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Chapter 2

ROAD TRAFFIC EMISSION AND FUEL CONSUMPTION MODELLING: TRENDS, NEW DEVELOPMENTS AND FUTURE CHALLENGES

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Abstract

This chapter investigates current models designed to predict air pollutant emissions and fuel consumption for road traffic. It will consist of two parts: 1) a review of current road traffic emission modelling around the world, and 2) expected direction of further model development (outlook). The review will use a model classification framework that facilitates a structured discussion of model features, complexity, model application and prediction accuracy. The outcomes from the review are then discussed in light of current developments with respect to emission measurements, traffic control and in-vehicle technology.

Introduction

Transport is a major source of air pollution and greenhouse gas emissions around the world, and its significance in this respect is increasing. The problems and issues relating to traffic are (perhaps) surprisingly similar in the affluent nations around the world. From an air quality perspective, road traffic is particularly significant since it emits large quantities of harmful chemicals close to populated areas. In fact, around the world, road traffic is the dominant anthropogenic source of air pollution in urban areas (e.g. Fenger 1999). We can expect this to remain the case as reductions in emissions from individual vehicle (e.g. due to stricter vehicle emissions standards) are at least partially offset by continued growth in traffic and elevated congestion levels.

Emissions from individual vehicles are a function of many, often interacting, variables. First, air pollutant emissions and fuel consumption vary substantially with vehicle design characteristics, which include, but are not limited to:

- vehicle size and weight;
- engine type;
- type of fuel;
- transmission type;
- presence and type of emission control technology;
- presence of auxiliary equipment such as air conditioning; and
- aerodynamic characteristics.

In addition to these vehicle-related factors, the way a vehicle is being driven (driving behaviour) also affects vehicle emissions and fuel consumption. Driving behaviour itself is the result of many factors such as the interaction with road features (speed limits, intersections, road width, road condition, gradient, and so forth), level of congestion, road grade, personal driving style (aggressive, gentle, etc.), gear shift behaviour, use of auxiliary equipment and weather related conditions (ambient temperature, humidity, rain, fog, etc.).

Finally, various other factors impact on emission levels, such as:

- driving mode (cold, hot; running, idling, parked);
- deterioration of engine and emission control components (ageing effects);
- engine tuning and maintenance;
- fuel composition and characteristics; and
- geographic location reflected in e.g. air density and altitude.

Importantly, these factors are often interrelated and may influence different “types of emissions”, namely:

- Hot running emissions: exhaust emissions that occur under "hot stabilized" conditions, which means that the engine and the emission control system (e.g. catalytic converter) have reached their typical operating temperatures.
- Start emissions: exhaust emissions that occur in addition to hot running emissions because engines and catalysts are not (fully) warmed up and operate in a non-optimal manner.
- Evaporative emissions: non-exhaust hydrocarbon losses through the vehicle's fuel system.

For instance, ambient temperature and humidity affect air conditioning use, and thus hot running emissions, but also affect the magnitude of evaporative emissions. Clearly, the many factors that influence individual vehicle emissions make the relationships between road traffic, air pollution and greenhouse gas emissions quite complex.

Furthermore, impact assessment is a multidisciplinary exercise, which adds to the complexity of the subject. This is illustrated in Figure 1, which shows how road traffic exerts its effects through different multidisciplinary steps.

The intensity and spatial distribution of human and economic activity within an area creates a demand for transport. How, where and to what extent this demand is met depends on the supply of transport facilities, i.e. the transport infrastructure. Demand and supply of transport are both reflected in, and are a function of land use. The interaction between supply and demand determines the level and distribution of transport activity in an area, which is the starting point for the modelling of road transport impacts on air quality. The magnitude of emissions and its spatial and temporal distribution are determined by fleet characteristics, traffic activity and the quality of traffic flow (traffic performance). Once vehicular emissions are released into the atmosphere, dispersion processes transport and dilute these emissions. In addition to dispersion, pollutants can also undergo physical and chemical transformation and deposition. Depending on location, these processes results in certain ambient concentration levels, the extent of which is a function of meteorological conditions, topographical characteristics and distance between source and receptor. The level of exposure to air pollutants depends on ambient concentration levels and where sensitive receptors (e.g. population) are situated in time and place. For instance, health effects depend on exposure-effect relationships, which may be obtained from epidemiological or clinical studies. The magnitude of the combined effects on health, structures and the environment subsequently determine the economic effects (costs) of air pollution.

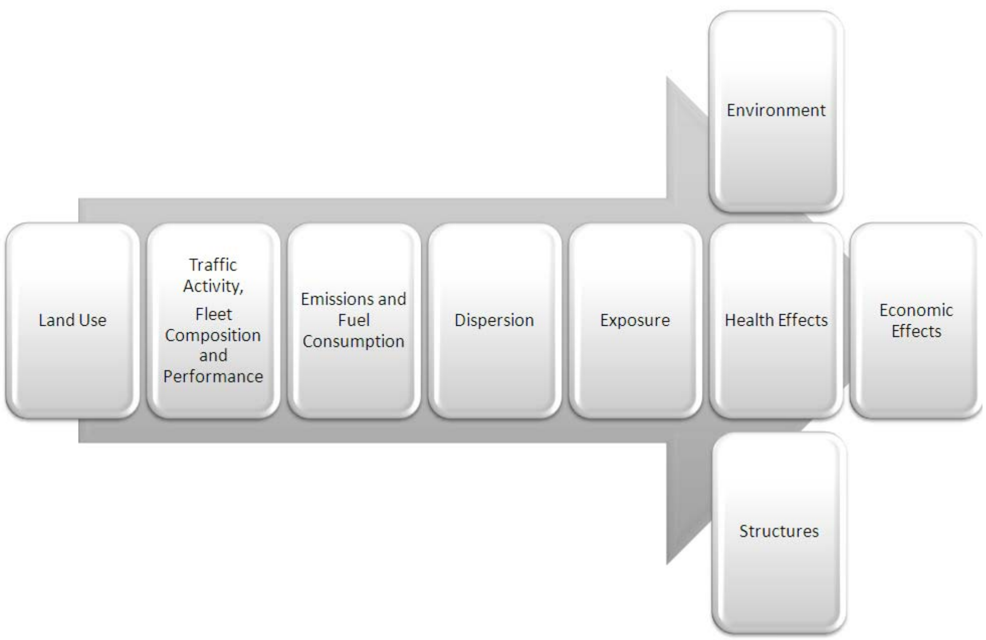

Figure 1. Multidisciplinary Relationships Between Road Transport and its Effects.

This chapter will focus on the second and third step in the assessment of air quality and greenhouse gas impacts from road traffic, namely the generation of air pollutant emissions and greenhouse gases from road traffic. It is noted that in the remainder of this chapter, for readability purposes, the term "emissions" is used as a generic term for emissions of air pollutants and greenhouse gases, the latter which is strongly correlated to fuel consumption.

Generic Structure of Emission Models

Due to the complex relationships between road traffic and air pollution, models (Smit et al. 2008a) are commonly used to predict and evaluate impacts and determine solutions. As will be seen later, this occurs at different scales, ranging from local road projects (e.g. hot spot analysis, traffic management) to entire urban or regional transport networks and even national or global emission inventories. Before current emission models are discussed, this section discusses relevant terminology and some generic aspects of emission models:

1. empirical base of emission models;
2. generic computation procedure;
3. vehicle classification scheme; and
4. modelling of driving behaviour.

Empirical Base of Emission Models

Emission models are developed from emission measurements. There are different emission measurement methods available, namely laboratory engine bench testing, laboratory chassis dynamometer testing, on-board measurements, near-road measurements and tunnel studies. A review of emission models (Smit, 2006a) revealed that the majority of current emission models are based on laboratory emission testing using driving cycles[1], although different driving cycles are used in different models. An advantage of laboratory measurements is that they are conducted under controlled conditions. This enables investigation of specific aspects that influence emissions such as driving pattern and ambient temperature. A disadvantage of this method is the limitation on the number of vehicles or engines that can be tested due to time and budget constraints. As a consequence, certain types of vehicles may not be adequately reflected in the test data. For instance, owners of high emitting vehicles[2] tend not to register their vehicles, thereby reducing the chance for inclusion in a test programme. In addition, emissions from high-emitting vehicles are much more variable than emissions from normal emitters and thus require a large sampling fraction to obtain reasonably accurate emission estimates (Schulz et al., 2000). So, models based on laboratory test data are potentially biased and may significantly underestimate traffic emissions. This issue generally seems to receive more attention in the USA than in Europe, and only US models explicitly model high emitting vehicles.

[1] A driving cycle is a speed-time profile that is assumed to be representative of (a mixture of) certain traffic and road conditions in a particular geographic area, and which has been synthesized from a set of driving patterns.

[2] These vehicles have very high emissions due to equipment malfunctioning (e.g. less-robust emission controls, neglect of maintenance), tampering or incorrect repairs (e.g. fifty times higher than normal emitters as reported by Barth et al., 2000). This appears to be a significant issue as several (remote sensing) studies (e.g. Zhang et al, 1995; Singh and Huber, 2000) have shown that on-road vehicle emissions are highly skewed, which effectively means that a small proportion of the fleet (20%) make up a large proportion of the total traffic emissions (60-80%).

Laboratory vehicle exhaust emission testing may be conducted using tedlar sample bags (denoted as “bag measurement”) that are analysed after completion of the driving cycle, or may be conducted using continuous measurement at a high time resolution (typically 1-10 Hz) . As it is the method prescribed by emission legislation around the world, bag sampling has traditionally been the dominant approach. As a consequence, a large body of bag test data is available and these data have traditionally been used in the development of emission models. The second method of continuous measurements has become increasingly common for emission rate calculation and engine development. There are some additional aspects that specifically concern this second method such as correction for the time lag and mixing dynamics in the sampling and analysis system before measured emission values can be correctly correlated with driving conditions (Atjay and Weilenmann, 2004). Continuous test data is required for the development of emission models that operate at a high temporal and spatial resolution, as will be discussed later.

Laboratory measurements were traditionally based on “standard” (vehicle) driving or (engine) test cycles (e.g. FTP, NEDC, ESC), but in time have included driving or test cycles that are believed to better reflect real-world driving conditions (“off-cycle”), and therefore emissions (e.g. CADC, AUC, ETC). It has been reported that emission factors based on the standard driving cycles for light-duty vehicles underestimate emissions in “real-world” driving by up to 50-60% (Joumard et al., 2000), or even higher (Watson, 1995). On the difference between standard (steady-state) engine tests and real-world driving, Rexeis et al. (2005) report errors for NO_x emissions of heavy-duty vehicles between about -30% to +190%. Thus, use of standard cycles only in the development of emissions models may lead to biased emission models.

In addition to dynamometer testing, researchers have used vehicles with on-board measurement systems to collect emissions and driving pattern data while they are driving on the road. Although research of this sort has provided valuable insights in real world vehicle emissions, it has traditionally not been used in the development of traffic emission models. This may have been due to the costs, the size and weight of these on-board systems, detection limits and possible data quality issues (Elst, Smokers and Koning, 2004). This, however, appears to be changing now and developments of improved new systems are being reported (North et al., 2005). Further advances in measurement technology such as portable on-board instruments (Frey, Unal and Chen, 2002) show increased use in general (El-Shawarby et al., 2005; Qiao et al., 2007) and increased use of on-board test data in emission models, particularly over the last few years (US EPA, 2002; Panis et al., 2006; North et al., 2006; Krishnamurthy et al., 2007; ISSRC, 2008). On-board testing is particularly interesting for developing nations as a relatively cost-effective way to generate real-world test data and calibrate models (ISSRC, 2008). However, measurement on a large number of vehicles can still be restricted by labour time and costs, particularly for older vehicles (North et al., 2005).

