EC4MACS

Uncertainty Treatment

The TREMOVE / COPERT Transport Models

European Consortium for Modelling of Air Pollution and Climate Strategies - EC4MACS

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March 2012

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Project Title	**Contract No**
EC4MACS - European Consortium for Modelling of Air Pollution and Climate Strategies	LIFE06 ENV/AT/PREP/06
Report Title	**Reference No**
Road Transport Projections Uncertainty	11.RE.0040.V2
Project Manager	
Prof. Zissis Samaras	A project funded by LIFE
Author(s)	
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Summary

This is a report of the LIFE EC4MACS project, which describes the uncertainty associated with road transport emission projections. For the characterisation of uncertainty, Monte Carlo simulations have been conducted on complete national inventories and projections. This work was conducted in the framework of a different European Commission project and key implications for the EC4MACS activity are presented in the current report. Also, some particular issues of importance are discussed, such as the effect of high emitters, the disparity in emission standard over emission factor levels, and the impact of advanced vehicle technologies. The report makes quantifiable statements about the uncertainty of current emission inventories and also recommends steps that have to be taken to reduce uncertainties in future emission projections.

Keywords

COPERT, projections, uncertainty, emission factors, high emitters

Internet reference

http://www.ec4macs.eu/

Version / Date	**Classification statement**
Final / October 2010	PUBLIC

No of Pages	**Price**	**Declassification date**	**References**
63	FREE	N/A	6

Contents

1 Introduction

1.1 Objectives of the report

Aim of the EC4MACS project is to bring together most of the widely used policy assessment models in Europe in the areas of pollutant emissions. The long-term objective is to develop the links between the models in order to perform consistent policy impact assessments and scenario evaluations.

A very dynamic field is present in the area of transport emissions with a large area of policies in place and foreseen in the future, and an equally large number of technologies to address the policy requirements. Therefore, detailed models are required to describe the transport emissions and to make reliable projections.

This report describes the uncertainty associated with estimating emissions from road transport vehicles. Both the uncertainties in the emission models used, as well as input data, are characterized in quantitative terms. Then, the impact of some specific issues is discussed, mainly in order to qualitatively consider their impact in projections.

The uncertainty characterisation of the COPERT model, that has been used in the framework of Ec4MACS, has been conducted in a separate study (Kouridis et al., 2010). However, results obtained in that study are relevant also in the EC4MACS activity and relevant conclusions have been also transferred in this report.

1.2 Background

Emission projections in EC4MACS have been compiled by using the COPERT model and appropriate input data to characterize emissions, introduced by TREMOVE. The input data required are number of vehicles categorized into different sizes, classes, fuel used and technology levels, their annual distance travelled, average speeds and shares in different driving modes, and environmental and fuel information. All of these data are obtained by statistical sources or estimated according to available information. Therefore, uncertainty exists also with the input data estimation.

COPERT is a software programme that is based on a methodology to estimate vehicle fleet emissions on a country-level. The methodology tries to balance the need for detailed emission calculations on one hand and use of few input data on the other. Three different modes of emissions are taken into account, that is hot emissions, cold-start emissions, and emissions due to gasoline evaporation. COPERT 4 (since version 7.0) also includes non-exhaust PM emissions (tyre, break). COPERT methodology consists of vehicle-specific emission factors which are combined with activity data to calculate total emissions. The main activity data comprise number of vehicles distinguished into different emission categories/technologies, the travelling speed under urban, rural and highway conditions and the mileage driven over the same driving conditions. The main methodological elements of COPERT have been developed in the framework of several scientific projects, including:

- The CORINAIR Working Group on Emissions Factors for Calculating 1985 Emissions from Road Traffic (Eggleston S., N. Gorißen, R. Joumard, R.C. Rijkeboer, Z. Samaras and K.-H. Zierock (1989), Volume 1: Methodology and Emission Factors).
- The CORINAIR Working Group on Emissions Factors for Calculating 1990 Emissions from Road Traffic (Eggleston S., D. Gaudioso, N. Gorißen, R. Joumard, R.C. Rijkeboer, Z. Samaras and K.-H. Zierock (1993), Volume 1: Methodology and Emission Factors).
- The COST 319 action on The Estimation of Emissions from Transport
- MEET (Methodologies to Estimate Emissions from Transport), a European Commission (DG VII) sponsored project in the framework of the 4th Framework Programme in the area of Transport
- The Inspection and Maintenance programme, a European Commission (DG XI, DG VII, DG XVII) sponsored project in the framework of the 4th Framework Programme in the area of Transport
- The European Commission (DG Transport) ARTEMIS project, which was funded to develop a new database of emission factors of gaseous pollutants from transport (http://www.trl.co.uk/artemis).
- The European Commission (DG Transport) PARTICULATES project, which was funded to develop a new database of PM emission factors and particle characteristics of exhaust emissions from road transport (http://lat.eng.auth.gr/particulates).
- A European Commission (DG Enterprise) study on potential options for emission standards of Euro 3 mopeds
- The joint EUCAR/JRC/CONCAWE programme on the effects of gasoline vapour pressure and ethanol content on evaporative emissions from modern cars.

The many sources increase the uncertainty of the estimates. Therefore, it is necessary to estimate the uncertainty estimated with calculations associated with COPERT.

1.3 Objectives of this deliverable

The objectives of this deliverable were the following:

1. Evaluate the uncertainty linked with road transport emission calculations at a national level.

2. Explain the impacts of this uncertainty in the framework of the EC4MACS project.

3. Provide a qualitative discussion on the effect of uncertainty sources not included in the modeling.

2 Uncertainty of Input Data

This chapter presents a description of the input and internal variables and parameters to COPERT. All data are presented in a tabulated form, where the use, range and hints for the quantification of the variability are given. In the sensitivity and uncertainty calculations performed, input data and internal variables were treated in the same way, i.e. they both contribute to the uncertainty of the total calculation in the same manner. For purely clarification reasons, we split in this chapter the input data and variables in three individual sections, one discussing the uncertainty in the calculation of the vehicle stock, one that discusses the uncertainty of the emission factors, and a last one discussing the uncertainty of other variables and parameters.

The uncertainty has been calculated for year 2005 in the cases of Italy and Poland. Year 2005 was selected as this is a rather recent year, in the sense that uncertainty calculations for the Year 2005 should be similar to today. On the other hand, it is already old enough so all relevant databases with information should have been updated for the particular year. The selection of Italy and Poland was made in an effort to simulate two cases, one with detailed statistical information (Italy) and another one with more poor data (Poland). The latter is a consequence of the fact that eastern European countries joined the EU-standards of motor vehicle emission control at a later stage than their introduction in Europe. For example, catalyst vehicles were first introduced in the Polish stock only in the period 1995-1997. In addition, pre-catalyst vehicles did not follow the ECE standards but a national-based system. The conversion of these old vehicles to the COPERT classification increases this uncertainty. Therefore, we expect that comparison of the Italian and Polish calculations will provide a measure of the uncertainty due to the stock of vehicles.

Of course, the main interest of EC4MACS is not so much on historic calculations but on the uncertainty related to the future projections in activity and emission data. It should be made clear though, that the road transport calculations conducted in the framework of EC4MACS are based on rather fixed activity projections (fuel consumption) received by the PRIMES model output. These fixed projections are then fed to the fleet classification module which allocates them to the different vehicle categories based on historic fleet structure data. Therefore, the additional uncertainty introduced to the fixed projections is basically the one related to the structure of the historic stock data and the one related to the emission and fuel consumption (COPERT) calculations. Therefore, this report calculates the uncertainty in these two areas and does not address the uncertainty related to the PRIMES projections. For the same reasons, a study addressing the uncertainty of the TREMOVE model (Kouridis et al., 2011) is not so much relevant in the framework of the current activity.

2.1 Uncertainty of the vehicle stock

In order to estimate the uncertainty of the stock, we have based our calculations to the database of the *FLEETS* project, which, in addition to Ec4MACS, have been also used in the latest TREMOVE versions (v3.3 and v3.4). FLEETS is a short name for a project funded in 2008 by the European Commission (DG Environment), with the task to collect detailed stocks and activity data of vehicles for all EU27 member states, and in addition, Croatia, Norway, Switzerland, and Turkey (Ntziachristos et al., 2008). The stock data in that project were collected from several national and international sources and, in particular, the experts of the Task Force of Emission Inventories and Projections, Eurostat, ACEA, ACEM, and national statistical authorities. As one might expect, not all sources contained the same value of stock vehicles for the above countries. However, in the framework of the FLEETS project, these data were streamlined by means of mathematical processing and a consolidated dataset was presented. In the current report, we look back to the individual sources of information to quantify uncertainty of the data. The final dataset from the FLEETS has only been taken as the 'central' estimate of the calculation.

