Technical Note

USE OF OVERSEAS EMISSION MODELS TO PREDICT TRAFFIC EMISSIONS IN URBAN AREAS

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A previous Technical Note (Smit and McBroom 2009a) has commented on potential discrepancies between traffic emissions predicted by microscopic simulation models and those actually measured under Australian conditions. This Note will explore potential discrepancies between Australian test data, a newly developed Australian emission algorithm and predictions from two commonly used international traffic emission models. These emission models require input that can readily be extracted from macroscopic traffic models. We have found substantial discrepancies, i.e. mean NOx prediction errors for a stretch of freeway are a factor of 1.6 to 2.0 higher for overseas models, when compared to an Australian average speed model that was developed using Australian test data.

INTRODUCTION

Overseas traffic emission models such as COPERT in Europe and MOBILE and EMFAC in the United States are well-known and often used in practice. This is particularly so for the development of urban emission inventories as they require input that can readily be extracted from strategic planning models such as EMME2 (Smit, Dia and Morawska 2009). An important feature of these models is that emission factors (g/km) are a function of average speed, where average speed is defined as the overall speed on a section of road or for an entire journey – hence the term ‘average speed model’. Average speed generally shows a significant (but not perfect) correlation with emissions and fuel consumption, but does not explain all variations in the test data as will be discussed later.

Information on average speed is relatively easy to obtain as it can be sourced from traffic models or travel time surveys. This partly explains its historic and common use in traffic emission modelling. Apart from their own jurisdictions, COPERT and

MOBILE are used all over the world, either directly or in a modified form. For instance, COPERT is also used in South America (Corvalán and Urrutia 2002) and MOBILE is used in Canada (Scott et al. 1997) and Asia (Mukherjee and Viswanathan 2001). In Australia, both COPERT and MOBILE have partly been used in the development of urban emission inventory models (QGEPA 2002).

One important concern, however, is obtaining reliable emissions and fuel consumption output on Australian road and/or vehicle conditions. Both COPERT and MOBILE are based on overseas vehicle emissions datasets and driving behaviour, which do not adequately reflect Australian conditions. For example, Australia has:

- a larger fleet proportion of six/eight cylinder engines and automatic gear boxes;
- a significantly lower fleet percentage of diesel cars;
- a different fuel composition; and
- different emission standards.

This raises concern about the validity of directly using overseas emissions and fuel consumption algorithms in Australian traffic emissions modelling. To illustrate the importance of this issue we have examined – to a limited extent only – prediction errors that result from the use of (calibrated) MOBILE 6 and COPERT IV algorithms in Australia.

AUSTRALIAN TEST DATA

The validity of using overseas models in Australia is tested by comparing COPERT IV and MOBILE 6 emission predictions to observations. Some data preparation and verification is needed before this can be done. We have used recent Australian emissions test data on 18 Australian passenger vehicles and light commercial vehicles (petrol, model years 1998-2002). The vehicles represent a vehicle category prominent on Australian metropolitan roads. These emissions data (Orbital 2005) were collected in an emissions testing laboratory on a second-by-second basis by driving these vehicles over a half-hour real-world driving cycle (speed-time profile) called 'CUEDC-P', which was developed from Australian driving pattern data collected in the field. The CUEDC-P includes arterial, residential, freeway and congested driving conditions. The driving cycle is shown in *Figure 1.*

The mean absolute error (MAE) in instantaneous speed for each vehicle was verified to be less than 2.0 km/h, with an average MAE of 1.14 km/h. This indicates that the 18 vehicles have all been driven in a similar fashion. This means that the second-by-second emissions test data can be aggregated for comparison to overseas emissions models. As a next step, the CUEDC-P cycle was broken up into thirteen stop-go-stop segments, i.e. so-called 'microtrips'. The segmented cycle is shown in *Figure 1*. Five additional driving segments were manually selected from the CUEDC-P cycle to represent 'free-flow driving conditions' and 'very congested driving conditions'. The combinations of microtrips and selected driving segments are referred to as speed-time traces in the remainder of this note.