Other methods such as remote sensing (e.g. Ekström et al., 2004), tunnel studies (Staehelin et al., 1998) and on-road or near-road modelling (e.g. Morawska et al., 2001) are commonly used for emission model validation purposes and have contributed to an increased understanding of model accuracy and real world emission behaviour of vehicles (e.g. high emitters). There are, however, some issues with these approaches that complicate its direct use in emission models such as a limited range of operating or traffic conditions.

Generic Computation Procedure

Three levels of analysis can be distinguished for prediction of vehicle emissions:

- vehicle;
- traffic stream (road link); and
- network.

Irrespective of the level of analysis, total emissions (E, unit mass) for moving vehicles are predicted by multiplication of an emission factor or emission rate with appropriate traffic activity data for each vehicle class. Emission factors quantify the amount of pollutant emitted and they are usually expressed as mass per unit distance (e_x) at link and network level, although others such as mass per kg of fuel burned (e_f) may be used instead. Emission rates are expressed as mass per unit time (e_t) at vehicle level, as will be seen later in this chapter. The corresponding traffic activity data follows from these units, i.e. vehicle kilometres travelled (VKT[3]), total fuel consumption or total time spent in particular driving conditions (e.g. idling). As will be discussed later, the spatial resolution for e_x is typically restricted to a section of road (link) or an entire network area and e_t is typically used at higher spatial resolutions.

For parked vehicles (with engines off), start and evaporative emissions are computed using emission factors that align with the required input data, i.e. mass per start (cold and hot start), mass per engine shutdown event (hot soak) and mass per hour of day (diurnal, resting loss).

Vehicle Classification

We have seen before that vehicle design characteristics significantly impact on emissions and fuel consumption. A vehicle classification scheme is normally used in emission modelling to take differences in vehicle design characteristics into account. Given the large number of vehicle design characteristics, an almost infinite number of vehicle classes could be defined. However, the level of detail in vehicle classification should be comprehensive (i.e. include all important classes[4]) as well as practical (i.e. level of detail that matches available data on fleet or traffic composition). In addition, a vehicle classification scheme should be up-to-date.

In practice, vehicle technology classes are usually defined by a taking into account a limited number of factors such as “main vehicle type” (e.g. passenger car, light-commercial vehicle, motorcycle, articulated trucks, buses, etc.), “fuel type” (e.g. diesel, petrol, LPG) and “emission standards”. However, more detailed vehicle classification schemes are sometimes used. For instance, the VERSIT+ model (Smit et al., 2007a) also considers vehicle weight, fuel injection technology, emission reduction technology and type of transmission and the

[3] At road level, VKT is computed as the product of road length (km) and traffic volume (vehicles/hour).

[4] It is noted that in reality only a few specific vehicle classes dominate traffic emissions due to their relatively high emission levels and/or high usage. For instance, Smit (2006b) illustrated that about 70% of mean traffic NO_x emissions are caused by only three main vehicle classes, i.e. diesel and petrol passenger cars and articulated trucks. This implies that a vehicle classification scheme should at least consider the most important classes.

CMEM model (Barth et al., 2000) also uses power-to-weight ratio, mileage, model year, after-treatment technology and emitter type (normal, high emitter) as classification variables. The choice for classification variables generally appears to reflect an established but arbitrary decision process, although in some cases it may actually involve statistical analysis to group vehicles according to their emission characteristics (Fomunung et al., 2000; Rakha et al., 2004).

With respect to practicality it is noted that the more detail that is used in the vehicle classification scheme, the larger are the demands that are imposed on the traffic input data. This is because a similar breakdown of VKTs by vehicle class is needed to be able to compute road traffic emissions. In practice, detailed information is, however, often not available. Traffic models, for instance, commonly generate traffic volume data for just two vehicle classes ("light", "heavy"). In addition, there is a need to make future predictions on fleet composition. As a consequence, fleet composition models are needed to generate information on the proportion of total travel for each individual vehicle class in an emission model. Fleet composition models take into account vehicle sales, scrapage rates, growth rates and vehicle activity (e.g. mean annual VKT), which are a function of vehicle age, calendar year or (vehicle) model year (e.g. Keller and Kljun, 2007). These proportions or "weighting factors" are then used to compute composite emission factors or emission rates reflecting a less detailed vehicle classification scheme that matches the available traffic input data.

As will be discussed later, emission models can be "incomplete" because they predict emissions for specific vehicle categories only (e.g. passenger cars) or because they are outdated (e.g. based on test data that do not reflect the latest developments in vehicle technology). Use of incomplete models introduces errors. It effectively restricts emission prediction to a specific part of a traffic stream, and additional models would be needed to estimate total traffic emissions. So, from a practical point of view, models with a comprehensive vehicle classification scheme are most useful for model users.

Modelling of Driving Behaviour (Model Classification)

As was discussed before, the way in which a vehicle is being driven on the road is affected by many factors. Given the almost infinite number of combinations of driving conditions and vehicle characteristics (e.g. power to mass ratio, vehicle size), a large variety in driving behaviour is observed in the real world (Holmén and Niemeier, 1998; Smit, 2007b), which is very specific in terms of time and location (Brundell-Freij and Ericsson, 2005). Driving Behaviour is usually measured and quantified through a speed-time profile, which can be either a driving pattern[5] or a driving cycle. An example of a driving pattern is provided in Figure 2.

[5] A driving pattern is defined as a speed-time profile that has been recorded (measured) on the road or generated by a traffic model. In this chapter the difference between a driving pattern and a driving cycle is not relevant.

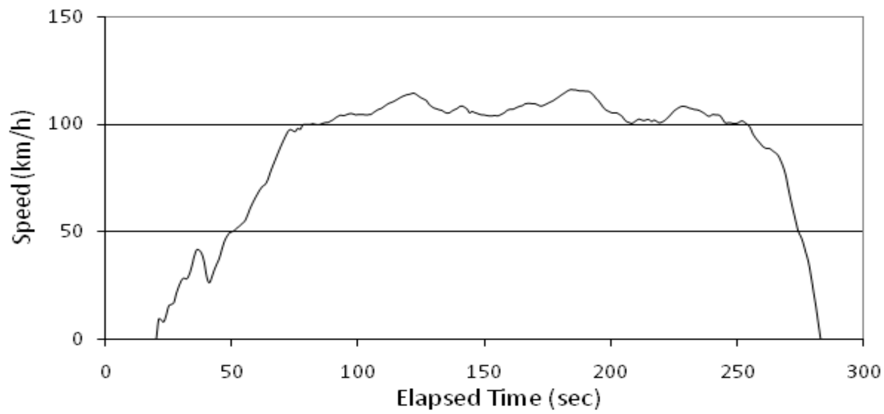

Figure 2. Example of a Driving Pattern.

The characteristics of a particular speed-time profile are commonly described (i.e. quantified) by statistics called "cycle variables" such as average speed, number of stops per kilometre, mean acceleration, percentage idle time, mean acceleration power, etc. (e.g. André et al., 2006). It is noted that other relevant aspects of driving behaviour such as gear shift profiles exist as well, but they are not commonly available, as will be discussed later.

In general, the level of *model complexity*, i.e the extent to which influencing factors are incorporated in an emission model, depend on the actual (type of) emission model that is considered.

For a structured review of emission models, it is useful to consider a classification framework. In line with the classification used by Smit et al. (2008b), emission models are classified in terms of the way driving behaviour is incorporated in the model. The following categories of emission models can then be distinguished:

- models that have incorporated speed-time profiles in the development phase of the model (Type 1);
- models that generate speed-time profiles as part of the emission modelling process (Type 2); and
- models that require speed-time profiles data as input (Type 3).

These three main model types will be used and discussed in the next section. Typically, Type 2 and 3 models are well suited for analysing changes to emission levels at the local level (e.g. intersections, small networks), whereas Type 1 models are better suited to operate at a larger scale (e.g. urban regions, small areas) (Smit et al., 2007a).

Review of Current Traffic Emission and Fuel Consumption Models

Possibly the earliest emission model was developed by Rose et al. (1965) who found that the empirical relationship between HC and CO emissions (pounds mile^{-1}) and mean journey speed less than about 80 km/h was best satisfied by using a power function. Since then, considerable work has been conducted in the field of emission and fuel consumption modelling, resulting in a large number of models available to model users today.

The development of emission and fuel consumption models has undergone significant changes over the last forty years or so. Not only have models become increasingly complex and detailed, as will be shown in this section, also the number of models has increased significantly. In time, specific types of emission models have become more comprehensive and detailed with respect to simulation of driving behaviour (type 3A) and the number of pollutants and vehicle classification (all types). The last factor is in response to an ongoing diversification in fuels (e.g. biofuels) and vehicle types (e.g hybrids, SCR trucks) in on-road fleets. As will be seen later, there is at this time no emission model that provides a detailed simulation of all aspects of traffic emissions at all scales, although some models are close to achieving this.

This section reviews current emission and fuel consumption models. As models quickly become outdated due to ongoing changes in fleet composition, the focus of this chapter will be on models that are either under development or that are used in practise, regularly updated and actively maintained. Although it is not possible to discuss all specific models that are developed around the world, this chapter is comprehensive in that it discusses all relevant model types. As mentioned in the previous section, the model types follow from earlier work (Smit et al., 2008b).

Type 1 Models

Driving cycles are fundamental building blocks in the development of Type 1 models. As was discussed before, they form the basis for emissions testing data, which is subsequently used to develop distance-based emission factors (g km^{-1}) or fuel-based emission factors (g kg^{-1} of fuel). Three subtypes can be distinguished:

- 1A Model “aggregate model”: emission factors are constant, as is the case for area-wide and fuel-based models.
- 1B model “average speed model”: emission factors are a function of one (continuous) driving pattern variable, i.e. average speed.
- 1C model “traffic situation model”: emission factors are defined in terms of discrete quantitative or qualitative descriptions of a particular traffic situation.

The Type 1A Model

The Type 1A aggregate models use a top-down approach and are applied at low spatial (e.g. national, state, area) and temporal resolution (e.g. year). VKT-based models combine data on total VKT (derived from for example national statistics) and a single distance-based emission factor to compute total area emissions (e.g. AGO, 2003; Lyons et al., 2003; Gerard et al., 2007). Similarly, fuel-based models use data on total fuel consumption and fuel-based emission factors to compute total area emissions (e.g. Singer and Harley, 1996; IPCC, 1996; Pokharel, Bishop and Stedman, 2002; Davies et al., 2007; Guo et al., 2007).

The Type 1B Model

The Type 1B model is commonly referred to as average speed emission model. Emission factors (g km^{-1}) 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. Average speed shows a significant correlation with emissions and fuel consumption (e.g. André and Hammarström, 2000). In addition, information on average speed is relatively easy to obtain as it can be sourced from traffic models or travel time surveys. This (at least partly) explains its common use in emission modelling for a long time (e.g. Kurtzweg, 1973; Evans, 1978), as will be seen later.

