ADR37-00 petrol	23.6	3.4	2.5	63
PC-M ADR37-00 petrol	24.8	3.5	2.7	65
PC-L ADR37-00 petrol	38.1	2.8	2.6	90
SUV-C ADR37-00 petrol	21.5	2.2	1.5	88
LCV ADR37-00 petrol	-0.8	1.8	1.8	70
PC-S ADR37-01 petrol	14.4	1.6	1.4	61
PC-M ADR37-01 petrol	15.4	1.6	1.2	88
PC-L ADR37-01 petrol	24.7	2.5	2.6	99
SUV-C ADR37-01 petrol	24.8	1.5	1.0	82
SUV-L ADR37-01 petrol	33.9	2.5	1.2	103
LCV ADR37-01 petrol	23.6	3.8	2.2	98
PC-S ADR79-00 petrol	8.4	0.6	0.5	57
PC-M ADR79-00 petrol	8.1	1.2	0.8	72
PC-L ADR79-00 petrol	13.3	1.5	0.4	102
SUV-C ADR79-00 petrol	11.7	1.0	0.7	89
SUV-L ADR79-00 petrol	4.7	1.0	0.1	112
LCV ADR79-00 petrol	18.6	1.3	0.7	90
PC-S ADR79-01 petrol	4.2	0.6	0.3	45
PC-M ADR79-01 petrol	4.6	0.7	0.2	75
PC-L ADR79-01 petrol	6.8	0.6	0.5	98
SUV-C ADR79-01 petrol	3.4	0.5	0.4	77
SUV-L ADR79-01 petrol	15.5	0.9	0.4	101
LCV ADR79-01 petrol	8.3	1.0	0.8	92

non-typical cold start profile for this vehicle class (*i.e.* lower boundary of the normalized CO profile in Figure 3). A negative cold start emission factor effectively means that it corrects (reduces) hot running emission predictions. This shows that the reference cold start emission factors should not be regarded in isolation but rather at on-road fleet level to ensure mean emission factors are based on a sufficient sample size.

The benefit of the approach outlined in this paper is that it fully utilizes Australian emissions and trip distribution data, and therefore should be representative for Australian conditions, at least in terms of a reference emission factor for ambient temperatures of approximately 20°C and higher and a soak time of 12 hours. In reality, deviations from the reference situation are common (*i.e.* lower ambient temperatures and shorter soak/parking time), so corrections are needed to account for this. It would be interesting to see to what extent cold start emission factors would vary when trip distance distributions from other Australian cities were used.

One particular issue is that the cold start profile, *i.e.* the relationship between cold start emission factors and trip distance, is fixed in this approach. It has been shown that this profile is a function of both average speed and ambient temperature (André and Joumard, 2005), *i.e.* lower temperatures and speeds both increase the cold start distance. This effect is accounted for by first correcting the "cold start distance" (derived using phase detection functions) for average speed and temperature and second, application of a generic function to describe the cold start profile. The problem is that these algorithms are based on a limited amount of data, and therefore have unknown reliability. In other words it is unclear which model choices generate the largest potential errors in the modelling of cold start emissions. Further research will be conducted to examine the impact of these model choices.

NETWORK APPLICATIONS

Modelling of the air quality impacts from motor vehicles requires traffic input data for all relevant roads in the road network. Output from transport models is commonly used for this purpose as they provide reasonable road network coverage as compared with more limited availability of measured traffic information (*e.g.* traffic volumes, average speeds). In addition, transport models are needed to make predictions for future situations.