For each speed-time trace, so-called 'cycle variables' were computed including average speed, distance

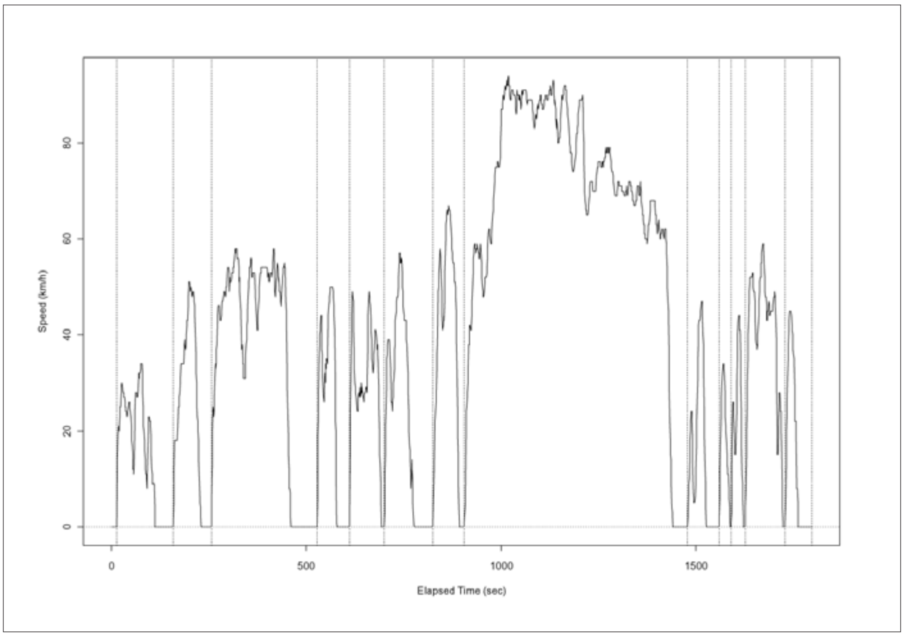

Figure 1
Segmented CUEDC-P driving cycle

driven, proportion idle time and speed noise. An overview of computed values, including road/flow type (residential, arterial, freeway, congested), is presented in *Table 1*. Most cycle variables are self-explanatory, except perhaps for speed noise (σ_v), which reflects the level of speed fluctuation and is computed as in *Equation 1*:

$$\sigma_v = \left[\sum_{t_{start}}^{t_{end}} \left(v_t^+ - \bar{v}_{run} \right)^2 \div T_{run} \right]^{0.5} \tag{1}$$

where v_t^+ represents instantaneous positive speed (i.e. speed>0 km/h) at time t (km/h),

$\bar{v}_{run}$ represents mean running speed (i.e. speed>0 km/h) of microtrip (km/h) and T_{run} represents the number of speed-time points with speed>0 km/h.

Subsequently, second-by-second emissions test data for the 18 petrol vehicles were used to compute total emissions (g) of NO_x for each speed-time trace. Emission factors (g/km) were then computed by dividing total emissions (g) for each speed-time trace by their respective distances (km), as tabulated in *Table 1*.

AVERAGE SPEED BASED EMISSION FACTOR ALGORITHMS

Figure 2 shows observed mean NO_x emission factors (dots) and a fitted Australian Average Speed Model (ASM, solid black line) of the form in *Equation 2*:

$$EF = 0.39 - 0.0037\,v + 0.00006\,v^2 \tag{2}$$

There is substantial variability in observed emission factors for particular mean speeds. This is a well-known characteristic of NO_x traffic emissions. Low correlations between measured and predicted NO_x emissions from petrol cars have been reported in different parts of the world, even when more sophisticated (multivariate) traffic emission models were used than the relatively simple average speed model (e.g. Atjay et al. 2005; Smit et al. 2007). So, accurate prediction of NO_x emissions is a challenging task. As a consequence, the fitted model explains only a small fraction (28%) of the variation in the observations (R^2 = 0.28). The use of additional model variables (e.g. speed noise, power) would improve this, but would make application of the emission algorithm more difficult as data on these additional variables are not readily available from macroscopic transport models or traffic field data.