Although several average speed models exist around the world (e.g. Singh and Huber, 2000; Reynolds and Broderick, 2000; Park et al., 2001; Pekol et al., 2003; Noland and Quddus, 2006), the primary Type 1B emission models currently in use are MOBILE (US EPA, 2008a) and EMFAC (CARB, 2008) in the United States and COPERT in Europe (LAT, 2008). These models are also used, possibly in a modified or augmented form, in other countries. For instance, COPERT is used in South-America (Corvalán et al., 2002) and MOBILE is used in Canada (Scott et al., 1997) and Asia (Hao et al., 2000; Mukherjee and Viswanathan, 2001). In addition, (part of) these models are sometimes incorporated as sub-models in other models (Mellios et al., 2006) or (partly) used in the development of new models (QGEPA, 2002; ISSRC, 2008).

One characteristic of average speed models is that they have become comprehensive in the number of pollutants, vehicle categories, influencing aspects and types of emissions that are covered (i.e. increased complexity). For instance, original average speed models (e.g. Evans, 1978) predicted emissions for a specific vehicle class (e.g. catalyst petrol car), emission type (e.g. hot running) and certain regulated pollutants (CO, HC, NO_x) only. In contrast, COPERT IV now considers 218 vehicle classes including new technology vehicles (hybrids) and emerging fuels (biodiesel), 122 pollutants and greenhouse gases including emerging ones (e.g. active particulate surface area, particle number by size range), correction for several aspects (e.g. deterioration, fuel quality, road gradient, loading) and all types of emissions (hot running, start, evaporative) in its modelling process.

However, treatment of driving behaviour effects remains somewhat simplistic in average speed models. To a certain extent, average speed models take driving dynamics into account as lower mean speeds are naturally the result of, for example, more speed fluctuation and idle time. But driving dynamics are not explicitly modelled and this may introduce substantial errors in the emission predictions at the local scale, as will be discussed later. For instance, Smit et al. (2007a) showed that NO_x emissions from an average Euro 3 petrol car could vary between about – 80% to + 200% around the COPERT estimate for an average speed of 60 km/h, depending on the driving pattern. Others (Negrenti, 1999) reported a difference in emissions of up to a factor of 4 for the same mean speed with different levels of speed fluctuation. This implies that application of current travel speed models is valid as long as level of speed fluctuation does not substantially depart from the values inherently used by the model. However, information on the level of speed fluctuation for each mean speed in average speed models is not readily available from model documentation and requires additional driving cycle analysis (e.g. Smit et al., 2008b).

Another issue is the common use of a single (mean) speed for all vehicles on a section of road. In reality a distribution of average speeds would apply to a traffic stream. Smit et al. (2008a) showed that this can potentially lead to substantial errors (up to 75%) in road link emissions. This issue can be addressed by considering average speeds of individual vehicles, either by using a mean speed post-processing method, traffic field data or an appropriate traffic model.

The Type 1C Model

The type 1C traffic situation models use discrete emission factors (g km^{-1}) for certain "traffic situations", which are defined either quantitatively (set of quantitative variables) or qualitatively (verbal descriptions). For instance, TNO (Veurman et al., 2002) developed a quantitative traffic situation model for passenger cars in freeway driving conditions. Emission factors are provided for nine congestion classes, which are defined in terms of (ranges of) traffic volume, space mean speed and speed limit. Smit et al. (2008a) extended this model and developed a discrete quantitative emission model for both urban and freeway conditions and for all major vehicle classes. The majority of traffic situation models are, however, qualitative models (e.g. Neylon and Collins, 1982; Anyon et al., 2000; Keller, 2004; Klein et al., 2006; INFRAS, 2007). Similar to type 1B models, type 1C models have become more complex in time. For instance, early models only used a few traffic situations, whereas others the latest models are quite comprehensive. For instance, Neylon and Collins (1982) and Carnovale et al. (1997) used only four traffic situations (freeway, arterial, residential and minor roads, congested), whereas the ARTEMIS model (Keller and Kljun, 2007) uses 280 traffic situations[6].

Traffic situation models require information on vehicle kilometres travelled and determination of which particular traffic situation apply to which specific road link(s). Application of qualitative traffic situation models may present some difficulties with respect to the last point, as the boundaries between traffic situations are in some cases not clearly established. For instance, the extent to which "stop-and-go" conditions apply to particular links in a network, or the decision that perhaps another traffic situation would be more suitable, is a matter of opinion of the model user. This is not an issue for quantitative traffic situation models because traffic situation boundaries are clearly defined.

Type 2 Models

Type 2 "traffic variable" emission models generate (simplified) driving pattern data as a function of a number of traffic variables relating to traffic characteristics (e.g. traffic volume, average speed, traffic density, queue length) and road infrastructure characteristics (e.g. link length, number of lanes, free-flow speed, type of intersection, signal settings). These driving patterns are then combined with instantaneous (e.g. Matzoros, 1990; Coelho et al., 2005) or fundamental driving mode (Akçelik, 2006) emission rates (g s^{-1}), possibly derived from other (Type 3) emission models, or are used to compute correction algorithms for incorporated emission factor tables (g km^{-1}) derived from other (Type 1) emission models (e.g. Negrenti, 1999).

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[6] 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^{-1}), and congestion level ("free-flow", "heavy", "saturated", "stop and go").

Type 3 Models

Type 3 models have been developed since the 1970s. Over recent years, international research has focused more strongly on the development of these emission models as it is generally believed that this will lead to more accurate emission assessments at local scale compared to more aggregate models. However, emission model prediction accuracy is an area that requires more research, as will be discussed later. Two main types of Type 3 models can be distinguished:

- 3A Model “cycle variable model”: emission factors or rates are a function of specific driving pattern variables at a high resolution (several seconds to several minutes).
- 3B model “modal model”: emission rates are a function of specific engine or vehicle operating modes at the highest resolution (typically one to several seconds).

As will be seen later, Type 3 emission models have generally developed from relatively simple models to more complex ones. This is not only the case with respect to their computation of driving behaviour effects on emissions, but for some particular models also with respect to other aspects. For instance, early modal models typically predicted hot running emissions of regulated pollutants from light-duty vehicles only (e.g. Kunselman et al. 1974; André and Pronello, 1997). Some recent modal models are still limited in a similar way (e.g. Krishnamurthy et al., 2007), but others are more comprehensive. For instance, CMEM now considers 31 vehicle classes (cars, trucks, petrol, diesel), correction for several aspects (deterioration, high emitters) and both hot running and start emissions in its modelling process. Although modal emission models have become substantially more comprehensive, they generally do not match current average speed and traffic situation models on certain aspects such as number of pollutants and comprehensiveness with respect to types of fuels and emissions included. An exception is the anticipated modal MOVES model (US EPA, 2008b), which will replace the average speed model MOBILE 6.2. MOVES will have the same functionality as MOBILE plus additional capabilities (energy consumption, GHGs, well-to-wheel). It will include many vehicle types (e.g. conventional, hybrids, electric) and fuels (e.g. conventional, E85, M85, electricity).

The Type 3A Model

Type 3A “cycle variable” models require driving pattern data to quantify selected cycle variables and possibly other variables, which are then used to estimate emission factors or emission rates (expressed as g km^{-1} or g s^{-1}) for different vehicle classes. The temporal resolution depends on the length of the driving patterns on which the model is based, which could be short driving pattern segments of several seconds, stop-go-stop segments or entire driving cycles. They could be described as average speed models with additional model variables to take speed fluctuation into account. Type 3A models are not new, although they have become more sophisticated in time.

Following earlier work by Evans, Herman and Lam (1976), the PKE-average speed model was developed by Watson and co-workers (Watson et al., 1982). The model computes emissions as a function of average speed, idle time and “positive acceleration kinetic energy” or PKE. Recent examples of Type 3A models are MEASURE (Fomunung et al., 2000;

Hallmark et al., 2002), NEMO (Rexeis and Hausberger, 2005) and VERSIT+ (Smit et al., 2007a). MEASURE predicts instantaneous emission rates (g s^{-1}) for different light-duty vehicle classes as a function of 114 cycle and vehicle-related variables (e.g. transmission, mileage), which depend on the pollutant considered. NEMO uses five cycle variables (average speed, maximum and minimum speed, average acceleration and deceleration) and vehicle specifications to compute the cycle average engine power, which is subsequently used to compute emission factors (g km^{-1}) for different model classes. VERSIT+ computes emission factors (g km^{-1}) using multivariate regression functions that incorporate several cycle and vehicle-related variables (e.g. mass) for different vehicle classes. It uses statistical optimisation software to select the best combination of a pool of fifty driving cycle variables and also predicts confidence intervals.

The IVE model (ISSRC, 2008) uses instantaneous data on speed, acceleration and road grade to estimate vehicle specific power (VSP) for each second of driving as well as another variable called engine stress. Engine stress reflects mean power over the last 20 seconds of driving, and uses derived instantaneous engine speed in its computation. VSP and engine stress are used to correct for (binned) driving behaviour effects on average "base" emission levels.

The input data requirements for Type 3A models are similar to Type 3B models. The advantage of Type 3A models is believed to be enhanced prediction accuracy as Type 3A models are typically based on substantially larger bodies of emission test data then Type 3B models, as will be shown later. This large body of test data is believed to better reflect the large variability in vehicle emissions.

The Type 3B Model

Classical "driving mode" emission models have been around for a long time (e.g. Ludwig, Sandys and Moon, 1973; Benson, 1989; Taylor and Young, 1996). Here, emissions are not estimated for each second of driving, but rather for each "fundamental driving mode" (e.g. cruise, idle, acceleration, deceleration). The emissions module in the Type 2 SIDRA Intersection model (Akçelik, 2006) and other models (Zito and Taylor, 2001; Midenet et al., 2004) are current examples of such models.

In the 1970s and later, instantaneous emission rates were computed using (continuous) empirical analytical functions that used instantaneous speed and acceleration as variables (e.g. Kunselman et al., 1974; Kent and Mudford, 1979; Cernuschi et al., 1995). More recent examples of this type of model are the VT-micro model (Rakha et al., 2004) and a model developed by Panis et al. (2006).

A few decades ago modal models often consisted of discrete two-dimensional empirical lookup tables for emission rates (g s^{-1}) with rows representing a "speed" interval and the columns representing an "acceleration interval[7]" (e.g. Kent et al., 1982; St. Denis and Winer, 1994; André and Pronello, 1997).

From this work, a more theoretical approach emerged where instantaneous emissions are modelled as a function of the engine power needed to propel a vehicle (e.g. Post et al., 1985). Model variables include instantaneous speed and acceleration and possibly vehicle variables such as engine capacity, vehicle mass, road gradient, aerodynamic drag coefficient and frontal

[7] Expressed as "acceleration" or "acceleration times speed".

area. Examples of current power-based are the Australian CVEM (Leung and Williams, 2000) and SIDRA TRIP (Açkelik and Besley, 2003). Another example is the MOVES model which uses instantaneous speed and vehicle specific power (VSP), the latter which is computed as a function of instantaneous speed, acceleration and road grade (Sonntag and Gao, 2007). VSP is also used in other models to estimate instantaneous emissions directly (e.g. Coelho et al., 2006).