Symbol:	Ncat	**Name:**	Vehicle population at category level
Type:	Check item	**units:**	vehs.
Description:	The number of operating vehicles in the country, falling in one of the five categories (passenger cars, light duty trucks, heavy duty trucks, busses, power two wheelers). The number of operating vehicles should in principle correspond to the number of registered vehicles of the national fleet in the country. Deviations from this rule include vehicles registered but not operating or partially operating (e.g. abandoned or old cars), unregistered or falsified registration vehicles (stolen, illegal imports). Vehicles registered in a different country do not correspond to the national fleet of the country inventoried and should, in principle, be taken into account in the inventory of the country of registration.		
Sources:	The number of registered vehicles is known in national authorities. These also report data to Eurostat (online database under Transport-> Road Transport-> Road Transport equipment - stock of vehicles). There are also independent (market) sources of such information, such as the national associations of car importers in each country. A summary of this work has been conducted by ANFAC on behalf of ACEA (http://www.acea.be/index.php/news/news_detail/vehicles_in_use/).		
Typical Range:	There is no typical range, as parc size depends on the country. For passenger cars, one should estimate between 400 and 600 cars per thousand citizens. For power two wheleers, the range is even larger, between 30 to 200 vehicles per thousand citizens. Trucks range between 10 and 25 trucks per thousand citizens.		
Quantification of variability (Italy & Poland):	The uncertainty per vehicle category has been characterized by collecting data on the Italian fleet from four different sources. These include Eurostat, ANFAC (from the ACEA site), ACEM and ACI. Most of the variability in the reported values occurs for mopeds, while this is practically zero for cars. In the case of Poland, the same international sources have been used and, in addition, Statistics Poland.		

The uncertainty of the Ncat parameter has been quantified on the basis of information collected from different sources. This is shown in Table 2-1 for Italy and Table 2-2 for

Poland. It is shown that the total stock of vehicles in the different categories is rather well known in both countries.

Table 2-1 Vehicle population from different sources, mean value and standard deviation for Italy

ITALY	ACEA 2005	ACEM 2005	ACI 2005	Eurostat 2005	μ	σ
Passenger Cars	34 667 485		34 667 485	34 636 400	34 657 123	17 947
Light Duty Vehicles	3 257 525			3 633 900	3 445 713	266 137
Heavy Duty Vehicles	1 070 308			958 400	1 014 354	79 131
Buses	94 437		94 437	94 100	94 325	195
Mopeds		5 325 000	4 560 907		4 942 954	540 295
Motorcycles		4 938 359	4 938 359	4 933 600	4 936 773	2 748

Table 2-2 Vehicle population from different sources, mean value and standard deviation for Poland

POLAND	ACEA 2005	ACEM 2005	Poland 2005	Eurostat 2005	μ	σ
Passenger Cars	12 339 353		12 339 000	12 339 000	12 339 118	204
Light Duty Vehicles	1 717 435		2 304 500	2 178 000	2 066 645	308 968
Heavy Duty Vehicles	587 070			737 000	662 035	106 017
Buses	79 567		79 600	80 000	79 722	241
Mopeds		337 511			337 511	0
Motorcycles		753 648		754 000	753 824	249

The second variable that determines the stock of vehicles is their split in the different subsectors Nsub.

Symbol:	Nsub	**Name:**	Vehicle population at sub-category level
Type:	Check item	**units:**	vehs.
Description:	This is the population of vehicles in one of the 39 COPERT 4 sub-categories. The sum of these vehicles should amount to the sum of Ncat as well. The subcategory level distingusihes vehicles per fuel used (gasoline, diesel, LPG, CNG, biodiesel, hybrids), engine size (for passenger cars, and motorcycles), and vehicle weight (heavy duty vehicles).		
Sources:	Some classification of vehicles in these classes is availabe in Eurostat, however not as detailed as required by COPERT for the emission estimation. More detailed classification can be found in national statistics.		
Typical Range:	The classification of vehicles range between countries. In several central European countries (AT, BE, FR) the stock of gasoline and diesel cars is about the same, with the latter in an ,increasing trend over the last years. In other countries, the passenger car stock is dominated by gasoline cars (FI, GR, SE). Trucks are dominated by diesel vehicles and motorcycles are solely gasoline.		
Quantification of variability (Italy & Poland):	To quantify the variability national statistics were gathered. For Italy in particular such data was available in detail containing not inly the total number of vehicles classified by vehicle category but also the uknown vehicles not currently classified. For Poland however national statistics do not contain sufficient information, and data are not dissagregated in the form required for the calculations. For this reason the uncertainty was estimated based on the available data. Poland was selected for this particular reason, to demosntrate the uncertainty of the calculations when sufficient information is not available.		

Table 2-3 shows the statistical data for Italy, separated in known and unknown values. The unknown values are vehicles in the ACI database which are not identified to any of the subsectors. To calculate the maximum range of uncertainty that this leads to, it was decided to produce 3 alternative datasets. The first one allocates all unknown values to the vehicle categories with the smallest engine capacity (cars, motorcycles) or the smallest vehicle weight (trucks); the second one allocates the same values to the largest engine capacity or the largest vehicle weight and the third one allocates these values homogenously to all vehicle categories within the same vehicle sector. The standard deviation that this leads to is shown in Chapter 3.

Table 2-4 shows the average value and the standard deviation for the vehicle categories in Poland. The average value was derived from Poland's national statistics. In the absence of more detailed data, assumptions were made to estimate the standard deviation. In the case of passenger cars the standard deviation was calculated by estimating the standard deviation as one third of the difference of the national statistics and FLEETS project data for each subsector. In case of Light Duty Vehicles the uncertainty was calculated from national statistics and was proportionally allocated to the stock of diesel and gasoline trucks. For all other vehicle categories the standard deviation was estimated 7% of the average value.

For both countries, data from the four weight categories to the fourteen weight categories of diesel trucks was made with the conversion file which is available at http://lat.eng.auth.gr/copert/BugsFaqs.htm

Table 2-3 Vehicle population per subsector category for Italy for known and unknown values

Sector	Subsector	Known Values	Unknown values
Passenger Cars	Gasoline <1,4 l	18.025.703	627
Passenger Cars	Gasoline 1,4 - 2,0 l	5.090.465	
Passenger Cars	Gasoline >2,0 l	408.278	
Passenger Cars	Diesel <2,0 l	7.987.956	145
Passenger Cars	Diesel >2,0 l	1.822.935	
Passenger Cars	LPG		
Passenger Cars	2-Stroke		
Light Duty Vehicles	Gasoline <3,5t	280.005	7.580
Heavy Duty Vehicles	Gasoline >3,5 t	4.343	
Light Duty Vehicles	Diesel <3,5 t	2.695.478	35.174
Heavy Duty Vehicles	Diesel 3,5 - 7,5 t	190.842	
Heavy Duty Vehicles	Diesel 7,5 - 16 t	187.804	
Heavy Duty Vehicles	Diesel 16 - 32 t	206.345	
Heavy Duty Vehicles	Diesel >32t	1.905	
Buses	Urban Buses	2.281	92
Buses	Coaches	66.548	
Mopeds	<50 cm³		
Motorcycles	2-stroke >50 cm³	1.397.575	927
Motorcycles	4-stroke <250 cm³	1.545.423	
Motorcycles	4-stroke 250 - 750 cm³	1.488.571	
Motorcycles	4-stroke >750 cm³	505.863	

Table 2-4 Vehicle population per subsector category for Poland

Sector	Subsector	Poland μ	σ
Passenger Cars	Gasoline <1,4 l	5.890.018	194.212
Passenger Cars	Gasoline 1,4 - 2,0 l	2.853.116	187.552
Passenger Cars	Gasoline >2,0 l	253.264	38.415
Passenger Cars	Diesel <2,0 l	1.660.117	113.710
Passenger Cars	Diesel >2,0 l	314.139	60.785
Passenger Cars	LPG	992.755	231.352
Light Duty Vehicles	Gasoline <3,5t	980.551	9.244,7
Heavy Duty Trucks	Gasoline >3,5 t	108.400	1.022,0
Light Duty Vehicles	Diesel <3,5 t	732.359	7.323,6
Heavy Duty Trucks	Rigid <=7,5 t	73.538	5.147,7
Heavy Duty Trucks	Rigid 7,5 - 12 t	53.445	3.741,1
Heavy Duty Trucks	Rigid 12 - 14 t	25.422	1.779,5
Heavy Duty Trucks	Rigid 14 - 20 t	31.993	2.239,5
Heavy Duty Trucks	Rigid 20 - 26 t	28.597	2.001,8
Heavy Duty Trucks	Rigid 26 - 28 t	7.342	513,9
Heavy Duty Trucks	Rigid 28 - 32 t	8.928	625,0
Heavy Duty Trucks	Rigid >32 t	10.925	764,7
Heavy Duty Trucks	Articulated 14 - 20 t	10.741	751,8
Heavy Duty Trucks	Articulated 20 - 28 t	9.284	649,9
Heavy Duty Trucks	Articulated 28 - 34 t	15.037	1.052,6
Heavy Duty Trucks	Articulated 34 - 40 t	35.608	2.492,6
Heavy Duty Trucks	Articulated 40 - 50 t	8.083	565,8
Heavy Duty Trucks	Articulated 50 - 60 t	3.461	242,3
Buses	Urban Buses Midi <=15 t	1.813	126,9
Buses	Urban Buses Standard 15 - 18 t	35.035	2.452,5
Buses	Urban Buses Articulated >18 t	25.575	1.790,3
Buses	Coaches Standard <=18 t	15.944	1.116,0
Buses	Coaches Articulated >18 t	2.216	155,1
Mopeds	<50 cm³	337.511	0,0
Motorcycles	2-stroke >50 cm³	454.508	31.815,5
Motorcycles	4-stroke <250 cm³	75.694	5.298,6
Motorcycles	4-stroke 250 - 750 cm³	128.674	9.007,2
Motorcycles	4-stroke >750 cm³	94.124	6.588,7

The last variable that determines vehicle stock is the split into the different technology classes (N_{tech}).