Table 1
Computed cycle variables for microtrips and driving segments

Microtrip (type*)	Time	Travel time (sec)	Distance (km)	Average speed (km/h)	Prop. idle time (%)	Speed noise (km/h)
1 (Res)	14 : 158	145	0.592	15	32%	7
2 (Res)	159 : 256	98	0.630	23	28%	14
3 (Res)	257 : 527	271	2.617	35	25%	11
4 (Art)	528 : 610	83	0.502	22	40%	12
5 (Art)	611 : 699	89	0.723	29	9%	10
6 (Art)	700 : 824	125	0.717	21	40%	15
7 (Art)	825 : 904	80	0.851	38	16%	18
8 (Fwy)	905 : 1477	573	10.783	68	7%	17
9 (Con)	1478 : 1558	81	0.306	14	42%	15
10 (Con)	1559 : 1588	30	0.150	18	7%	11
11 (Con)	1589 : 1625	37	0.211	21	14%	13
12 (Con)	1626 : 1727	102	1.095	39	5%	14
13 (Con)	1728 : 1796	69	0.265	14	52%	14
14 (Fwy)	1011 : 1133	123	3.049	89	0%	2
15 (Con)	1441 : 1495	55	0.063	4	69%	7
16 (Res)	274 : 332	59	833	51	0%	4
17 (Con)	1637 : 1648	12	171	51	0%	1
18 (Con)	1636 : 1680	45	616	49	0%	6

* Res = Residential, Art = Arterial, Fwy = Freeway, Con = Congested

Figure 2 also shows predictions from COPERT IV (LAT 2005) and MOBILE 6 (US EPA 2001). The model predictions were made for vehicle classes that are subjected to equivalent (or similar) overseas emission standards, i.e. 'Euro 1 petrol passenger car' (COPERT IV) and 'Tier 0 light-duty petrol vehicle, normal emitter' (MOBILE 6)[1].

Figure 2 shows that the shape of the emission factor curves is quite different for the three models. The location of the minimum value and the actual shape and degree of non-linearity of both legs (left and right of the minimum value) of the curves are most relevant in this respect. In fact, the MOBILE 6 model is almost a mirrored version of the Australian model. Whereas the Australian model roughly shows an increase in NO_x emission factors with average speed, the opposite is true for MOBILE 6. This has a large effect on the accuracy of traffic emission predictions, as will be discussed later.

RMSE (root-mean-square-error) is a frequently used measure of accuracy. It translates the differences between observations and predictions (residuals) into a single measure of predictive power (*Equation 3*).

$$RMSE = \sqrt{\frac{1}{n}\sum (e_i)^2} \qquad (3)$$

Here, ε_i is the residual (observation minus prediction) for observation *i* and *n* represents the number of observations. The following RMSE values were computed for the three models:

- ASM Australia 0.08,
- COPERT IV 0.12,
- MOBILE 6 Arterial 0.30, and
- MOBILE 6 Freeway 0.17.

These values confirm what is already visible from *Figure 2*; that is, the fitted Australian model performs best and MOBILE 6 performs worst, when direct predictions of the models are compared.

The fact that the Australian model performs best is not surprising as it is based on the actual observations, whereas the overseas models are not. It does, however, show the value of having an Australian average speed model and it showcases the risks of poor emission predictions when overseas models are applied directly in Australia.

In order to make a fair comparison between the three models, the overseas algorithms have been calibrated with the Australian data. This was done by vertically shifting the emission factor curves and looking for an offset value (g/km) that results in a minimum RMSE value for each model. The following