Another recent modelling approach involves the use of artificial neural network models. Dia and Boongrapue (2008) developed a neural network model to predict fuel consumption and emissions for individual vehicles using speed, acceleration, air fuel ratio and torque as explanatory variables. These workers compared the neural network model with simple/multiple/non-linear and hybrid regression techniques, based on the same laboratory test data, and demonstrated superior prediction accuracy of the neural networks over the other regression-based approaches tested. Smit and McBroom (2009a; 2009b) are currently developing a high-resolution traffic emission model that is based on (n-order) autoregressive multivariate regression functions for individual vehicles in a traffic stream. Model variables include traditional variables such as instantaneous speed, acceleration and power, but also newly developed variables that quantify the change in power and oscillation in either speed or power over a pre-defined period of time prior to the point in time for which the prediction is made. These variables aim to quantify and include "operating history effects" into the model. Preliminary results show that the new modelling approach delivers satisfactory results in terms of model accuracy, reliability and robustness (e.g. R^2 ranging between 0.62-0.85 for NO_x and 0.88-0.94 for CO_2).A more complex approach that has emerged more recently computes instantaneous (engine-out or tailpipe) emission rates (g s^{-1}) as a function of engine variables such as engine speed (rpm) and engine load (torque) or brake mean effective pressure and change in manifold pressure and possibly other variables such as injection timing, oil temperature, air-to-fuel ratio and operating mode (soak time, stoichiometric operation, enrichment, enleanment)[8]. These relationships can be incorporated in the model as (discrete) emission matrices (e.g. Koupal and German, 1995) or as continuous algorithms (e.g. Zalinger, Ahn and Hausberger, 2005). Additional modules are usually required to simulate gear shift behaviour and to compute instantaneous engine load and engine speed from input data such as vehicle parameters (e.g. gear ratios, wheel size), speed-time data, road gradient data and use of accessories (e.g. air conditioning)[9]. In addition, modules that simulate catalyst reduction efficiency may be included to account for the effects of emission control technology. Examples are the European PHEM (Hausberger et al. 2003a; Zalinger et al. 2005; 2008) and DIVEM (Atjay et al. 2005) models and the US CMEM model (Barth et al., 2000; Barth et al., 2004).

A characteristic feature of modal models is that they require a substantial amount of input data, such as instantaneous (usually second-by-second) speed-time data and information on vehicle-specific parameters. The implications of this will be discussed later.

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[8] It is noted that complex models such as ADVISOR (Markel et al., 2002) exist that provide detailed simulations of predefined vehicle configurations (e.g. conventional, hybrid, fuel cell) in different driving conditions. However, these models are not used to estimate traffic emissions, but rather are vehicle system analysis tools used for vehicle system optimisation and impact assessment of changes to a particular vehicles aspects.

[9] There are also models that directly require engine-related variables as input (e.g. Krishnamurthy et al., 2007), making their application to estimate traffic emissions difficult.

Overview of Model Features

Table 1 (next page) presents an overview of various modelling aspects for 35 different models that have been developed over time. The information has been gathered from available literature and from personal correspondence with model developers. A number of interesting observations can be made from table 1. First of all it is clear that the complexity of emission models has clearly increased in time, and this is the case for all model types. This increasing complexity is reflected in the increasing number of vehicles types, fuel types, pollutants and emission types considered in the models. For instance, emission models developed in the 1970s and 1980s generally predict hot running emissions of criteria pollutants from light-duty petrol vehicles only, using test data from standard driving cycles. In contrast, current models generally include many more vehicle types including heavy-duty vehicles and motorcycles, other fuels such as diesel, additional pollutants and fuel consumption, other types of emissions and are (at least partly) based on real-world driving behaviour.

Similarly, the size of the test database has generally increased in time with models of the pre 1990s typically based on less than 100 vehicles, whereas more recent Type 1B, 1C and 3A models are typically based on thousands of test vehicles. This is graphically shown in the following chart where size of test database and year of publication are plotted for the different model types. The trend of increasing test databases is less evident for Type 3A models, which are still typically based on a few tens to a few hundred test vehicles. For the other model types the available data are too limited to reveal any trends. One interesting aspect of the fuel-based type 1A models is the very large test database for these models. These models are based on remote sensing data. This method is able to efficiently measure many thousands of vehicles at specific locations in the road network. A few other observations that emerge from table 1 are that average speed models include the largest number of pollutants and that average speed and traffic situation models typically include all emission types. In particular, evaporative emissions are often not included in Type 2 and 3 models, with a few exceptions.

Model Application

Modelling Objectives

Traffic emission models operate at different scales, depending on the modelling objective. Smit (2006a) distinguished three main modelling objectives:

- modelling to verify compliance with air quality standards;
- development of emission inventories; and
- evaluation of transport policies (scenario testing).

Assessment may be conducted at the local, regional, national or even global scale. For instance, it may involve local air quality impacts (e.g. Nagendra and Khare, 2002) due to new road projects or the implementation of (new) traffic management measures (e.g. lower speed limits, traffic signal coordination, metering signals).

Table 1. Overview of Various Model Features

Model Type	Model Name	Number of Vehicle Classes	Main Vehicle Types					Main Fuel Types					Emission Type			Pollutants					Code Number of Tested Vehicles (*)	Type of Driving Cycles	Reference (**)
			PCs, LDTs	LCVs	MCs	Trucks	Buses	Petrol	Diesel	LPG	CNG	Others	Hot Run-ning	Start	Evap-orative	Criteria (CO, HC, NOx, PM)	Non-Exhaust PM	Spec. HCs	Others (GHGs, NO2, SO2, NH3, EC, etc.)	FC			
1A	Fuel Based Model	36	x	x	-	-	-	x	-	-	-	-	x	-	-	2	-	-	-	-	9	RW	Singer & Harley, 1996
1A	Fuel Based Model	48	x	x	-	-	-	x	-	-	-	-	x	-	-	2	-	-	-	-	9	-	Singer & Harley, 2000
1B	Average Speed Model	1	x	-	-	-	-	x	-	-	-	-	x	-	-	3	-	-	1	-	2	RW	Rose et al, 1965
1B	Average Speed Model	1	x	-	-	-	-	x	-	-	-	-	x	-	-	1	-	-	-	-	2	ST	Evans, 1978
1B	QGEPA	73	x	x	x	x	x	x	x	x	x	-	x	x	x	4	-	90	4	-	7	RW/ST	QGEPA, 2002
1B	MOBILE 6.2	28	x	x	x	x	x	x	x	-	x	-	x	x	x	4	1	10	7	-	-	RW/ST	USEPA, 2008; Sonntag & Gao, 2007
1B	EMFAC2006	13	x	x	x	x	x	x	x	-	-	-	x	x	x	4	-	-	4	1	9	RW/ST	p.c. B. Hancock 12-8-2008
1B	COPERT IV	218	x	x	x	x	x	x	x	x	x	x	x	x	x	4	1	88	29	1	6	RW	LAT, 2008; p.c. L. Ntziachristos 20-8-2008
1C	Aggregate Modal Model	2	x	-	-	-	-	x	-	-	-	-	x	-	-	1	-	-	-	-	-	ST	Ludwig et al. 1973
1C	Traffic Situation Model	5	x	x	x	x	-	x	x	-	-	-	x	x	x	3	-	-	-	-	3	ST	Neylon & Collins, 1982
1C	Traffic Situation Model	2	x	-	-	-	-	x	x	x	-	-	x	-	-	4	-	-	1	-	2	RW	Veurman et al,2002
1C	ARTEMIS 0.4D	505	x	x	x	x	x	x	x	x	x	x	x	x	x	4	-	15	11	1	8	RW	Keller & Kljun, 2007; p.c. M. Keller 12-8-2008
1C	HBEFA 2.1	295	x	x	x	x	x	x	x	-	-	-	x	x	x	4	-	5	4	1	5	RW	Keller, 2004; INFRAS, 2007; p.c. M. Keller 12-8-2008
2	TEE-KCF	44	x	x	x	x	x	x	x	x	x	-	x	x	-	1	-	-	-	1	4	RW	Negrenti, 1999
2	SIDRA Intersection	2	x	x	-	x	x	x	x	-	-	-	x	-	-	3	-	-	1	1	2	ST/RW	A&A, 2008, p.c. R. Akcelik 26-8-2008
3A	PKE model	1	x	-	-	-	-	x	-	-	-	-	x	-	-	3	-	-	1	-	1	RW/ST	Watson et al, 1982
3A	MEASURE	up to 120	x	x	-	x	x	x	x	-	-	-	x	x	x	4	1	>1	3	-	9	RW/ST	Fomunung et al, 1999; 2000; p.c. R. Guensler 22-8-2008/S. Kimbrough 9-9-2008
3A	NEMO 1.7	Var	x	x	-	x	x	x	x	-	-	-	x	x	-	4	1	5	6	1	8	RW/ST	p.c. M. Rexeis 28-7-2008
3A	VERSIT+ 3	103	x	x	x	x	x	x	x	x	x	-	x	x	-	4	-	-	2	1	6	RW/ST	Smit et al, 2007; p.c. N. Ligterink 8-7-2008
3A	IVE model	1372	x	x	x	x	x	x	x	x	x	x	x	x	x	4	-	5	5	-	8	RW/ST	ISSRC, 2008; p.c. J. Lents 23-8-2008
3B	Modal Analysis Model	11	x	-	-	-	-	x	-	-	-	-	x	-	-	3	-	-	-	-	7	ST	Kunselman et al., 1974
3B	Modal Model	6	x	-	-	-	-	x	-	-	-	-	x	-	-	3	-	-	1	-	3	ST	Kent & Mudford, 1979
3B	Matrix Model	2	x	-	-	-	-	x	x	-	-	-	x	-	-	3	-	-	-	1	4	ST	Post et al, 1985
3B	CALINE 4	1	x	-	-	-	-	x	-	-	-	-	x	-	-	1	-	-	-	-	4	ST	Benson, 1989
3B	VEMISS	-	x	-	-	-	-	x	-	-	-	-	x	x	-	3	-	-	-	1	3	RW/ST	Koupal & German, 1995
3B	Analytical Model	-	x	-	-	-	-	x	x	-	-	-	x	x	-	3	-	-	-	-	1	RW/ST	Cernushi et al., 1995
3B	Aggregate Modal Model	1	x	-	-	-	-	x	-	-	-	-	x	-	-	1	-	-	-	1	1	ST	Taylor & Young, 1996
3B	DRIVE MODEM	4	x	-	-	-	-	x	x	-	-	-	x	-	-	3	-	-	1	1	4	RW	André & Pronello, 1996; 1997
3B	CVEM	5	x	-	-	x	-	x	x	-	-	-	x	x	-	3	-	-	-	1	6	RW/ST	Leung & Williams, 2000
3B	DIVEM	3	x	-	-	-	-	x	x	-	-	-	x	-	-	3	-	-	1	-	2	RW	Atjay and Weilenmann, 2004
3B	Analytical Model	5	x	-	-	x	x	x	x	x	-	-	x	-	-	3	-	-	1	-	3	RW	Panis et al., 2006
3B	MOVES	13	x	x	-	x	x	x	x	-	x	-	x	x	x	4	1	12	7	1	-	RW	Sonntag & Gao, 2007
3B	CMEM 3.01	31 (Var)	x	x	-	x	-	x	x	-	-	-	x	x	-	3	-	-	1	1	5	RW/ST	p.c. G. Scora 5-8-2008
3B	VT-Micro	10	x	-	-	x	-	x	x	-	-	-	x	x	-	4	-	-	1	1	4	RW/ST	Rakha et al., 2004; p.c. Rakha 22-8-2008
3B	PHEM 08	Var	x	x	-	x	x	x	x	-	x	-	x	x	-	4	-	-	2	1	5	RW/ST	p.c. M. Rexeis 28-7-2008

(*) Number of Vehicles Tested: “1” 0-10 vehicles, “2” 11-20 vehicles, “3” 21-50 vehicles, “4” 51-200 vehicles, “5” 201-500 vehicles, “6” 501-1000 vehicles, “7” 1001-2000 vehicles, “8” 2001-5000 vehicles, “9” > 5001 vehicles.