To calculate the technology split for each country and vehicle category, the following procedure was followed. First, the probability of vehicles to remain in the stock, as a function of their age, was approached with a Weibull distribution. In fact, the Weibull distribution provides the survival probability for each vehicle category with age $\varphi_i(age)$, and this can be used to calculate the age distribution of the fleet. This probability is given by the following equation:

$$\varphi_i(age) = \exp - \left[\left(\frac{age + Beta_i}{Tau_i} \right)^{Beta_i} \right] \quad \text{where } \varphi(0) = 1 \qquad (2\text{-}1)$$

The probability uses two parameters, (Beta and Tau). The two parameters do not have an exact physical meaning. However, it can be considered that they approximate the useful life of the vehicle (Tau) and a characteristic (Beta) of the rate by which the probability decreases. By taking an initial age distribution at a historical year (in our case: 1995) and by introducing the new registrations per year (vehicles of age 0) and the Weibull scrappage probability, one may calculate the age distribution of the vehicles at any given year. We calculated the age distribution for the year 2005 by introducing to our calculations the stock and new registrations from the FLEETS project.

Symbol:	Ntech	**Name:**	Vehicle population at technology level
Type:	Input Variable	**units:**	vehs.
Description:	This is the population of vehicles classified to one of the 241 different vehicle technologies in COPERT 4. The technology level per "Euro" standard for passenger cars is more or less available in national statistics. For earlier years (non-catalyst cars or first generation of catalysts), the distinction was not as detailed and some uncertainty may exist. Also, uncertainties may exist for heavy duty vehicles.		
Sources:	The information (in particular for passenger cars) should be available in national statistics. For categories where such information is not available, one may consider an age distribution according to year of first registration and take into account the emission standard implementation matrix, to construct a technology classification. In order to estimate the age distribution, we follow the TRENDS methodology, i.e. the vehicle survival probablity is considered to follow a Weibull curve with a high probability at young age, decreasing as the vehicles become older. The Weibull distribution is defined by two parameters: The "beta" parameter defines the steepness of the probability drop with age. The "tau" parameter defines a characteristic service lifetime of a vehicle. By editing these two parameters, one has clearly defined the survival probability. The age distribution for the reporting year may then be calculated starting from an initial (rough) age distribution at a historic year and respecting the new registrations the the stock increase over the period from the historic year to the reporting year.		
Typical Range:	The classification to vehicles classes is country specific. A good indication of the classification to difference classes is the mean vehicle age which ramges between 7 and 12 years for passenger cars.		
Quantification of variability (Italy & Poland):	The distribution of cars into different technologies is largely known in Italy, as vehicles are registered according to the emisssion standard. There is only a small fraction of cars which are reported as unidentified in the ACI classification, which is less than 1% for the Italian fleet (30 thousand cars in a stock of more than 30 million). Data was considered to be known and the national statistics was used to perform the calculations.The variance In Poland, this information is more scarce. Therefore, the beta and tau parameters for Poland have been calculated in a wider range. It was assumed that the values would wange between an uncertainty of +-5% for the age of 5 years and a +-10% for the age of 15.		

At a second step, the technology split for each country is calculated by applying the technology implementation matrix of the particular country to the age distribution. The technology implementation matrix contains the distribution of new registrations of different years to the various technologies.

In the case of Italy, the technology classification was considered exact, i.e no variability was introduced for the variable N_{tech}. The only variability in the stock was introduced from the uncertainty in the N_{cat} and N_{sub} variables. However, in the case of Poland, the uncertainty in classification to different technologies was translated to a problem of age distribution. The central estimate for the age distribution of vehicles of Poland was based on the FLEETS data and the *Beta* and *Tau* parameters were calculated on this basis. Then, an artificial uncertainty range was assigned to the probability function of Poland. This artificial uncertainty is schematically shown in Figure 2-1. It was in principle assumed that the survival probability for vehicles with age of five and fifteen years ranges between +/- 5 and +/- 10 percentage units respectively from the central value. Figure 2-1 shows the original Weibull distribution function for gasoline passenger cars <1.4 l, the range assumed for the uncertainty of the survival probability, and three alternative curves which fulfill the selected uncertainty range.

By using the above methodology a number of *Beta* and *Tau* pairs were calculated for each vehicle category, that fulfilled the uncertainty range introduced. From these couples, 100 were finally selected by sampling percentiles from the joint probability distribution function of *Beta* and *Tau*. They served as data pool providing each time the required couple of values used for the calculations.

As an example of this method, Figure 2-2 shows the distribution of the vehicle stock of Euro 1 gasoline cars <1.4 l used in the runs for Poland. The values form a normal distribution with a standard deviation which is 3.7% of the mean value. Similar distributions have been produced for all vehicle technologies in the case of Poland. The influence of this uncertainty to the calculations is represented by reference to the tau value.

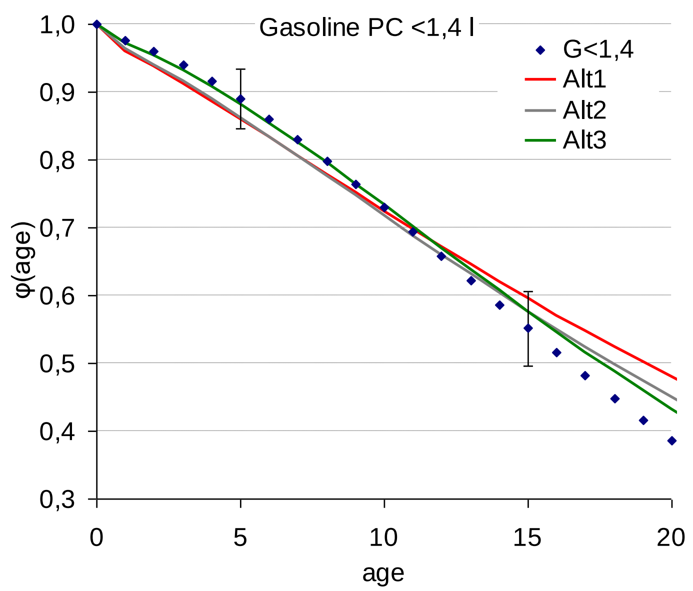

Figure 2-1 Weibull distribution function in the case of Poland, Gasoline cars <1.4 l, and three alternative solutions that fulfill the artificial uncertainty introduced

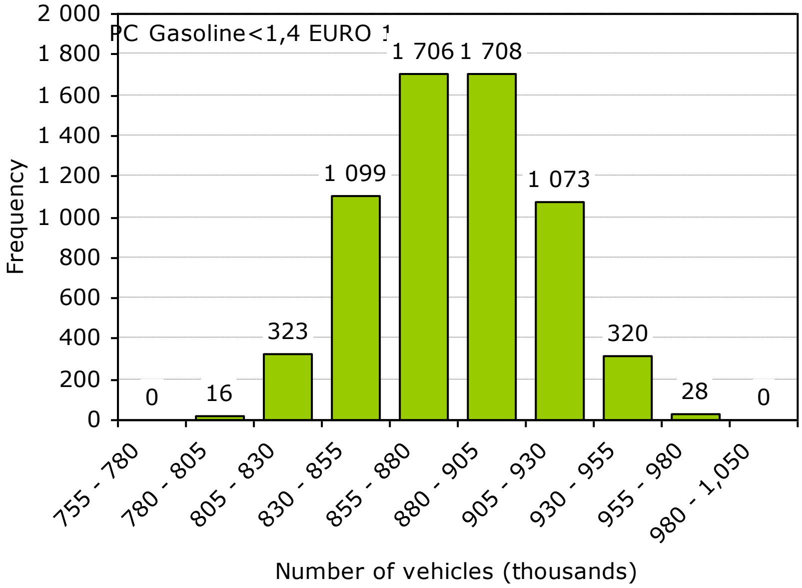

Figure 2-2: Probability distribution of the vehicle stock of Gasoline Euro 1 passenger cars <1.4 l used in the runs for Poland

2.2 Emission factors and parameters

The uncertainty of emission factors is a major part of the uncertainty in all transport emission models, as they constitute the core of the emission calculation. The uncertainty of the emission factors originates from the variability of the underlying experimental data, i.e. the variability in the emission level of each individual vehicle which has been included in the sample of vehicles used to derive the emission factors. A typical range of the variability of individual measurements for emission factors is shown in Figure 2-3 for gasoline passenger cars of Euro 3 technology. In COPERT, there are two sets of emission factors, the hot ones and the cold-start ones. The hot emission factors originate from individual measurements of vehicles/engines mainly conducted in the Artemis project. Some older measurements were based in previous projects, such as CORINAIR89, COST319, MEET, etc. The uncertainty of old emission factors has not changed since the previous Monte Carlo exercise conducted in Copert 3. However, emission factors for Euro 1 and later technologies are solely based on Artemis. Emission factors on non-exhaust PM and the related uncertainty has been taken from the relevant chapter in the Atmoshperic Emission Inventory Guidebook. The N_2O and CH_4 uncertainty has been based on work conducted at the Laboratory of Applied Thermodynamics. The uncertainty of cold-start emission factors was more difficult to assess, as the values used in COPERT are a hybrid of the Artemis and the older CORINAIR methodologies. In the absence of detailed data and in order not to neglect the contribution of cold start variability, we assumed that the ratio of standard deviation over mean for the cold emission factors is equal to the hot ones. This is an approximation which was introduced in the absence of more detailed data.