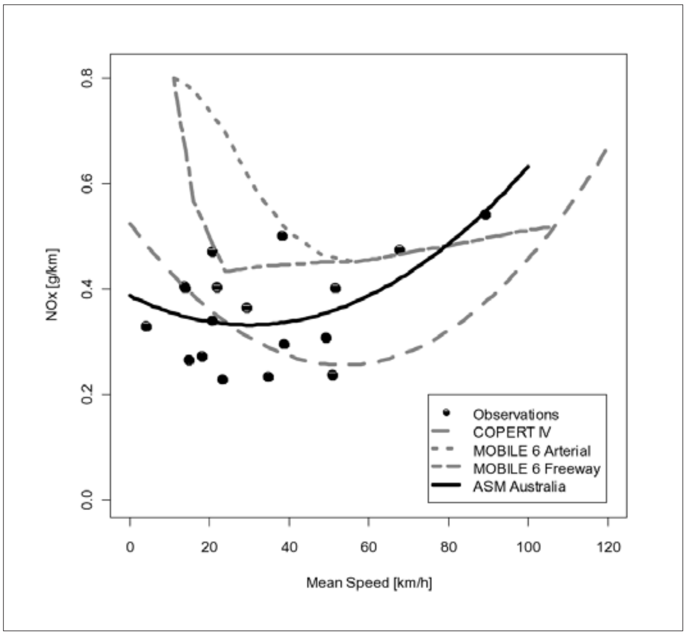

Figure 2
Observed mean NO_x emission factors for light-duty petrol ADR37/01 vehicles, Australian Average Speed Model (ASM), COPERT IV and MOBILE 6 predictions

[1] MOBILE 6 uses discrete emission factors for four roadway types namely 'arterial/collector' (13 speed bins), 'freeway' (13 speed bins), 'freeway ramp' (single emission factor) and 'local roads' (single emission factor). At mean speeds below 11 km/h (7 mph) and above 48 km/h (30 mph) the arterial and freeway emission factors are equivalent. In order to compute an emission factor for every mean speed value, emission factors have been computed through interpolation.

optimum RMSE values were computed for the two calibrated models (offset within brackets):

- COPERT IV 0.12 (+0.03 g/km),
- MOBILE 6 Arterial 0.18 (-0.24 g/km), and
- MOBILE 6 Freeway 0.12 (-0.12 g/km).

The calibrated models are shown in *Figure 3*.

ERRORS IN EMISSION PREDICTIONS

The effects of using the three (calibrated) emission factor algorithms to predict road traffic emissions were further examined by applying them to a (hypothetical) freeway situation with different levels of congestion. The speed-time traces 8 to 15 in *Table 1* were selected to represent different freeway driving conditions.

Firstly, vehicle kilometres travelled or VKT (veh-km/h) were estimated for a 1 km stretch of a 3 lane freeway with a road capacity of 2000 veh/h.lane and a free-flow speed of 120 km/h, using the formula in *Equation 4*:

$$VKT = L \times V \times lanes \qquad (4)$$

where 'L' represents road length (km), 'lanes' number of lanes (-) and 'V' traffic volume (veh/h.lane). Traffic volume was estimated using an Australian congestion function (Akçelik 1991), which quantifies the effects of mean speed on traffic volume. The computation was constrained by traffic jam density (167 veh/km) and maximum (bottleneck) flow rate (equal to road capacity). The results are shown in *Figure 4*. It can be seen that VKT quickly reaches its maximum value when mean speed drops from the free-flow speed, then largely remains stable, and then quickly drops once mean speed falls below 10 km/h, when traffic density reaches jam density.

Secondly, the mean speed for each speed-time trace was used to derive the corresponding VKT from the relationship shown in *Figure 4*. This information, in combination with observed and predicted NO_x emission factors (g/km) for each speed-time trace, was then used to assess prediction errors. We have focussed on two aspects of prediction errors, namely the magnitude and direction of these errors. The methodology used to compute prediction errors is presented and discussed in the Appendix. It is noted that the computations are based on 36 possible combinations of speed-time traces (n = 36).

Table 2 presents an overview of the computed errors.

Directional errors are expressed as a percentage of predictions that show an opposite direction to observed values. It can be seen that directional errors are quite high for all algorithms, which reflects the large degree of scatter in observed NO_x emission factors. Nevertheless, directional errors can be significantly higher, up to 13%, for the overseas algorithms. It is noted that performance of the Australian ASM could probably be improved by developing emission algorithms for specific road types such as 'arterial' and 'freeway', as is done in MOBILE 6.