(**) p.c. means personal correspondence.

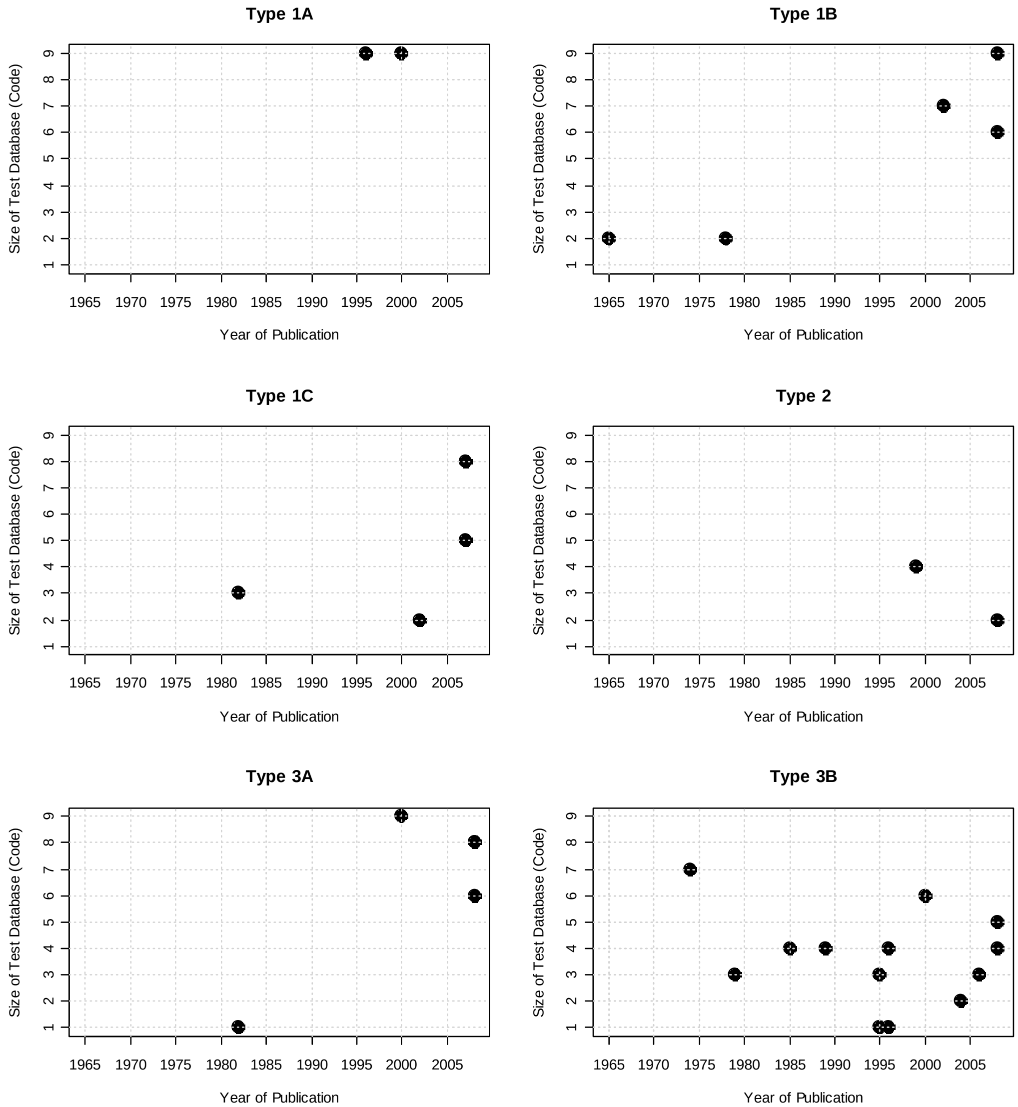

Figure 3. Size of Test Database (Number of Vehicles Tested), Data taken from Table 1, Database Code: "1" = 0-10 vehicles, "2" = 11-20 vehicles, "3" = 21-50 vehicles, "4" = 51-200 vehicles, "5" = 201-500 vehicles, "6" = 501-1000 vehicles, "7" = 1001-2000 vehicles, "8" = 2001-5000 vehicles, "9" > 5001 vehicle.

Assessment of regional air quality are commonly based on emission inventories and may involve modelling of key pollutants such as NO_x, SO_2 and particulate matter (PM_{10} or $PM_{2.5}$) (e.g. Owen et al., 2000), but is often directed towards the analysis and prediction of photochemical smog levels (e.g. Harley et al., 1993). National emission inventories are needed to verify compliance with international agreements (e.g. national emission ceilings, greenhouse gas emissions).

The actual study objective determines the size of the study area (and thus size of the modelled road network, i.e. the number of links and nodes) that needs to be considered. For instance, modelling of photochemical smog formation requires consideration of a large regional area (e.g. Helali and Hutchinson, 1994), whereas an air quality assessment in the direct vicinity of a new road requires consideration of only a small road network or possibly a single road (e.g. Meng and Niemeier, 1998).

Model Input

The use of field data as input to emission modelling has a clear advantage in terms of accuracy when compared to modelled data[1]. Smit (2006a) distinguished four levels of availability with respect to input field data. Infrastructure-related input data are (in principle) available for every road in a network and include speed limit, type of road (e.g. arterial, freeway, residential), road length, type of intersection (e.g. signalised, roundabout) and signal settings. Certain types of traffic data such as traffic count data are commonly collected at a representative grid of points in the road network by urban traffic control systems. Others such as (average) speed[2] and vehicle classification[3] are less commonly measured and typically restricted to major roads. Finally, some types of traffic data, such as speed-time profiles and queue data are rarely measured, although the advent of GPS and video sensor and image processing technology is expected to greatly enhance data availability of these types of data, as will be discussed later.

As modelling of emissions requires input data for preferably all relevant roads in the network, traffic models are usually needed to fill in the data gaps. In addition, traffic models are needed to make predictions for future situations. Two main types of traffic models may be distinguished, i.e. macroscopic and microscopic models. Macroscopic traffic models simulate the performance and behaviour of a traffic stream and typically generate output for road links such as traffic volume, mean speed and mean vehicle delay. Examples are, with increasing complexity, strategic planning models such as EMME2 and TRIPS (Brindle et al., 2000), dense network models such as SATURN (Van Vliet, 1982) and CONTRAM (Taylor, 2003) and traffic performance models such as SIDRA (Açkelik and Besley, 2003) and the Highway Capacity Manual (TRB, 2000). Microscopic traffic models simulate the movement of individual vehicles in space and time, and are thus able to generate detailed data on driving behaviour. Examples are AIMSUN, VISSIM and PARAMICS (EC, 2000). It is noted that input data for emission models are not restricted to actual output data from traffic models (e.g. link VKT, link travel speed), but may also concern input data to traffic models (e.g. link length, free-flow speed). From the perspective of emission modelling, traffic models can be regarded as a data source from which all relevant input data can be conveniently extracted.

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[1] It is noted that it may be quite acceptable (e.g. from the point of view of cost-effectiveness), depending on the modelling purposes (e.g. screening study), to use less accurate output from other sources such as traffic models.

[2] (Mean) travel times, and thus (mean) travel speeds, can be measured on specific segments of road or entire routes using travel time studies. These studies are commonly conducted on major roads, for example, to measure the effectiveness of a transport system. Space mean speed data is directly measured by dual-loop detectors (i.e. two *closely spaced* induction loop detectors), which may be used on major roads (e.g. freeways). In case of single-loop detectors, space mean speed may be estimated from measured traffic volume and occupancy data. Speed data for short sections of road may be collected manually using e.g. radar guns or video analysis.

[3] Basic vehicle classification data (e.g. light vehicle, heavy vehicle, perhaps a few heavy vehicle sub classes) is usually available for major roads. More comprehensive classification data is usually collected by manual classified counting surveys or video image surveys.

As discussed in the previous section, the size of the study area (i.e. road network) is determined by the modelling objectives. However, the size of the modelled network affects the availability of emission model input data. The demand for resources to generate and process input data for emission models from either traffic models, field data or both, increases with network size.

As a consequence, the extent and the level of detail of available input data are effectively reduced in practise when network size increases. On the other hand, the amount and types of required input data are a function of emission model complexity. More complex emission models impose a larger demand for input data on the model user.

The trade-off between model complexity and network size leads to the following observation: in practise, complex traffic and emission models are usually applied at small networks and large networks require less complex traffic and emission models. The next table shows this and is based on a literature review of 55 air quality studies in which road traffic emission models were used.

Table 2. Number of Traffic and Air Quality Studies by Traffic Input Data Source, Emission Model and Scale (N = National, R = Regional, L = Local) (Source: Smit, 2006a)

Type of Input Data	Emission Model Type						
	1A. Aggregate Model	1B. Average Speed Model	1C. Traffic Situation Model	2. Traffic Variable Model	3A. Cycle Variable Model	3B. Modal Model	Total
Field Data		4 (R) 2 (N)	8 (R)	1 (L)			15
Macroscopic Model & Field Data	1 (R)	5 (R)	3 (R)				10
Macroscopic Model		15 (R) 2 (L)	1 (R)	1 (R)		5 (L)	22
Microscopic Traffic Model					1 (L)	3 (L)	5
National Statistics	1 (R)						1
Unspecified Model		1 (R)	1 (R)				2
Total	2	29	13	2	1	8	55

The table shows that in particular average speed models are often used in air emission modelling (53%) at a regional scale, generally using input traffic data from macroscopic traffic models.

Traffic situation models are also regularly used in air emission modelling (24%) at a regional scale and regularly use traffic field data as input. Type 3 emission models have been used in air emission modelling (16%) in combination with both macroscopic and microscopic traffic models, and they are always applied to small urban networks. Microscopic models are always applied at the local scale. Other emission model types such as the traffic variable models and the aggregate models have found some limited practical application in emission modelling (together 7%).

It is noted that that these published studies do not necessarily accurately reflect actual usage of various emission model types in practise.

For instance, it is possible that large scale air quality studies would tend to publish their results more than small scale local studies with relatively limited budgets, so the table may present biased results.

Also there is an increasing interest in local effects of road traffic, as will be seen later, that will likely lead to higher application of Type 2 and 3 models[4].