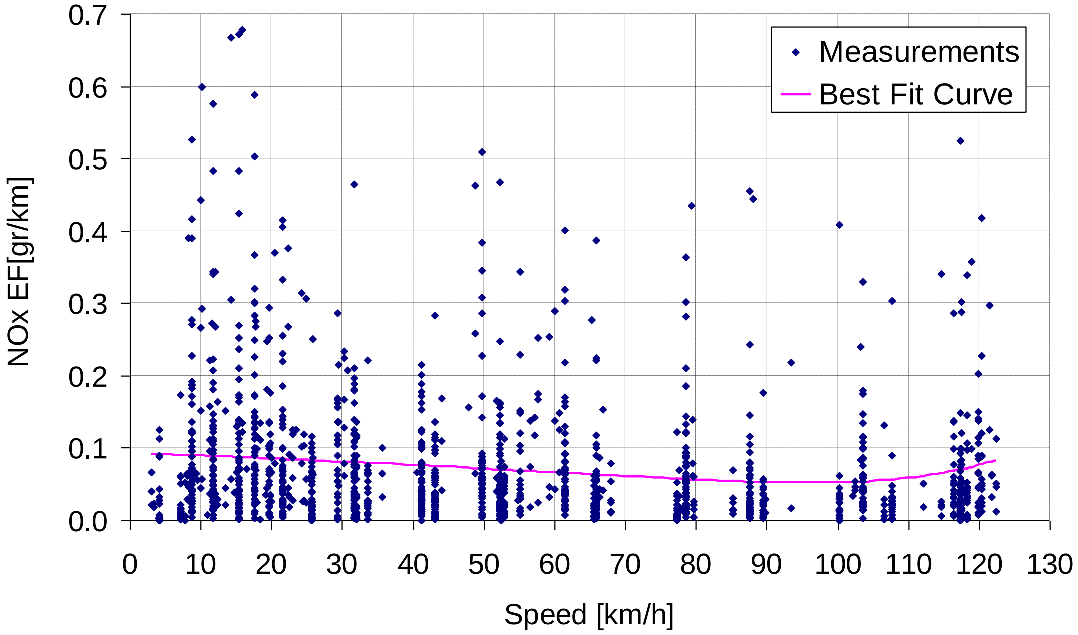

Figure 2-3: Example of variability of individual measurements for the derivation of emission factors. Gasoline Euro 3 passenger cars. Source: ARTEMIS database.

Symbol:	ehot, tech	**Name:**	Hot emission factor
Type:	Model parameter	**units:**	g/km
Description:	The emission rate of vehicles of a specific technology in g/km, under thermally stabilised engine operation. In COPERT the emission factors are expressed as a function of mean travelling speed. In cases with limited information, emission factors are expressed as a function of the drving mode (urban, rural, highway).		
Sources:	Hot emission factors have been derived from measurements conducted in several research programmes. The most important ones include COST319, FP4 MEET, and FP6 ARTEMIS. Vehicles are driven over specific driving cycles, considered representative of actual driving conditions and the emission level is associated with the mean travelling speed over the cycle. A function is then drawn using regression analysis to associate emission level with travelling speed.		
Typical Range:	There is no typical range, as this depends on the uncertainty of the experimental data used to develop the emission factor.		
Quantification of variability (Italy & Poland):	For all pollutants and fuel consumption, the uncertainty range has been expressed as standard deviation of the experimental data per 10-km/h speed class intervals. The uncertainty has then been modelled with a lognormal around the emission factor value at the mean speed of each speed class interval. The lognormal model has been selected as the uncertainty is assymetric, i.e. there are no experimental data below 0, while ultra-emitters may emit several times above the average.		

The detailed standard deviations of the hot emission factors are quoted by Kouridis et al. (2010) for the different pollutants and fuel consumption. The fourteen classes in these tables correspond to fourteen classes of 10-km/h speed intervals (from 0 to 140 km/h). The uncertainty of the emission factors per class is approached with a log-normal model, having as a mean the emission factor value at the mean of the speed class (i.e. for class 1 is 5 km/h, class 2 is 15 km/h, etc.) and as a standard deviation, the one given in these Tables.

Symbol:	ecold/ehot,tech	**Name:**	Cold-start emission factor
Type:	Model parameter	**units:**	-
Description:	The ratio expressing cold-start over hot emission. Cold-start emissions lead to higher emissions as both the engine and the emission control system have not reached their normal operation temperature.		
Sources:	The over-emission ratio in COPERT has been derived as computed value out of a detailed cold-start study conducted in the framework of FP4 MEET and further elaborated in FP6 ARTEMIS (Andre and Joumard, INRETS report LTE 0509). Since these are computed values, it is difficult to obtain independent (literature) sources to quantify it.		
Typical Range:	There is no typical range, as this depends on the uncertainty of the experimental data used to develop the emission factor.		
Quantification of variability (Italy & Poland):	Cold emission factors in Copert have been produced as a hybrid of the Copert II, MEET and ARTEMIS methodologies, using approximations to convert the MEET approach (as corrected in ARTEMIS) to the older CORINAIR cold-start approach. Cold-start modelling is one of least elaborate items of Copert 4. As it was not possible to estimate the uncertainty of the emission factors from the uncertainty in the experimental data, we have assumed that the standard deviation over mean for ecold/ehot is the same with the standard deviation over mean of the hot emission factor. In this way, the contribution of cold-start to undertainty is estimated in a realistic (albeit not exact) way.		

Three more variables are used in COPERT 4 to calculate emission relevant information. These are summarized in Table 2-5 and in the remaining tabulated forms.

Table 2-5 Variables used in COPERT to calculate emissions

Symbol	Parameter Description
b	Cold-trip distance
Dftech	Degradation factor
Ltrip	Mean trip length

Symbol:	b	**Name:**	Cold-trip distance
Type:	Model parameter	**units:**	-
Description:	The fraction of total annual mileage driven before the engine and the emission control system have reached their normal operation temperature. The cold-trip distance depends on the distirbution of trip lengths (short trips lead to relatively higher cold-trip fractions), and the vehicle emission standard (new concepts reach their operation temperature faster).		
Sources:	COPERT 4 suggests a cold-trip distance function, which has been based on older observations. The cold-trip distance requires specific studies to assess, as driving conditions (mean speed, ambient temperature) and driving pattern (short frequent trips or longer, e.g. intercity, trips) affect its value. COPERT provides some guidance on what is the average time it takes to reach normal operation temperature, for each technology concept. This can be used as a reference to estimate the cold-trip distance.		
Typical Range:	The mileage fraction under cold-start conditions is in the rnge of 10-30% depending on the trip distribution, the ambient temperature and the gasoline vehicle technology considered.		
Quantification of variability (Italy):	It depends on the vehicle technology and the driving profile. No huge uncertainty expected at a fleet level. Proposal: 3s=0,13×μ		

Symbol:	Dftech	**Name:**	Degradation factor
Type:	Model parameter	**units:**	-
Description:	The degradation of emissions with vehicle age. This should in principle take into account two effects: First, the effect of normal degradation of emission components on increasing emissions, and second the effect of malfunctions (ultra and high emitters) on increasing the average emission level.		
Sources:	COPERT provides values based on a study conducted in the framework of the FP4 MEET project. Alternative sources of information include published studies by EPA and CARB and some technical papers.		
Typical Range:	The degradation factor depends on vehicle technology and mileage. The maximum degrdation factor may be 2 or even higher for old vehicles.		
Quantification of variability (Italy):	No explicit calculation available. Although potentially important, no uncertainty range is proposed for DF due to absence of experimental data		

Symbol:	Ltrip	**Name:**	Mean trip length
Type:	Input Variable	**units:**	km
Description:	The average distance travelled by a trip of passenger cars in a country. Probably the best definition of a trip is as "a one-way course of travel having a single main purpose". This means that a trip is a not a complete journey, which may involve several stops and may serve for different purposes. A trip is an activity with an origin, a destination, and a purpose. For example, a trip from home to work, or a businees or leisure trip from one city to another. A trip is not split by intermediate stop-overs. For example, a ten-minute break in a travel between two cities does not split the trip in two. If we would allow for this, this would mean that the purpose of the first trip was to leave the origin city and reach a destination to have a break. However, the purpose of this trip is to reach the destination city. However, if the first stop is an overnight stay in some intermediate city, then the trip is actually split because the target of the first trip would be to reach a city to have a break and then continue with a second trip in the following day. The value in COPERT refers to passenger cars as this is the only category where detailed statistics are required to calculate cold-start emissions.		
Sources:	The trip length can be found from national surveys but also from international statistics (some countries). International statistics sources include		
Typical Range:	The European-wide average value is 12.4 km		
Quantification of variability (Italy):	$s = 0{,}2 \times \mu$, according to French COPERT Uncertainty report		