As will be explained in more detail below, output from a macroscopic transport model was used to estimate total annual network hot running and start emissions using link based and trip based data. As the COPERT Australia software was not released yet at the time of this paper, a first order emission inventory for South East Queensland (SEQ) was created by using the hot running emission factors developed for the software

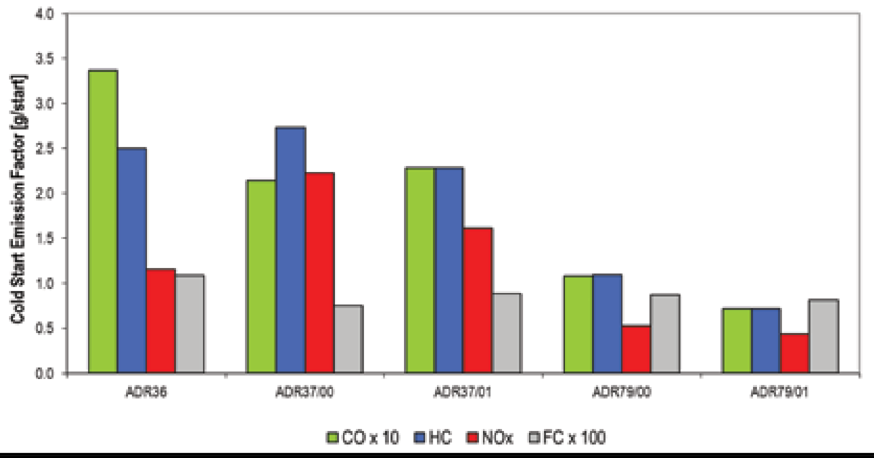

Figure 7. Average Cold Start Emission Factors by ADR Class and Pollutant

Table 3: Total Hot Running and Cold Start Air Pollutant Emissions for SEQ (T y-1)

Pollutant	Hot Running	Cold Start	Total
CO	59,720	31,889	91,609
THC [1]	3,941	3,272	7,213
NOx	29,919	2,383	32,302

1) Evaporative emissions not included.

(Smit and Ntziachristos, 2012) and the cold start emission factors presented in this paper.

The (Queensland) Department of Transport and Main Roads (DTMR) provided transport data for 2011 from the 'Brisbane Strategic Traffic Model' or BSTM (DTMR, 2012a). Network link data for almost 46,000 links for SEQ were used to estimate speed-dependent hot running emissions. The link data provides detailed information on the spatial location of roads (represented by links, A and B nodes) and traffic volumes (vehicles per time period), link length (km) and average speed (km h^{-1}) for each link by main vehicle type (LDV, HDV) and time of day (AM peak, PM peak, off-peak and night time).

One particular challenge is that the vehicle classification required in vehicle emission modelling is much more detailed than the vehicle breakdown in the transport model output (2 vehicle classes). As a consequence, a fleet composition model is needed to generate information on the proportion of total travel (VKT) for each individual COPERT vehicle class (223 in total). Fleet composition models are developed from vehicle registration and vehicle sales data, and they use algorithms for (age-dependent) vehicle use and scrapage rates, as well as base year dependent growth rates. The relative proportions for each COPERT vehicle class are then used to compute composite emission factors that match the classification in the transport model (LDV, HDV). An in depth analysis of Australian fleet data and vehicle use data (e.g. ABS, 2011; BITRE, 2011) provided these weighting factors to compute composite emission factors for LDVs and HDVs for base year 2010.

Trip matrices were used to compute cold start emissions. Trip matrices provide data on the number of trips that are made between traffic analysis zones (TAZs) by main vehicle type (LDV, HDV) and time period of day. In effect, the emission factors in Table 2 are aggregated to LDV cold start emission factors (HDV is assumed to have 0 g $start^{-1}$ emission factors) and then multiplied with the total number of trips per annum to compute total cold start emissions. The results are shown in Table 3. It can be seen that cold start emissions can make a significant contribution to total emissions, but that this depends on the pollutant, varying from 7% (NOx) to 45% (THC).

It is noted that evaporative (THC) emissions are not included in Table 3, as their estimation requires an analysis of the number of parked vehicles and parking behaviour, which is currently ongoing. Evaporative emissions can make a substantial contribution to total THC emissions. For instance, the latest NSW motor vehicle emissions inventory (NSW EPA, 2012) estimates that 50% of total HC emissions is generated by evaporative emissions. It is also noted that parking time and temperature corrections are not yet included in the cold start simulation, and they are expected to impose a net reduction in annual cold start emission predictions. So the cold start predictions in Table 3 should be regarded as conservative estimates.