[4] A current example of the detailed microscopic approach as applied to Intelligent Transport Systems (ITS) is provided by Dia and Gondwe (2008). The authors conducted a simulation study which aimed to quantify the

The definitions used with respect to traffic data need to be considered carefully. A difference in definitions could lead to significant errors in emission predictions. An example is the use of “speed” for which five different definitions (space mean speed, time mean speed, running speed, travel speed, instantaneous speed) were identified by Smit (2006a). For instance, the correct speed definition for average speed emission models would correspond to “travel speed”, which is defined as the overall speed between two points of “sufficient” distance (i.e. distance corresponding to driving cycles used in emission model development), including all delays, for either an individual vehicle or a traffic stream. In contrast, use of space mean speed measured by dual loop detectors measures speed over only a short distance (a few meters) and would only be appropriate to use in average speed models if this speed is relatively constant over a sufficient distance (homogeneous traffic flow, e.g. on a section of freeway).

To illustrate this point, Figure 4 shows that driving cycles on which commonly used average speed models are based, have a cycle length that varies between 130 m to 98 km and a median value of 6 km. Shorter driving cycles typically occur at lower more congested mean speeds, whereas longer cycles tend to occur at higher mean speeds.

This has implications for the appropriate spatial resolution at which these average speed models should be applied. For instance, a driving cycle with an average speed of 70 kmph that represents a journey through a road network may involve driving on residential, arterial and freeways (as is shown in Figure 5) and would be expected to have significantly different driving characteristics, and thus emissions, than a driving pattern with the same mean speed for a 100 m stretch of arterial road that would represent free-flowing driving conditions.

As a consequence, depending on the model, the correct spatial application of certain average speed models that are (partly) developed from journey-based driving cycles such as EMFAC and COPERT is likely to be at network level[5]. This is indeed suggested in model documentation (e.g. Ntziachristos and Samaras, 2000), but not always followed in practise where average speed models are applied at link level (e.g. Carslaw and Beevers, 2002).

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impacts of incidents and evaluate the benefits of selected ITS and incident management strategies. The evaluation was based on the development of a large scale micro-simulation model covering an area approximately 122 kilometres squared, including 43 kilometres of Motorway and about 85 kilometres of arterial roads on the Gold Coast, Australia. This is a very large network for microscopic modelling. More than 10,000 vehicles were simulated during the AM and PM peak periods. The simulator collected second-by-second data on each vehicle as they traversed the road network. A type 3B emissions model was interfaced to the simulator. The inputs to the emissions model comprised speed and acceleration and the output comprised fuel consumption and pollutant emissions. The results showed that the incidents resulted in an average increase of 1.5 percent in CO emissions and fuel consumption, and 5.0 percent increase in operating costs. The simulation approach and the interfacing of emissions models to data from the simulator was successful in quantifying the environmental impacts of incidents and evaluating the benefits of ITS management strategies terms of reduction in travel times, emissions and operating costs.

[5] It is noted that some average speed models such as MOBILE (6) are link-based and not journey-based. Here, driving cycles have been explictly developed to represent driving on certain types of roads and levels of congestion. Application of link-based models at link level is the main aim of these models.

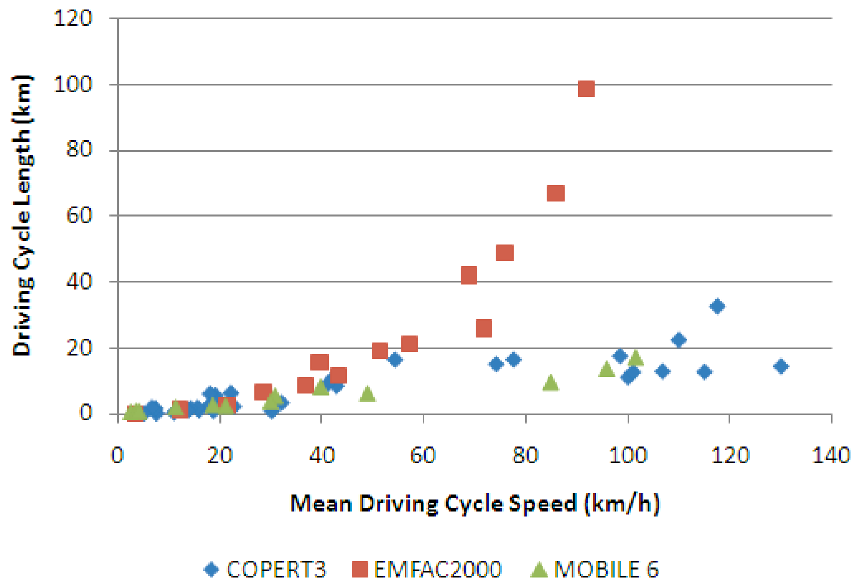

Figure 4. Variation in Cycle Length with Mean Speed for Three Average Speed Models.

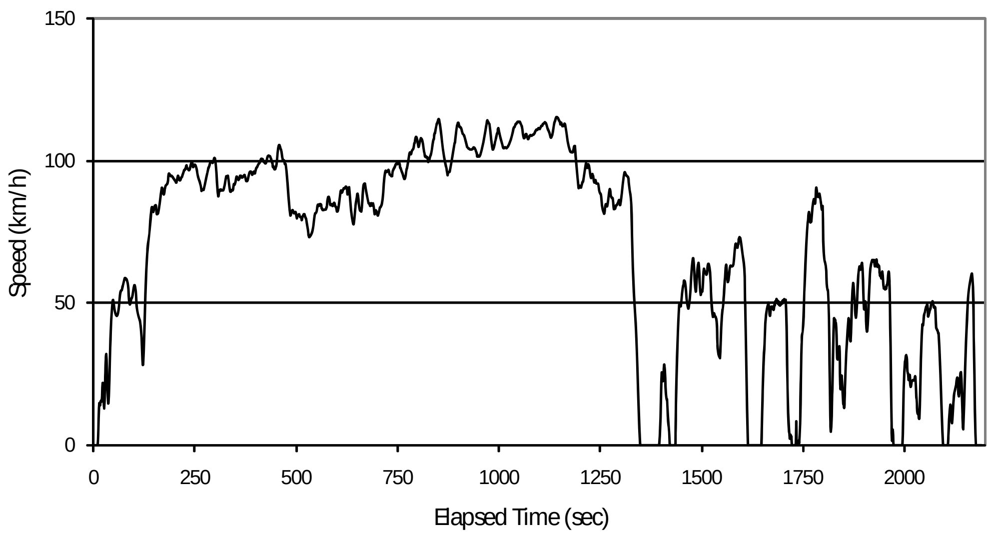

Figure 5. Example of a Journey Driving Cycle (UCC50) used in EMFAC 2000.

To complicate the issue further, cycle length may not be the only variable to examine correct spatial resolution for a particular emission model. A driving cycle may be long, but could reflect relatively homogeneous traffic conditions. For instance, it could represent low speed stop-and-go conditions or typical arterial or freeway driving. An example of typical arterial driving behaviour is given in Figure 6.

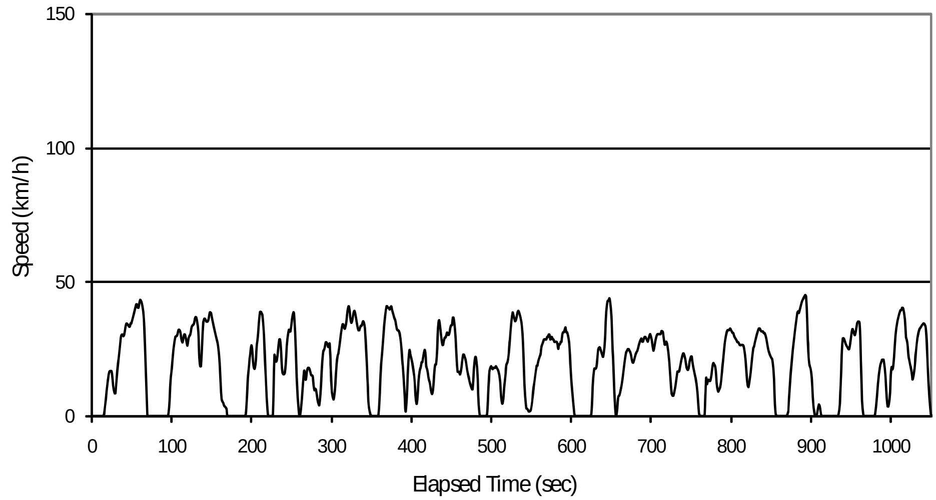

Figure 6. Example of a Driving Cycle (UFLUI2) used in COPERT III.

It can be conceived that these cycles are a combination of driving behaviour samples from different vehicles on the same section of road. So in this case, it may be acceptable to apply the average speed model at road level. However, as Type 1B models are often developed from emissions test data based on various driving cycles, using statistical techniques (regression), it is difficult to arrive at a general recommendation on appropriate spatial resolution, so the issue remains unresolved and requires further research.

Spatial and Temporal Resolution

Traffic flows in urban areas and on roads are by nature highly variable in time and space (Taylor et al., 2000). Because of this large variability, emissions from road traffic are highly variable as well and, in order to capture this variability, emission modelling requires a high temporal and spatial resolution.

In practice, a time resolution of one hour is generally regarded as being sufficient because it aligns with air quality standards for which averaging times typically ranging from 1 hour to 1 year are of practical interest (Reynolds and Broderick, 2000)[6]. This time resolution also aligns with the time period in which highest congestion levels are commonly observed in road networks, i.e. peak hour or peak period. All emission models can be applied at this temporal resolution as long as emission model input data is provided at this resolution. It is noted that higher temporal resolutions may become more important for (emerging) pollutants with perhaps more relevant health impacts at peak exposures less than one hour such as $PM_{2.5}$ (e.g. Greaves et al., 2008).

The appropriate spatial resolution depends on the study objectives and scale of interest. For local level studies, and particular when near-road concentration levels are predicted using dispersion models, a high spatial resolution appears appropriate. An emission model should at least distinguish between traffic conditions that are relatively homogeneous such as stop-and-

[6] It is noted that higher resolutions may be required for specific components, such as 15-minute averaged WHO standards for CO (WHO, 2002).

go queuing and mid-block free-flow conditions. In this respect, Hallmark et al. (2002) observed that arterial road segments of about 60 m show relatively homogeneous driving behaviour. Higher resolutions, e.g. 10 m road segments, may seem even better, but prediction accuracy of emission models at this resolution may become questionable, as will be discussed shortly. For regional level studies, emissions data can be generated for area grid cells or for individual road links. Link level predictions would reflect a network segmentation that represents road environment conditions that are relatively constant, e.g. in terms of road capacity. For national level studies, national or perhaps large regional areas (States) would seem appropriate.

Prediction Accuracy

To the knowledge of the authors, emission model prediction accuracy is not subject to specific criteria, e.g. as established by legislation or codes of practise. In practise, the required level of prediction accuracy would depend on the type of study. An emission model used for “screening” purposes would not be required to be accurate, but instead would be required to be conservative. For other "non-screening" applications, accurate emission predictions are important. For instance, accurate emission predictions would be necessary in cases with poor air quality close to guideline values (e.g. at critical locations such as a new residential area near a busy highway, hotspots) or in cases where policy measures are likely to cause relatively small impacts on emissions and fuel consumption (e.g. specific traffic management measures[7]).