2.3 Uncertainty of mileage variables

Symbol:	Mtech	**Name:**	Annual mileage
Type:	Input Variable	**units:**	km/a
Description:	This is the annual mileage driven by vehicles of a specific category and technology level, at a national level. Currently, there is a discussion on whether this mileage should relfect the mileage of the national stock vehicles in the national territory or including abroad travelling. Also, the discussion should extend to whether this should cover foreign vehicles travelling in the national territory (see discussion in ECE/EB.AIR/GE.1/2007/15). For consistency, this mileage should refer to the fuel sold in the country. Problems arise when there is significant tank tourism (different country of refuelling and different country of consumption - usually to benefit from price differences) and the fuel consumed may be entirely different than the fuel sold. In the case of Italy, where no significant tank tourism exists, the annual mileage is compatble with fuel sold in the country. Relevant data for Poland are not available. Annual mileage differs with different technology and vehicle age, as older vehicles are used less with time.		
Sources:	Annual mileage per vehicle type may be found from national statistics on mobility. The effect of mileage with vehicle age can be inferred from questionnaires, field campaigns (e.g for trucks and busses) or review of inspection and maintenance data (mainly of passenger cars). These data can be obtained either from private (dealer) stations of vehicle manufacturers, or from stations used for the regular I&M inspection of vehicles in the country.		
Typical Range:	The annual mileage ranges between 10000-25000 km for passenger cars, 20000-35000 for light duty trucks, 40000-100000 for trucks and busses and 2000-8000 for motorcycles.		
Quantification of variability (Italy & Poland):	Mileage in COPERT calculation is considered to decrease exponentially with age. In Italy, mileage data was aquired from national statistics since such strong data existed with a small uncertainty. In Poland such data was not available, so mileage values were estimated using quality data from near by countries or countries with similar vehicle fleet. The uncertainty in the mileage was estimated as s=0,1xμ. Data was delivered per vehicle type. The correlation between the mileage and the vehicle age was also estimated. The correction factor, applied to the mileage, was calculated using a Weibull function. The uncertainty of these Weibull function parameters (bm and Tm) which influence the mileage was calculated with post analysis of the data. The same approach was used in both countries.		

The calculation of the annual mileage for a particular vehicle technology (Mtech) is a function of the annual mileage of a new vehicle (M0) and a correction function for the effect of vehicle age (φ(age)). The decrease of annual mileage with age has been approached by a Weibull function. This reflects the fact that new cars are driven more than old ones. The shape of the curve is considered to be a good approximation of the actual shape of the mileage reduction with age. An example of actual mileage degradation with age, which is based on recordings of Inspection and Maintenance data from the Italian passenger car fleet is shown in Figure 2-4 (Caserini et al., 2007). It is evident that the curves flat out after some years. The equation of the Weibull function used is given in (2-2) and (2-3). The modeling parameters (bm, Tm) and M0 are specific to country and vehicle subsector considered.

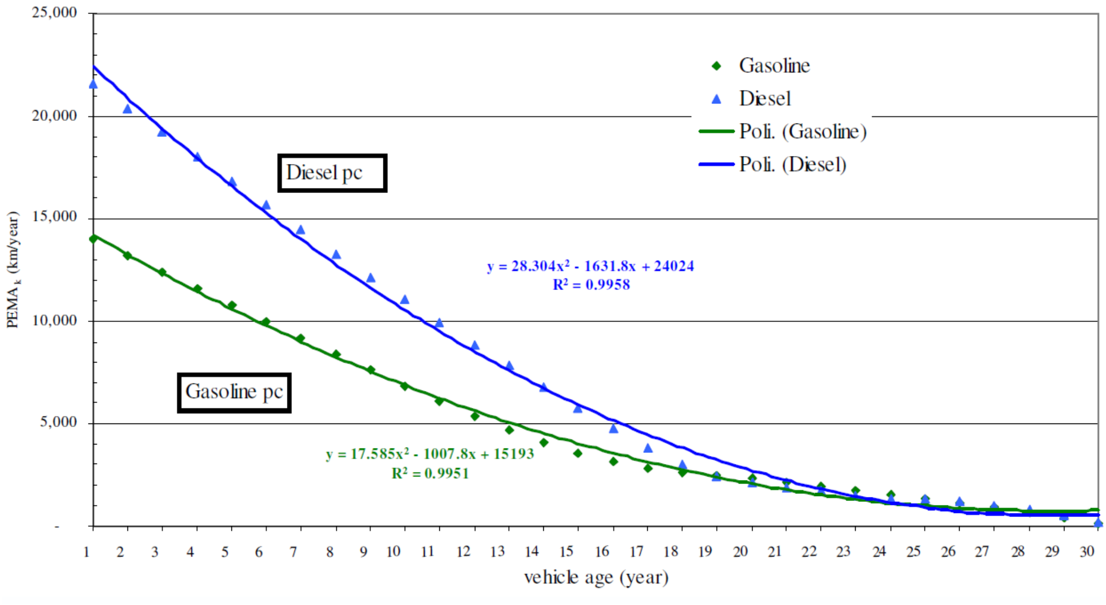

Figure 2-4: Annual mileage as a function of vehicle age for the Italian passenger car fleet. Source: (Caserini et al., 2007).

$$\varphi(age) = \exp - \left[\left(\frac{age + b_m}{T_m} \right)^{b_m} \right] \tag{2-2}$$

$$M_{tech}(age) = \phi(age) \cdot M0 \tag{2-3}$$

The uncertainty in the calculation of the Mtech parameter originates from the uncertainty in b_m, T_m and M0. In the case of Italy, central values for the three parameters were available from the FLEETS database. In case of Poland, no data were available. In order to estimate the central parameters in this case, all countries with detailed data of the FLEETS project (8 countries) were pooled together in a single dataset, and the averaged values that were derived in this way were used for Poland. Due to the robust dataset in Italy, the M0 value was considered of zero uncertainty. In case of Poland, the uncertainty of M0 was an estimation (s=0,1xμ).

The φ(age) is also assumed to range between a minimum and a maximum. These boundaries are defined from the extents of φ(age) functions of all countries that submitted such detailed data to FLEETS. These extents, for the example of gasoline passenger cars of <1,4 l are shown in Figure 2-5. It was therefore assumed in our case, that φ(age) can receive any value within these two boundaries. We then calculated all (bm, Tm) pairs that satisfied this limitation. With this procedure, a large number of bm and Tm couples were derived, different for each vehicle category. From these couples 100 were finally selected by sampling percentiles from the joint probability distribution function of bm and Tm. They served as data pool providing each time the required couple of bm and Tm used for the calculations.

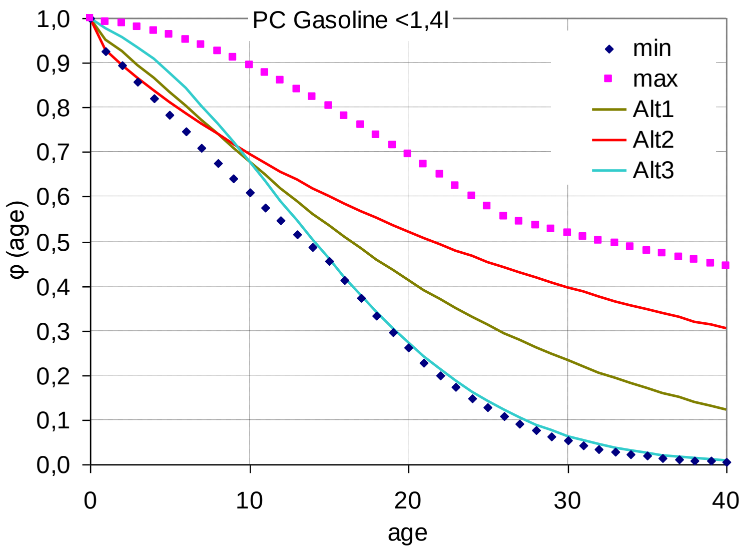

Figure 2-5: Example of b_m and T_m values fulfilling the selected criteria (min and max)

Symbol:	Mm,tech	**Name:**	Mean fleet mileage
Type:	Input Variable	**units:**	km
Description:	The mean cumulative mileage of vehicles of a particular technology. This is the average odometer reading of vehicles of a particular technology. This mileage increses with vehicle age and is used as input to calculate the degradation in the emission performance of vehicles as they grow older. This is an input to calculate the emission degradation and is only relevant for gasoline passenger cars and light duty trucks. The reason of focussing on gasoline cars only is that they are equipped with exhaust aftretreatment (three-way catalysts) which are the main source of emission degradation. The effect will become potentially important also for diesel vehicles, as they are also gradually equipped with exhaust aftertreatment.		
Sources:	This value is calculated by using the average vehicle age and the annual mileage driven for each vehicle technology.		
Typical Range:	This is specific to vehicle technology. Assuming that a car runs for 12000 km annualy over its lifetime, a Euro 1 car (1992) will have an average mileage of ~200000km, while a Euro 4 car (2007) will have about 25000 km looking at the odometer in year 2009.		
Quantification of variability (Italy & Poland):	This is calculated by the uncertainty in the bm and Tm values, and the uncertainty in the annual vehicle mileage.		