The mean prediction error of 435 grams/hour of NO_x is lowest for the Australian algorithm and substantially higher for the overseas algorithms

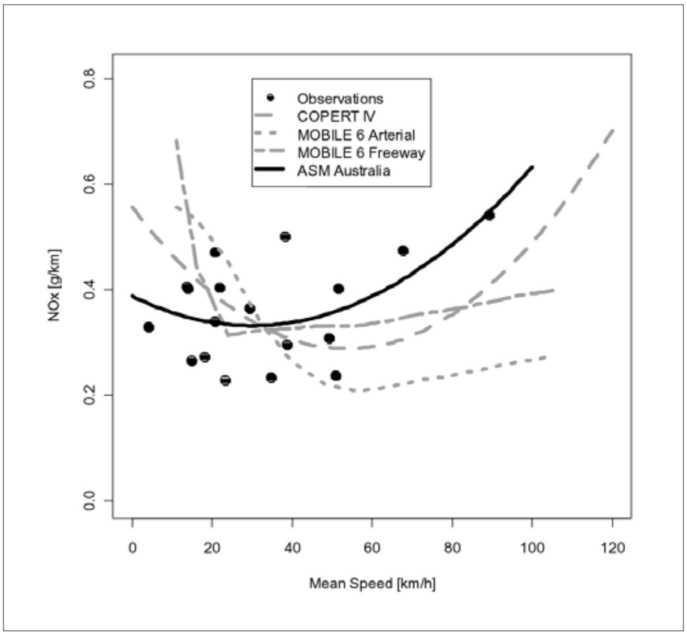

Figure 3
Observed mean NO_x emission factors for LD petrol ADR37/01 vehicles, Australian Average Speed Model (ASM), calibrated COPERT IV and calibrated MOBILE 6 predictions

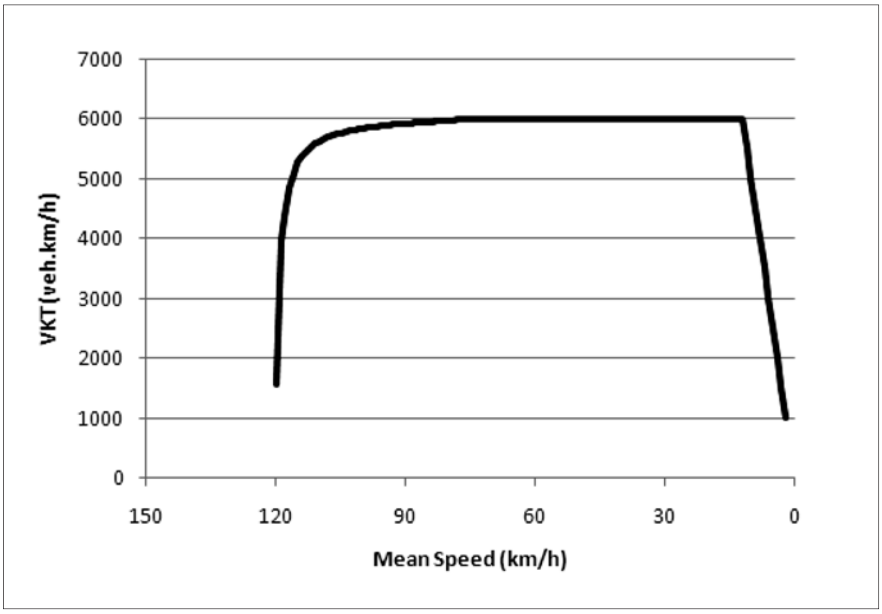

Figure 4
Computed relationship between VKT and mean speed for a 1 km stretch of freeway

Table 2
Overview of the computed errors

Error type	AUS ASM	COPERT IV (calibrated)	MOBILE 6 freeway(calibrated)
Directional error	36%	49%	43%
Mean error (g/h)	435	687	855
Maximum error (g/h)	1217	1809	1837

with a factor of 1.6 for COPERT and even a factor of 2.0 for MOBILE 6. A similar result is found for maximum prediction error, where COPERT IV and MOBILE 6 are both a factor of 1.5 higher. When the mean and maximum observed emissions of 2227 g/h and 3219 g/h are compared to these mean error values, it is clear that the choice of emission algorithm has a large effect on relative mean prediction errors (i.e. 20% (ASM Australia), 31% (COPERT IV) and 38% (MOBILE 6)) and maximum prediction errors (i.e. 38% (ASM Australia), 56% (COPERT IV) and 57% (MOBILE 6)).