The choice for a specific model (type) clearly affects prediction accuracy and Figure 7 illustrates this. It shows composite emission factors predicted by a type 1A average speed model (COPERT IV, line) and a Type 3A cycle variable model (VERSIT+ 2B, dots representing specific driving cycles).

It can be seen that for traffic situations with different dynamics but similar average speeds VERSIT + predicts different emission factors, whereas COPERT IV predicts the same emission factors for all these situations. Suppose now that the implementation of a particular local traffic management measure (e.g. improved signal timing) has smoothed the flow of traffic (i.e. reduced dynamics) and has increased the average speed from 20 to about 55 km h^{-1}. For this particular situation, COPERT IV would always predict a decrease in emissions. In contrast, VERSIT+ could predict either a decrease or an increase in emissions, or even no effect, depending on input driving pattern data in both the reference and the new traffic situation. This effect is shown by the dashed arrows. Clearly, for policy makers and transport planners the correct *direction* and *magnitude* of these effects is vital information for imposing the right (i.e. effective and cost-effective) measures in order to improve on local air quality and reduce greenhouse gas emissions.

[7] For instance, Midenet et al. (2004) report a CO_2 emission reduction of 4% due to an improved signal control strategy.

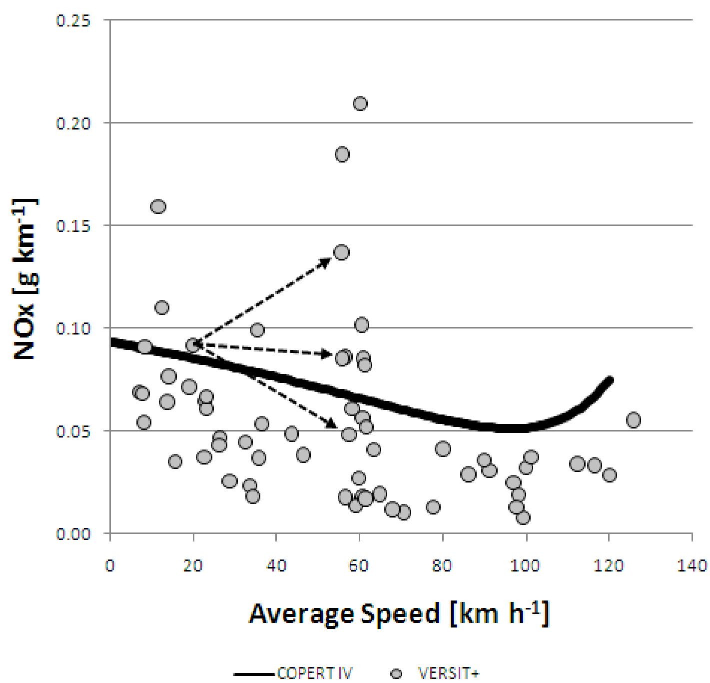

Figure 7. NO_x Emission Factors for an Average Euro 3 Petrol Car as Predicted by COPERT IV and VERSIT+ (Source: Smit, 2008).

Type 2 and 3 emission models are able to discriminate between various traffic situations with similar average speeds but different dynamics and are appropriate for applications where the response of emissions to actual traffic conditions is an issue. It is noted that certain Type 1C models such as the ARTEMIS model with many traffic situations would also, to a certain extent, be capable to distinguish between these situations. However, other Type 1 models such as the average speed models do not account for different levels of speed fluctuation at a particular average speed , and the model would usually only provide accurate predictions for large (urban) road networks, or perhaps substantially large parts of a road network (e.g. 1 km^2 grid cells).

On first sight it appears that application of the most detailed and complex emission model (Type 3B modal) would lead to the most accurate prediction of traffic emissions. However, the sensitivity towards many factors would also create additional uncertainty because more (types of) input data are needed, each with its own inherent uncertainty. So, a point of discussion is how accurate a particular emission model can be in practice. There are several aspects that influence this, namely:

- inherent variability in vehicle emissions,
- input data availability (modelling assumptions),
- input data quality, and
- model development aspects.

These aspects are discussed below.

Inherent Variability in Vehicle Emissions

Due to increasingly complex engine (management) and emission control technology, emissions of modern vehicles exhibit increasing (inherent) variability. Typically, modern spark-ignition vehicles show low base line emission rates (g s^{-1}), with various short-duration emission peaks due to vehicle operation outside the "window" of optimum emission control. An example of this erratic emissions behaviour is shown in Figure 8 for a three-way catalyst equipped passenger car.

Emissions from diesel vehicles have (traditionally) been modelled quite accurately using existing modal models (e.g. Hausberger et al. 2003), but emission controls in diesel vehicles are now also becoming more sophisticated (e.g. SCR, NO_x storage catalysts) in response to stricter emission standards. As a consequence, accurate modelling of diesel vehicle emissions is likely to become more challenging.

In addition, there is substantial variability among road vehicles, even if they are of similar type, make and model (e.g. Bishop et al., 1996). This is due to vehicle-specific engine management (e.g. fuel injection strategy), emission control technology (e.g. size of the catalyst, catalyst material) and other factors (e.g. ageing effects, presence of malfunctioning equipment). This large variance in emissions has implications for prediction accuracy. De Haan and Keller (2000), for instance, found it impossible to construct a speed-acceleration modal emission model that could accurately simulate this irregular emissions behaviour. Also, it is not clear if it is actually possible to accurately predict emissions at very short time intervals, and there are indications that this might not be the case (e.g. Hickman et al., 1999; Barth et al., 2000).

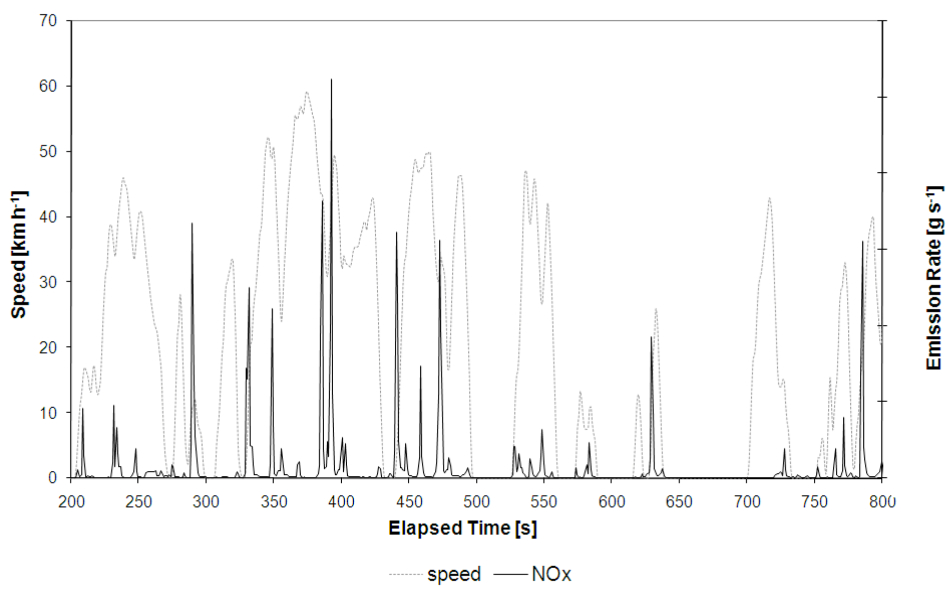

Figure 8. Example of Measured Second-by-Second Speed (Urban Driving Cycle) and NO_x Emission Rates for a Euro 3 Petrol Car.

Finally, inter-vehicle variability is further enhanced by differences in driving style. There is evidence that personal driving style (intensity of vehicle operation, gear shift behaviour) is quite important with respect to emissions. For instance it has been reported that its effect on vehicle emissions is larger than e.g. the frequency of time spent in a particular driving mode, which primarily reflects traffic conditions (Holmén and Niemeier, 1998).

In order to adequately reflect the large inter-vehicle variability in emissions in traffic streams, it appears that emission models need to be based on a large body of test data for as many (representative) vehicles as possible. As was shown in Table 1, there is a positive trend towards inclusion of large bodies of test data in models and current Type 1B and 3A models are based on relatively large test databases in terms of the number of vehicles when compared to the most complex Type 3B models.

Input Data Availability (Modelling Assumptions)

Another important issue is the trade-off between model accuracy and input accuracy. As was discussed, availability of detailed input data decreases with network size. If a complex emission model were run, requiring more detailed input than were available, simplifying assumptions would need to be made, leading to reduced accuracy. For instance, recent modal models simulate gear shift behaviour as part of the modelling process or offer the possibility to use this information as input. However, location-specific data on gear shift behaviour in traffic streams are rarely (if ever) available. This means that assumptions need to be made in order to run the model, introducing unknown errors to model predictions, possibly offsetting accuracy gains over less complex models. So, there may be an optimum level of modelling detail for a certain application. This hypothetical curve is shown in Figure 9.

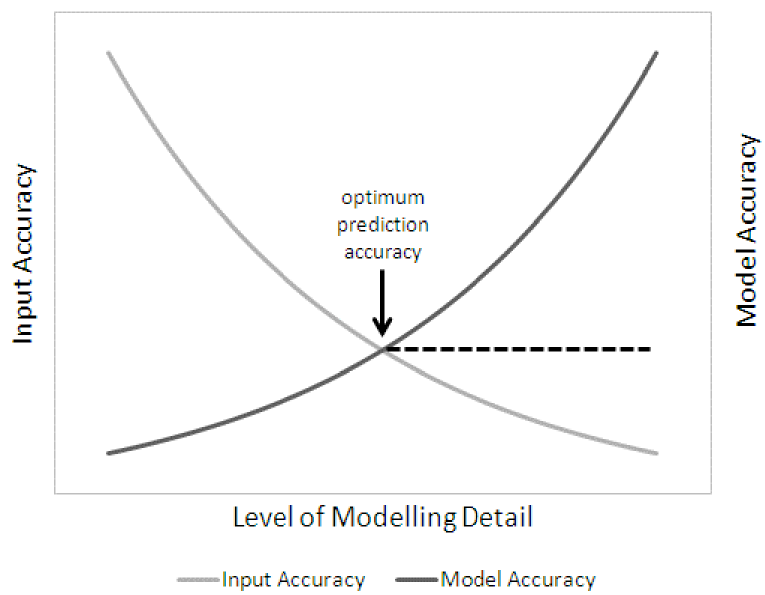

Figure 9. Hypothetical Relationship Between Input Accuracy, Model Accuracy and Level of Modelling Detail.

It shows that level of (overall) input accuracy (due to availability) decreases with level of modelling detail (model complexity), whereas (potential) model accuracy increases with model complexity. Prediction accuracy is a function of both input and model accuracy, and a cost-effective optimum level occurs where both curves cross. Beyond this point (more complexity), an increase in prediction accuracy is either small or does not exist. Even a small increase in prediction accuracy is not interesting, as the costs to run the model (data collection, computer runtime) will increase disproportionately.

Input Data Quality

In addition to data availability, the quality of the input data needs to be considered because errors in input data propagate through the emission modelling process. Similar to emission models, more complex traffic models are not necessarily generating more accurate input data. Each (type of) traffic model would have its own accuracy issues. Examples are the accuracy of predicted link speeds by macroscopic strategic planning models (Grant et al., 2000) and the validity of predicted vehicle trajectories by microscopic simulation models (Hallmark and Guensler, 1999). More research (e.g. model validation, sensitivity analysis, model comparison) is needed to establish which traffic-emission model combinations can achieve which levels of accuracy (in a relative and absolute sense) in field applications at various scales.