The Mean fleet mileage ($M_{m,tech}$) expresses the average odometer reading of a vehicle of a particular technology. This is a value calculated by using the average vehicle age and the average annual vehicle mileage. For this reason no separate uncertainty had to be estimated, as this was already derived from the annual mileage values used to calculate emissions. The formula used to calculate the mean fleet mileage is the following:

$$Mm, tech = \sum_{age=0}^{average\_age} M0 \cdot \phi(age) \qquad (2\text{-}4)$$

2.4 Other Parameters / Variables

Table 2-6 summarizes the remaining parameters used by COPERT to calculate emissions. Each of them is summarized in the subsequent tabulated forms. The "French uncertainty report" that is mentioned in several of the forms, is the comprehensive study of Duboudin et al. (2002) on the uncertainty and sensitivity analysis of COPERT. Although this has been specific to French conditions, the uncertainty ranges assumed for several of the parameters hold true for other countries as well

Table 2-6: Input variables used in COPERT to calculate emissions

Symbol	Parameter Description
H:C	Hydrogen-to-carbon ratio
HSPtech	Highway speed
Hstech	Highway share
LFHDV	Load Factor
O:C	Oxygen-to-carbon ratio
RSPtech	Rural speed
RStech	Rural share
RVP	Fuel reid vapour pressure
S	Sulfur level in fuel
tmax	Average max monthly temperature
tmin	Average min monthly temperature
TStech	Total share
USPtech	Urban speed
UStech	Urban share

Symbol:	H:C	**Name:**	Hydrogen-to-carbon ratio
Type:	Input Variable	**units:**	-
Description:	The ratio of atoms of hydrogen over carbon in the fuel molecule. Road transport fuels are blends of organic species and mostly contain carbon, hydrogen and oxygen. This ratio is the average for all molecule types in the blend. It can be determined by elemental analysis of the fuel. The exact H:C ratio may vary depending on the fuel origin (e.g. middle east, north sea, etc.) and processing (e.g. cracking, aromatics processing). The H:C ratio is required to estimate CO2 emissions on the basis of fuel consumption and is different for each of the fuel types (diesel, gasoline, natural gas, liguid petroleum gas).		
Sources:	The H:C ratio may be found by contacting refineries in the country and reqesting this information. In general, a high heating value of the fuel means a higher ratio of H:C.		
Typical Range:	Typically 1.8-2.1		
Quantification of variability (Italy & Poland):	Similar uncertainty for both Gasoline and Diesel. The ratio is expected to vary from 1.8 to 2.1, therefore, 3s = 0.15.		

Symbol:	HSPtech	**Name:**	Highway speed
Type:	Input Variable	**units:**	km/h
Description:	The mean travelling speed of a vehicle category in highway conditions, over the period considered in an inventory (year). In general, the mean travelling speed involved in highway conditions exceeds 75 km/h. The mean speed differs with vehicle category, with motorcycles and cars achieveing a higher mean speed than trucks.		
Sources:	Highway management authorities have precise recordings of mean travelling speed in several parts of the highways. These can provide a good estimate of the mean speed. In parallel, the speed limits existing in several highway s give a constrating that cannot be exceeded.		
Typical Range:	Typical highway speeds are between 70 to 120 km/h, depending on vehicle class		
Quantification of variability (Italy & Poland):	3s = 0,1×μ, according to French COPERT Uncertainty report		

Symbol:	Hstech	**Name:**	Highway share
Type:	Input Variable	**units:**	%
Description:	This is the share of annual mileage (in percentage units) driven in highways. The mean travelling speed under highway conditions in general exceeds 75 km/h.		
Sources:	The mileage over highways (motorways, autobahnen, autostrada, autoroutes, …) can be estimated from data of the authorities managing the highways. The length of highways is known and the vehicle volume is monitored in different parts of the highway. This gives a very precise value of the total veh.km (per vehicle category) performed in the highways of a country over a year. By division of this value with the total national stock number, and the mean mileage per year, one obtains a representative figure of the mileage share in highway conditions.		
Typical Range:	The share of highway mileage ranges between 10% and 25% for cars and light duty vehicles, 40-60% for trucks, and very low for motorcycles.		
Quantification of variability (Italy & Poland):	3s = 0,1×μ, according to French COPERT Uncertainty report		

Symbol:	LFHDV	**Name:**	Load Factor
Type:	Input Variable	**units:**	%
Description:	The loading as a fraction (in percentage units) of the total carrying capacity of trucks and busses. The correction is only introduced for heavy duty vehicles. The reason is that the difference between a loaded and an empty truck/bus is large, compared to passenger cars. For example, a truck may carry as much or even more weight than its empty weight, while a car cannot carry more than 30-35% of its weight. The large carrying capacity has a big effect on the emissions and consumption of a laoded vs. empty truck.		
Sources:	COPERT 4 suggests a 50% loading factor for trucks and busses. This can be modified by using appropriate statistics. Both ton-km by trucks and p-km by busses should be relatively well known in countries, as they are both recorded for taxation or business development purposes. If these are not known, then these can be found in models (e.g. PRIMES, GAINS, ...). The veh-km reported by trucks in COPERT, multiplied by the carrying capacity of each truck category and the loading factor should give the total ton-km in the country. Respectively, the veh-km by busses multiplied by an average carrying capacity per bus (in persons) and the loading factor should give the total p-km carries by busses in the country.		
Typical Range:	Typical ranges should be in the order of 40-80%.		
Quantification of variability (Italy & Poland):	There is no statistics on its value. A guess is 3s = 0,2×μ		

Symbol:	O:C	**Name:**	Oxygen-to-carbon ratio
Type:	Input Variable	**units:**	-
Description:	The ratio of atoms of oxygen over carbon in the fuel molecule. Oxygen carriers (oxygenates) in the fuel have been used for several years. Oxygenates (ethers) have been historically used in gasoline as octane number enhancers. More recently, they have been added in gasoline with the addition of (bio-)ethanol. In diesel, oxygen has been introduced with the biodiesel (esters) blends. The O:C ratio is required to estimate CO2 emissions on the basis of fuel consumption and is different for each of the fuel types (diesel, gasoline, natural gas, liguid petroleum gas). In principle, natural gas and liguid petroleum gas should only contain traces of oxygen.		
Sources:	The O:C ratio may be found by contacting refineries in the country and reqesting this information. In addition, information on the biofuel blends may provide relevant information.		
Typical Range:	Zero for non-oxygenated fuels. Up to 0.1 for typixal oxygenated ones.		
Quantification of variability (Italy & Poland):	Similar uncertainty for both Gasoline and Diesel. The ratio is expected to vary from 0 to 0.1, therefore, 3s = 0.05		

Symbol:	RSPtech	**Name:**	Rural speed
Type:	Input Variable	**units:**	km/h
Description:	The mean travelling speed of a vehicle category in rural conditions, over the period considered in an inventory (year). In general, the mean travelling speed involved in rural conditions is in the order of 60 km/h.		
Sources:	The precise rural driving speed is difficult to estimate as, often, there are limited statistics in non urban or highway areas. On top of this, rural networks involve a variety of roads with different characteristics. An approach in estimating rural speeds is to consider the proportion of rural roads with different speed limits (usually 50, 60, 70 and 80 km/h). By estimating the activity in the different roads and with the constraint that the mean speed cannot exceed the speed limit, one may produce an estimate of the mean rural driving speed.		
Typical Range:	Typical rural speeds are between 55 and 80 km/h.		
Quantification of variability (Italy & Poland):	3s = 0,2×μ, according to French COPERT Uncertainty report		

Symbol:	RStech	**Name:**	Rural share
Type:	Input Variable	**units:**	%
Description:	The share of annual mileage driven in rural conditions. Rural areas are in principle defined as what is not urban and not highway. The rural share is calculated as the difference of the sum of urban and highway conditions over 100.		
Sources:	This is difficult to estimate independetly. Unless there are detailed statistics in a country, a reasonable approach in estimating the rural share is to subtract the urban and highway shares from 100.		
Typical Range:	The share of rural mileage ranges between 30% and 50% for cars, and variable range for the other vehicle classes.		
Quantification of variability (Italy & Poland):	3s = 0,2×μ, according to French COPERT Uncertainty report		

Symbol:	RVP	**Name:**	Fuel reid vapour pressure
Type:	Input Variable	**units:**	kPa
Description:	The vapour pressure of gasoline (defined by a test at 38 oC). The vapour pressure is a measure of the fuel volatility. The higher the vapour pressure, the easier the fuel evaporates at a given temperature. The vapour pressure is important to calculate NMVOC emissions due to evaporation losses. These are only relevant for gasoline, due to the low volatility of the diesel fuel.		
Sources:	The maximum RVP is defined by the regulations. Some detailed data on RVP for different countries and relevant information and sources may be found in http://ec.europa.eu/environment/air/pdf/fqm_summary_2004.pdf.		
Typical Range:	The typical range in Europe is 60 kPa (summer grade) to 90 kPa (winter grade).		
Quantification of variability (Italy & Poland):	Limited uncertainty expected, as fuels are centrally produced and the refineries need to follow the regulations. Assumption 3s = 0,05×μ		

Symbol:	S	**Name:**	Sulfur level in fuel
Type:	Input Variable	**units:**	ppm
Description:	The content of sulfur in the fuel. Sulfur carriers are present in the crude oil before distillation and are removed during the fuel processing. Sulfur is converted to sulfur dioxide during combustion but it also accelerates the degradation of aftertreatment devices. Maximum levels of sulfur in the fuel is regulated throughout Europe.		
Sources:	Fuel sulfur in each country cannot exceed the levels set by the regulations. Refineries usually put a safety margin and actual sulfur levels are in the order of 10-20% lower than the regulatory limits. Refineries have detailed information the sulfur levels of the fuels delivered to the market.		
Typical Range:	For 2009 fuel specifications, about 8 ppm for Diesel and 40 ppm for gasoline		
Quantification of variability (Italy & Poland):	Sulfur is controlles by regulations in both gasoline and diesel fuel. Therefore, uncertainty is very low: 3s = 0,05×μ		