CONCLUSIONS

This paper presented and discussed the approach that was taken to create cold start emission factors for COPERT Australia, a new and dedicated modelling software for vehicle emissions. The method is based on an analysis of empirical Australian vehicle emissions data, a literature review and a sensitivity analysis using four possible methods (phase detection functions). It was concluded that rather than arbitrarily selecting a detection function method, it would be better to employ a new approach.

The new approach used in COPERT Australia directly combines empirical cold start emission profiles with a trip distance distribution to create technology specific cold start emission factors (g $start^{-1}$). The benefit of the approach is that it fully utilizes Australian emissions and trip distribution data, and therefore should be representative for Australian conditions, at least in terms of a reference emission factor for ambient temperatures of approximately 20°C and higher and a soak time of 12 hours.

These emission factors were used to create a first-order emissions inventory for South East Queensland using output data from a macroscopic transport model. It is estimated that cold start emissions make up a substantial part of air pollutant emissions with cold start to hot running emission ratios of about 0.10 (NOx), 0.50 (CO) and 0.80 (THC), which confirms the importance of cold start emissions for air quality modelling and assessments.

ACKNOWLEDGEMENTS

The Australian Government is acknowledged for commissioning vehicle emission test programs that have collectively provided the (unverified) empirical emissions data used in this research (the Second National In-Service Vehicle Emissions studies, NISE2).

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APPENDIX A – PHASE DETECTION FUNCTION ALGORITHMS

Regression Method:

This approach is a modification of the method used in Smit (2011). The regression approach uses a time-series of paired differences in segmented emissions (g) between hot running and cold start conditions:

$$e(i)_j = \sum_{1}^{m} \left(e_{cold,i,k} - e_{hot,i,k} \right) \div m_j$$

Where e(i)j represents the series of average cold start excess emission values (g) for segments i = 1 to i = n and vehicle class j (which consists of a total of m vehicles), e_{cold},i,k represents the cold start emissions (g) for segment i and vehicle k and $e_{hot,i,k}$ represents the hot running emissions (g) for segment i and vehicle k. It then performs a regression on the data of the form:

$$e_j = \alpha + \beta\, i + \varepsilon$$

where the (100m) segment index i is used as the predictor variable and α and β represent the regression coefficients. Once the coefficients are estimated, the "phase detection function" is computed as follows, where dcold is the cold start distance (m):

$$d_{cold} = -100\, \alpha / \beta$$

Robust (linear) least-squares regression (IWLS) is used in the phase detection function. Data points are iteratively re-weighted in IWLS so that extreme data points (noise) do not overly influence the fit, which is a known problem for (generalised) linear regression (Venables and Ripley 2002). It is noted that Weilenmann *et al.* (2005) also used a regression approach for modal data but in a different way. They fit a linear regression line to the cumulative differences between cold and hot emission profiles in the warm phase. The cold start excess emission follows from the value at which the regression line crosses the ordinate (t = 0). It is unclear how the start of the warm phase is determined and it assumes a monotonically increasing curve.

Standard deviation approach:

$$\sigma_i = \begin{cases} \sqrt{\left(1/(195-i)\right) \sum_{i}^{195} \left(e_{i,j} - \mu_i \right)^2} & if\ i < 195 \\ 0 & if\ i = 195 \end{cases}$$

$$\mu_i = \left(1 / (195+1-i) \right) \sum_{i}^{195} e_{i,j} \quad \forall i \in \{ 1, 2, \ldots, 195 \}$$

$$f_i = e_{ij} - \mu_i - \sigma_i$$

$$N = \{ i \in \{ 1, 2, \ldots, 195 \} : \quad f(i) \geq 0 \ \ and \ \ f(i+1) < 0 \}$$

$$d_{cold} = \left(min(N) + 1 \right) 100$$