Efforts to improve traffic emission modelling should focus on variables that have shown to have a large effect on emission predictions. In this respect, Smit (2006a) showed that the amount of travel (VKT) is a particularly important input variable. This is because errors in traffic volume will cause proportional errors in emission estimates, which may be amplified when other traffic variables such as average speed are derived from traffic volumes, as is the case in traffic models that use congestion functions (Smit, 2008d). For instance, an error in traffic volumes of 10-20% may result in errors in emissions of 50% (Reynolds and Broderick, 2000). As a consequence, particular attention should be directed at obtaining accurate information on traffic volumes.

A sensitivity analysis using two average speed models (Smit, 2008d) showed large errors in NO_x predictions (up to a factor of about 3.5) due to (in order of importance) variation in traffic composition, average speed and model choice, the actual magnitude depending on the level of congestion. The external errors due to input data quality were of the same order of magnitude as internal errors that have been reported from (partial) road validation studies. This implies that in terms of further improvements of traffic emission modelling, focus should be on both the quality of input data (application) and the quality of the actual emission models (model development).

Model Development Aspects

As was discussed before, there are several other aspects of emission models that affect model accuracy such as the use of standard and/or real world cycles, comprehensiveness of the model in terms of vehicle classification, the use of up-to-date emissions test data and other factors such as the use of local emissions test data. In this respect, Table 1 showed that less complex models such as average speed models may actually be more accurate than more complex emission models, because they use the largest empirical database, use real-world cycles and are regularly updated.

Summary

It is clear that determining whether one emission model is more accurate than another is not an easy task, and would require information from different validation studies (tunnel studies, on-road, etc.). To date, model validation studies that involve several types of emission model are limited and provide inconclusive evidence that certain model types provide substantially better results over others (Smit, 2006a). For instance, it has been found (Fomunung et al., 2000; Park et al., 2001; Lacour et al., 2001) that, depending on the pollutant, average speed models sometimes perform better and sometimes perform worse than more complex (Type 3) models in terms of prediction accuracy. Even if a particular study shows that one model performs significantly better than another (e.g. EC, 1995), the results are necessarily based on assumptions that are known to strongly influence emissions (e.g. percent cold vehicles), casting some doubt on the claims that are made. Finally, application of complex emission models such as CMEM (Rakha et al., 2004) or TEE (Smit, 2006a) has revealed peculiar prediction behaviour in certain traffic conditions, which indicates the need for further emissions testing, fine-tuning and model testing of complex emission models to ensure robust and valid model predictions in all situations. In summary, prediction accuracy of emission predictions is an important area that will require more research.

Outlook

It is expected that demand for detailed and comprehensive emission models will increase in the future. This is due to a number of developments. For example, there is a growing application of traffic control to improve traffic flow and reduce accidents. This is combined with an increasing interest around the world in the effects of local scale traffic measures on traffic emissions, air pollution and fuel consumption (e.g. Coelho et al., 2005; Akçelik, 2006). Similarly ongoing developments of in-vehicle technology will, when applied in practise, affect driving behaviour and hence emissions. The extent to which these technologies affect emissions and fuel consumption would be of interest to policy makers and perhaps the general public itself. An example is the ISA system (Intelligent Speed Adaptation system) investigated by Panis et al. (2006), which regulates (caps) vehicle speed by comparing GPS derived real-time speeds with the local speed limits, thereby reducing the number of accidents. There is also an increasing interest in the effects of road traffic on greenhouse gases and air pollutants other than the traditional criteria pollutants (CO, HC, NO_x, PM_{mass}). An example is the increasing importance of different ways to quantify particulate emissions such as particle number and particle area. Several issues with accurate modelling of particulate emissions (mass, number, etc.) at a high resolution in time and space are currently being addressed (Zalinger et al., 2008).

Probably one of the most important aspects that may improve current emission modelling is the development of input data. Ongoing developments in sensor, communications and computing technology create exciting opportunities to substantially improve both traffic emission model input data quality (e.g. field data) and to enhance availability (e.g. high temporal and spatial resolution). There is now an increasing use of automated data collection systems such as GPS (Global Positioning System) and video imaging technology, which are cost-effective ways of collecting large bodies of (real-time) data on vehicle behaviour in time and space (Midenet et al., 2004; Nesami and Subramanian, 2005; Brundell-Freij and Ericsson, 2005; Ahn and Rakha, 2007). At this stage, certain issues such as differences between GPS receivers and improving positional accuracy and spatial coverage (missing data due to e.g. buildings) need to be resolved before these data can be used to generate reliable high-resolution (1 Hz) vehicle speed and acceleration data (Jackson and Aultman-Hall, 2007; Toledo et al., 2007).

One good example of these developments is the MESSAGE project (Hoose et al., 2008). Here, a real-time computing environment for high resolution (30 m, 1 minute) road networks has been developed and tested that extracts information from various sources using wireless communication such as mobile air quality sensors (e.g. attached to vehicles with positioning devices), fixed pollution monitoring networks, field data on traffic control and weather information and traffic, emission and dispersion models.

Improvements in the amount and quality of traffic data will certainly lead to more accurate emission predictions. The developments with respect to input data will also facilitate application of more complex emission models leading to a finer spatial and temporal allocation of traffic emissions. It is therefore expected that application of more complex emission models, such as the Type 3 modal and traffic variable models, will increase in time. Whether this will actually lead to (substantial) improvements in emission prediction accuracy, compared to less complex emission models, is, however, a matter that requires further investigation – and this is an important but overlooked issue in the opinion of the authors. Relevant research questions in this respect include how accurate a particular (type of) emission model should be and can be in practise, and under which circumstances.

One advantage of increased use of complex models is that they can be used to develop a modelling framework (bottom-up), including separate models of various levels of complexity, that provides consistent results at all modelling scales. A modelling framework is necessary to choose the appropriate modelling approach in terms of modelling objectives (scale), study type (screening, other) and other factors (costs). This advantage is acknowledged in the development of the MOVES model in the USA (Sonntag and Gao, 2007), which is intended to predict traffic emissions at local, regional and national scale.

Given the large inter-vehicle variability in emissions, emission models should ideally be based on a large number of emission tests. As laboratory testing is expensive, current emission models are necessarily based on a relatively limited number of tests. With ongoing developments in the field of and application of on-board emission measurements, there are opportunities to create large and (complementary) databases in a cost-effective way that can then be used for emission model development. Due to ongoing diversification of the on-road vehicle fleet in terms of fuel and technology types, there will be a strong need to include these new types of vehicles into emission testing programs to allow for subsequent inclusion in model updates. As a consequence, it is expected that emission models will become increasingly complex and comprehensive in their modelling of vehicle types, fuel types, pollutants and greenhouse gases.

As was shown in this chapter, there are several issues with respect to the interaction between traffic models and emission models. Examples are issues with respect to spatial and temporal resolution, definition of model variables and balancing of prediction accuracy of both types of models. It seems a good way forward to further integrate specific traffic and emission models taking those issues into account. This may involve development of new emission models or modification of existing emission models that would match particular traffic models.

It is expected that emission models will be applied to address increasingly complex research questions and study objectives. A recent example of this is the investigation of the effects of changes to current road network configuration (e.g. longer merge sections, signal timing) and increases in road capacity on traffic emissions and fuel consumption, taking into account feedback mechanism such as induced traffic generation (Noland and Quddus, 2006). Complex type 3 emission models in combination with either microscopic traffic models or high resolution field traffic data in these cases seem the best way forward as they imply to increase the probability of correct outcomes, in both a relative and positive sense. However, the outstanding issues with respect prediction accuracy will require further research in order to make this probability a reality.

Conclusion

This chapter investigated current models designed to predict air pollutant emissions and fuel consumption for road traffic. Given the many factors that influence emissions and fuel consumption from individual vehicles, modelling of these emissions for many vehicles in road networks (traffic streams) is an involved, multidisciplinary and complex exercise. A review of current road traffic emission modelling around the world revealed that these models share various common features such as empirical base, generic computation procedure, vehicle classification and modelling of driving behaviour. Emission models were then classified and discussed in terms of the way driving behaviour is incorporated in the model and 6 (sub)types of models were identified.

When development of emission models is examined over time, a few trends emerge. Emission models have become increasingly complex (both more detailed and more comprehensive) with respect to various modelling aspects such as number of pollutants, type of emissions, type of vehicles and modelling of driving behaviour. Also, the number of test vehicles on which models are based have generally increased in time, which provides more confidence in predictions given the large inter-vehicle variability in emissions behaviour.

The most commonly used emission model is the average speed model. Although current average speed models are generally comprehensive, simulation of driving behaviour is somewhat simplistic. Therefore, these models are generally not suitable for local area impact assessment, which is a scale that attracts increasing interest around the world, and should be used at network level. However, the appropriate spatial resolution of a particular average speed model will depend on the driving cycles on which it is based, which is a subject that requires further examination. It is (logically) assumed that emission models that can discriminate between various traffic situations with similar average speed can be used for local scale studies, and they include (comprehensive) traffic situation models, traffic variable models, cycle variable models and modal models.

There may also be the perception that a more detailed and complex model will lead to more accurate predictions. There are, however, many factors to influence prediction accuracy such as type and source of emissions test data on which a model is based, size of the emissions database, input data availability and input data quality. With respect to available (partial) validation studies, there is inconclusive evidence at this stage that certain models perform better than others. As a consequence, model prediction accuracy is an area that requires further research.

It is envisaged that that emission models will be applied to address increasingly complex research questions and study objectives. As a consequence, it is expected that demand for detailed and comprehensive emission (type 3) models will increase in the future, leading to a finer spatial and temporal allocation of traffic emissions. This expectation is based on a number of ongoing developments that facilitate the development and application of high resolution emission models. Firstly, there is a growing application of (high-tech) traffic control measures and ongoing developments of in-vehicle technology. These developments create new opportunities to substantially improve both the quality and to enhance availability of emission model input data. Similarly, with ongoing developments in the field of and application of high-resolution on-board emission measurements, there are also opportunities to create large and (complementary) databases in a cost-effective way that can then be used for emission model development. Secondly, there is increasing interest around the world in the effects of local scale traffic measures on traffic emissions, air pollution and fuel consumption. Whether these developments will actually lead to (substantial) improvements in emission prediction accuracy, compared to less complex emission models, is, however, a matter that requires further investigation. Relevant research questions in this respect include how accurate a particular (type of) emission model should be and can be in practise, and under which circumstances. Due to ongoing diversification of the on-road vehicle fleet, there will be a strong need to include new types of vehicles and fuels into emission testing programs to allow for subsequent inclusion in model updates. As a consequence, it is expected that emission models will become increasingly complex and comprehensive in their modelling of vehicle types, fuel types, (number of) pollutants and greenhouse gases.

As was shown in this chapter, there are some issues with respect to the interaction between traffic models and emission models. Examples are correct spatial and temporal resolution, definition of model variables and balancing of prediction accuracy of both types of models. It seems a good way forward to further integrate specific traffic and emission models taking those issues into account. This may involve development of new emission models or modification of existing emission models that would match particular traffic models.

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