DISCUSSION AND CONCLUSION

This preliminary examination shows that direct use of overseas emission functions in Australia can lead to substantial errors when predictions are compared to Australian emissions test data – even when these functions are calibrated with the Australian data. This examination indicates that the European model COPERT IV performs better in freeway conditions than the US model MOBILE 6 when compared to observed Australian emission factors.

It is, however, emphasised that the results presented in this letter are limited in scope. They are based on observations of a small sample of only one specific vehicle class (petrol, light-duty vehicles, limited range of model years) and we have examined only one pollutant (NO_x). As a consequence, the outcomes of this preliminary analysis could be quite different when other vehicle classes and pollutants are examined. It is therefore important to know the overall effect of model choice on prediction errors at traffic stream level, i.e. through analysis and aggregation of the results for all relevant vehicle classes (e.g. diesel cars, trucks) and pollutants. In any case, this work demonstrates that there are clear benefits with respect to prediction accuracy when Australian emission factor algorithms are directly developed from Australian test data.

A remaining issue is that average speed alone may exhibit poor prediction capabilities for particular pollutants, as was shown to be the case for a specific vehicle class and NO_x. A way of dealing with this issue is to add additional variables (e.g. power, speed noise). However, this, in turn, can raise other issues such as limited availability of input data which makes model application impractical. Another option is to develop an Australian model with another model structure, such as a traffic situation model[2].

Yet another approach is to clearly define the appropriate scale of application. For instance, if the average speed based algorithms are applied at link level to compute total emissions for large road networks, or substantially large parts of a road network (e.g. 1 km^2 grid cells), it may be assumed that the (random) error introduced by not fully accounting for link-specific driving behaviour should more or less average out over the links within the area. This is because some links will experience higher than average driving dynamics and some will experience lower than average driving dynamics.

Although it appears reasonable, the validity of this assumption should be verified. This can for instance be examined by predicting emissions within an urban area using a microscopic simulation model to generate traffic data and two emission models, i.e. an average speed model and a more complex power-based emissions model (e.g. Smit and McBroom 2009b) that accounts for the variation in emission factors at a particular average speed. If errors are small, this would imply average speed models are valid for use at area level. If errors are large, this would imply that either more complex models should be used (depending on the aim of the study) or that correction factors should be developed to account for this effect.

We have demonstrated that there is a substantial risk of poor emission forecasting when overseas algorithms (calibrated or not) are directly used to predict traffic emissions and fuel consumption in Australia. This will cause poor infrastructure decisions and poor policy making decisions when left unchecked. We therefore recommend the development of an Australian traffic emission model that can readily interface with macroscopic traffic models and that is based on local and up-to-date test data that truly reflects Australian vehicle emissions and driving behaviour. The best structure for such a model, i.e. an average speed model (similar to COPERT), an average speed/road type model (similar to MOBILE) or a traffic situation model, needs to be examined through a feasibility study, as was discussed in QGDERM (2009).

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[2] Traffic situation models use discrete emission factors (g/km) for certain 'traffic situations'. For instance, the ARTEMIS model (Keller and Kljun 2007) predicts emissions for 280 different traffic situations. These are defined in terms of 'road type' (motorway, trunk road, distributor, collector, etc.), 'area type' (urban, rural), 'speed limit' (30, 40, …, >130 km/h) and 'congestionlevel' ('free-flow', 'heavy', 'saturated', 'stop and go').