Symbol:	tmax	**Name:**	Average max monthly temperature
Type:	Input Variable	**units:**	oC
Description:	The average of the maxima in daily temperature for a duration of a month. This maximum temperature is required as input to both evaporation and cold-start calculations. For countries with significant temperature differences over their area (e.g. south and north), the temperature should correspond to the average (possibly weighted average) of areas where most of the traffic is located. For example, in the case of Italy, it should correspond mostly to the northern half of the country, as the total activity in the southern part is weak compared to the north.		
Sources:	Historic information on temperatures may be received from the meteorological insitutes in each country. Internet datavases (i.e. www.weatherbase.com) also include detailed data for major cities in Europe.		
Typical Range:	Country and month specific. Average max temperature ranges between 12 - 31 C, depending on the month in Southern Europe to -3 to +21 in Northern Europe.		
Quantification of variability (Italy & Poland):	An uncertainty range required to cover national differences between north and south. 3s=3C		

Symbol:	tmin	**Name:**	Average min monthly temperature
Type:	Input Variable	**units:**	oC
Description:	The average of the minima in daily temperature for a duration of a month. This minimum temperature is required as input to both evaporation and cold-start calculations. For countries with significant temperature differences over their area (e.g. south and north), the temperature should correspond to the average (possibly weighted average) of areas where most of the traffic is located. For example, in the case of Italy, it should correspond mostly to the northern half of the country, as the total activity in the southern part is weak compared to the north.		
Sources:	Historic information on temperatures may be received from the meteorological insitutes in each country. Internet datavases (i.e. www.weatherbase.com) also include detailed data for major cities in Europe.		
Typical Range:	Country and month specific. Average min temperature ranges between 6 - 22 C, depending on the month in Southern Europe to -9 to +11 in Northern Europe.		
Quantification of variability (Italy & Poland):	An uncertainty range required to cover national differences between north and south. 3s=3C		

Symbol:	TStech	**Name:**	Total share
Type:	Check item	**units:**	%
Description:	The sum of shares in urban, rural and highway driving.		
Sources:	Equal to 100%		
Typical Range:	The share of highway mileage ranges between 10% and 25% for cars, 40-60% for trucks, and very low for motorcycles.		
Quantification of variability (Italy & Poland):	0		

Symbol:	USPtech	**Name:**	Urban speed
Type:	Input Variable	**units:**	km/h
Description:	The mean travelling speed of a vehicle category in urban conditions, over the period considered in an inventory (year). In general, the mean travelling speed involved in urban conditions does not exceed 35 km/h. The mean speed differs with vehicle category, with motorcycles usually achieveing a higher mean speed than passenger cars.		
Sources:	City planning and traffic management authorities have good estimations of the mean speed, via field campaigns they have conducted, orreal-time monitors of mean speed installed in key areas around the city.		
Typical Range:	Typical urban speeds are between 18 to 35 km/h		
Quantification of variability (Italy & Poland):	3s = 0,2×μ, according to French COPERT Uncertainty report		

3 Results

In this section two test cases at a national level are presented. The selected countries, namely Italy and Poland, demonstrate different levels of input uncertainty. The adopted methodological procedure was the same for both countries. At the first stage, the rather large number of uncertain input variables (51) has been filtered out from its non-influential inputs through a screening sensitivity analysis. At the second stage, the set of influential inputs is explored thoroughly by means of a quantitative sensitivity analysis to provide uncertainty and sensitivity estimates of total atmospheric emissions for the year 2005. Then, we evaluate the uncertainty of the COPERT prediction with reference to the statistical fuel consumption reported in each country, which is generally known with good confidence. Based on the fuel consumption comparison, the sample data set is corrected and the quantitative sensitivity analysis is repeated. This provides the corrected uncertainty and sensitivity analysis.

We do not present all details of the modeling approach in this report, as this would be too detailed for the objectives of the EC4MACS project. Instead we only present the basic steps. The reader who is interested in the mathematical details of the approach is directed to the report by Kouridis et al. (2010) which has been the original source of this information.

The sensitivity analysis for both countries has been performed through the following steps:

1. Prepare the Monte Carlo sample for the screening experiment using the Morris design.
2. Execute the Monte Carlo simulations and collect the results.
3. Compute the sensitivity measures corresponding to the elementary effects in order to isolate the non-influential inputs.
4. Prepare the Monte Carlo sample for the variance-based sensitivity analysis, for the influential variables identified important in the previous step.
5. Execute the Monte Carlo simulations and collect the results
6. Quantify the importance of the uncertain inputs, taken singularly as well as their interactions.
7. Determine the input factors that are most responsible for producing model outputs within the targeted bounds of fuel consumption.

3.1 Case Study 1: Uncertainty and sensitivity for Italy

3.1.1 Initial data sample

The relative importance of the 51 uncertain input factors is initially explored with the screening design of Morris. A sample of 510 simulations was generated containing 8 percentiles for each input factor. The estimated mean and standard deviation of each elementary effects distribution are displayed in Figure 3-1. A general order of importance for the examined factors can be established considering the Euclidean distance from the origin in the (MU, SIGMA) space. According to this distance, the most influential input set, for all the output variables considered, contains 16 entries:

- the total population of passenger cars, light duty vehicles, heavy duty vehicles and mopeds (PC, LDV, HDV, MOP)
- the annual mileage of passenger cars, light duty vehicles, heavy duty vehicles and two-wheel vehicles (milPC, milLDV, milHDV, milMO)
- the urban share of the passenger cars (UPC)
- the velocity of the passenger cars under all driving modes (VUPC, VRPC, VHPC)
- the average trip length (ltrip)
- the oxygen to carbon ratio in the fuel (O2C)
- the hot and cold emission factors (eEF, eEFratio)

None of these parameters were obtained directly by the PRIMES model in EC4MACS. Therefore, their complete uncertainty derives from the FLEETS project. The only value that was consistent between PRIMES and our analysis is total fuel consumption per fuel type. The effect on uncertainty of calibrating our results to a fixed fuel consumption value is shown in the next section.

The 16 most influential parameters identified from the screening analysis were used next in a quantitative sensitivity analysis. For this purpose, a sample was built by selecting 5904 design points over a particular space-filling curve in the 16^{th} dimensional input space so as to explore each factor with a different frequency. The uncertainty of the annual emissions of CO, VOC, CH_4, NO_x, N_2O, $PM_{2.5}$, PM_{10}, non-exhaust PM and CO_2 is presented in Figure 3-2 while their descriptive statistics are given in Table 3-1. The red line in the histogram of CO_2 corresponds to the cumulative uncertainty of the greenhouse gases (N_2O, CH_4, CO_2) and is presented as equivalent CO_2. This is calculated taking into account the 100-year GHG equivalent contribution of the three species (CO_2: 1, N_2O: 310, CH_4: 21). Apart from CO_2 and FC (Figure 3-3a) that are best fit by a normal distribution, uncertainty for all other pollutants is better represented by a log-normal distribution. Among them, the most skewed are N_2O followed by CO and CH_4. The coefficient of variation is 10% for CO_2, in the order of 20-30% for NO_x, VOC, $PM_{2.5}$, PM_{10} and non-exhaust PM, on the order of 50-60% for CO and CH_4 and over 100% for N_2O.

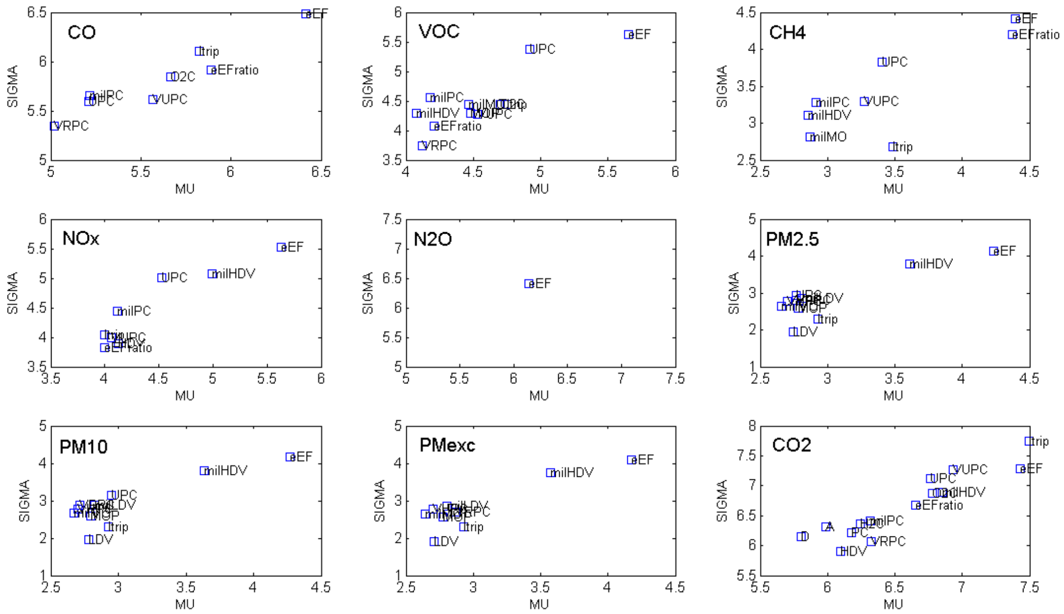

Figure 3-1: Morris results for Italy (year 2005). The influence of each variable for each pollutant increases with distance from the axes origin.