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APPENDIX – COMPUTATION OF PREDICTION ERRORS

In order to compare overall accuracy of MOBILE 6, COPERT IV and ASM Australia, aggregate measures of directional error and magnitude of error have been computed. The aggregate measure of **directional error** (D, %) is computed by counting the number of directional errors and dividing them by the total number of relevant speed-time trace comparisons (36 in total), i.e.

$$D = \frac{100\ d_{i,j(-)}}{d_{i,j(-)} + d_{i,j(+)}}$$

$$d_{i,j} = sign\left[\frac{\Delta P_{i,j}}{\Delta O_{i,j}}\right] = sign\left[\frac{VKT_j \times PEF_j - VKT_i \times PEF_i}{VKT_j \times OEF_j - VKT_i \times OEF_i}\right]$$

Here, ΔP_i and ΔO_i represent the difference in emissions (g/h) between two speed-time traces i and j. VKT represents the estimated vehicle kilometres travelled for either speed-time trace i or j (veh.km/h). PEF represents the predicted emission factor (g/veh.km) for either speed-time trace i or j. OEF represents the observed emission factor for either speed-time trace i or j. $d_{i,j}$ represents the directional error for a freeway traffic situation changing from i to j. If positive, then there is no error as both observations and predictions show either a reduction or increase in emission factors. If negative, then observations and predictions show opposite directions. For instance, the predictions show an increase in emissions per vehicle per unit distance, whereas the observations show a reduction. This is clearly an important error.

The aggregate measures of **magnitude of error** are computed as follows:

$$\varepsilon = \frac{1}{n} \sum \varepsilon_{i,j}$$

$$\varepsilon_{\max} = MAX(\ \varepsilon_{i,j}\ )$$

where $\varepsilon_{i,j}$ presents the mean error (g/h) and ε_{max} presents the maximum error (g/h) that was computed. The magnitude of error ($\varepsilon_{i,j}$, grams/hour) is quantified using the following equation:

$$\varepsilon_{i,j} = \left| \ \Delta P_{i,j} - \Delta O_{i,j} \ \right|$$

Here, $\varepsilon_{i,j}$ presents the absolute difference between the observed and predicted differences in emission factors (g/h) between two speed-time traces i and j.

To clarify this method, *Figure 5* provides an example for one pair of speed-time traces.

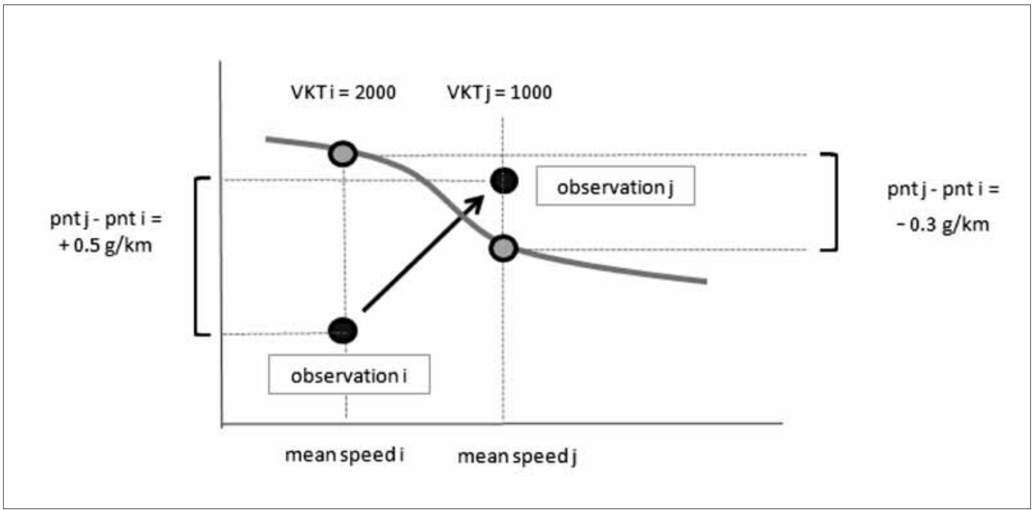

Figure 5 Schematic of method employed to compute prediction errors

Directional error and magnitude of error are then computed as follows:

$$d_{i,j} = sign\left[\frac{0.7\times 1000 - 1.0\times 2000}{0.9\times 1000 - 0.4\times 2000}\right] = sign\left[\frac{-1300}{100}\right] = -$$

$$\varepsilon_{i,j} = \left| -1300 - 100 \right| = 1400$$

This illustrative example shows that there is directional error (model predicts a reduction whereas observations show an increase). It also shows that there is an error of 1.4 kg of NO_x per hour.

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