The first and total order sensitivity indices (*extended-FAST*) are presented in Table 5.2. The first order index represents the fractional contribution of the uncertain input (i.e. its main effect) to the output variability, while the sum of all the S_i's represents the cumulative contribution of all the variables (main effects) to the output variance. The difference between the total effect and the first order index for an input variable indicates the fraction of the output variance that is accounted for by interactions in which the specific input variable is involved. This means that the input variable interacts with other input parameters but it does not indicate with which parameters this interaction occurs.

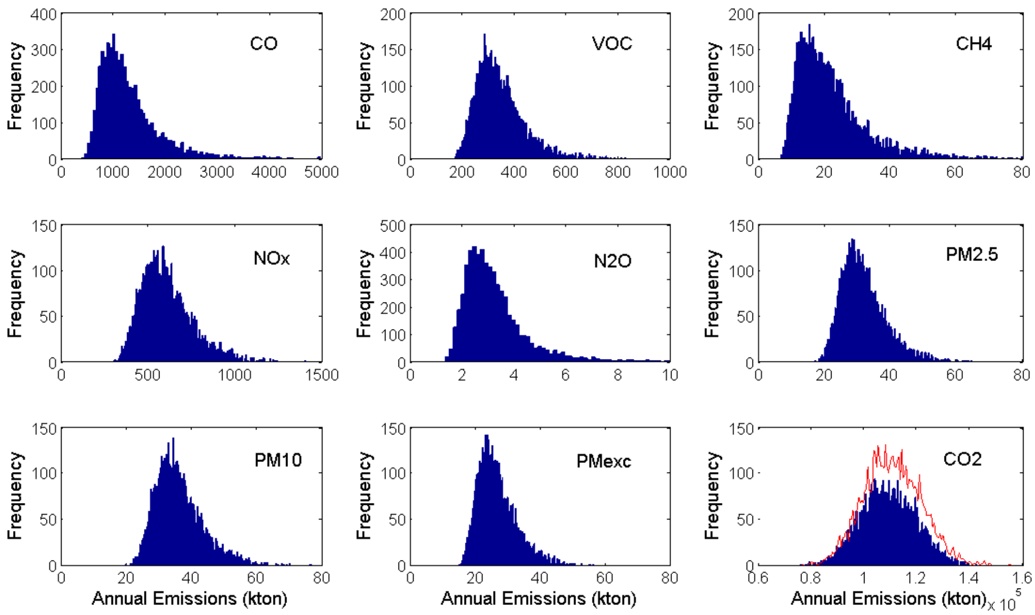

Figure 3-2: Uncertainty analysis of the annual emissions from road transport in Italy (year 2005). Red line stands for cumulative uncertainty of greenhouse gases (CO_2, CH_4, N_2O).

Table 3-1: Descriptive statistics of the histograms presented in Figure 3-2. Values are in ktonnes. CO_{2e} stands for total uncertainty of GHG equivalent.

	CO	VOC	CH_4	NO_X	N_2O	$PM_{2.5}$	PM_{10}	PM_{exh}	FC	CO_2	CO_{2e}
Mean	1,363	347	22	611	3.7	32	36	27	36,386	109,081	110,694
Median	1,162	328	19	586	3.0	31	34	26	36,311	108,859	110,236
St. Dev.	776	98	11	155	4	7	7	6	3,538	10,668	11,459
Coef. Var. (%)	57	28	50	25	108	22	19	22	10	10	10

Table 3-2: First and Total Order Sensitivity Indices (extended-FAST) for VOC, NO_X, $PM_{2.5}$, PM_{10}, $PM_{exhaust}$, CO, N_2O, CH_4, CO_2 and FC (2005).

VOC	S_I	S_{TI}	**NO_X**	S_I	S_{TI}	**PM2.5**	S_I	S_{TI}	**PM10**	S_I	S_{TI}	**PMexh**	S_I	S_{TI}
eEF	0.78	0.92	eEF	0.83	0.92	eEF	0.81	0.92	eEF	0.81	0.91	eEF	0.81	0.92
ltrip	0.03	0.14	milHDV	0.08	0.17	milHDV	0.07	0.17	milHDV	0.07	0.17	milHDV	0.07	0.19
eEFratio	0.02	0.14	HDV	0.01	0.10	HDV	0.01	0.12	HDV	0.01	0.11	VHPC	0.01	0.14
milMO	0.02	0.13	VHPC	0.01	0.11	VHPC	0.01	0.13	milPC	0.01	0.11	HDV	0.01	0.13
O2C	0.01	0.11	eEFratio	0.00	0.11	milPC	0.01	0.11	VHPC	0.01	0.12	milPC	0.01	0.12
HDV	0.01	0.12	VRPC	0.00	0.12	ltrip	0.00	0.09	ltrip	0.00	0.09	ltrip	0.01	0.10
MOP	0.01	0.16	LDV	0.00	0.08	milMO	0.00	0.09	LDV	0.00	0.10	milMO	0.00	0.10
milHDV	0.01	0.12	MOP	0.00	0.11	MOP	0.00	0.11	milMO	0.00	0.09	MOP	0.00	0.13
VUPC	0.01	0.12	milPC	0.00	0.08	LDV	0.00	0.10	MOP	0.00	0.11	eEFratio	0.00	0.13
LDV	0.00	0.10	UPC	0.00	0.09	VUPC	0.00	0.09	VUPC	0.00	0.08	LDV	0.00	0.12
PC	0.00	0.15	ltrip	0.00	0.07	eEFratio	0.00	0.12	eEFratio	0.00	0.12	VUPC	0.00	0.09
VHPC	0.00	0.12	PC	0.00	0.08	UPC	0.00	0.11	UPC	0.00	0.11	VRPC	0.00	0.15
VRPC	0.00	0.15	milLDV	0.00	0.09	VRPC	0.00	0.13	milLDV	0.00	0.11	UPC	0.00	0.13
UPC	0.00	0.13	milMO	0.00	0.07	milLDV	0.00	0.12	VRPC	0.00	0.12	milLDV	0.00	0.13
milPC	0.00	0.12	VUPC	0.00	0.07	O2C	0.00	0.09	PC	0.00	0.09	O2C	0.00	0.10
milLDV	0.00	0.11	O2C	0.00	0.07	PC	0.00	0.09	O2C	0.00	0.08	PC	0.00	0.10
ΣS_i	**0.91**	**2.86**		**0.95**	**2.35**		**0.93**	**2.62**		**0.93**	**2.52**		**0.93**	**2.79**
CO	S_I	S_{TI}	**N2O**	S_I	S_{TI}	**CH4**	S_I	S_{TI}	**CO2**	S_I	S_{TI}	**FC**	S_I	S_{TI}
eEF	0.64	0.87	eEF	0.19	0.83	eEF	0.36	0.53	eEF	0.63	0.71	eEF	0.64	0.73
eEFratio	0.05	0.31	eEFratio	0.04	0.81	eEFratio	0.36	0.54	milHDV	0.08	0.16	milHDV	0.08	0.16
HDV	0.01	0.27	ltrip	0.02	0.70	ltrip	0.02	0.22	eEFratio	0.05	0.16	eEFratio	0.05	0.16
LDV	0.01	0.20	MOP	0.02	0.82	VUPC	0.00	0.19	milPC	0.03	0.13	milPC	0.03	0.12
ltrip	0.01	0.22	VHPC	0.02	0.79	VHPC	0.00	0.21	O2C	0.02	0.09	ltrip	0.02	0.10
milHDV	0.00	0.23	HDV	0.02	0.76	PC	0.00	0.22	ltrip	0.02	0.10	HDV	0.01	0.10
milLDV	0.00	0.19	VRPC	0.02	0.82	HDV	0.00	0.16	HDV	0.01	0.10	LDV	0.01	0.08
milMO	0.01	0.21	milHDV	0.02	0.73	MOP	0.00	0.20	LDV	0.01	0.08	VUPC	0.01	0.07
milPC	0.00	0.23	milLDV	0.02	0.70	VRPC	0.00	0.21	VUPC	0.01	0.07	VHPC	0.01	0.09
MOP	0.01	0.35	milPC	0.02	0.74	milHDV	0.00	0.18	VHPC	0.00	0.09	PC	0.00	0.08
O2C	0.01	0.21	UPC	0.02	0.71	LDV	0.00	0.16	PC	0.00	0.07	UPC	0.00	0.09
PC	0.01	0.30	PC	0.02	0.80	UPC	0.00	0.18	UPC	0.00	0.09	MOP	0.00	0.09
UPC	0.01	0.24	LDV	0.02	0.73	milMO	0.00	0.15	MOP	0.00	0.09	milMO	0.00	0.09
VHPC	0.01	0.24	milMO	0.02	0.69	milLDV	0.00	0.14	milMO	0.00	0.09	VRPC	0.00	0.09
VRPC	0.01	0.31	O2C	0.02	0.66	milPC	0.00	0.16	VRPC	0.00	0.09	milLDV	0.00	0.09
VUPC	0.01	0.23	VUPC	0.01	0.77	O2C	0.00	0.18	milLDV	0.00	0.09	O2C	0.00	0.07
ΣS_i	**0.78**	**4.61**		**0.50**	**12.0**		**0.78**	**3.63**		**0.88**	**2.21**		**0.87**	**2.20**

The hot emission factors influence most the variability of the emissions; this characteristic is common for all the outputs. Specifically, 78-83% of the emissions variance of VOC, NO_X, $PM_{2.5}$, PM_{10} and $PM_{exhaust}$ is explained by the single contribution of the hot emission factors. The fraction of explained variance from hot emission factors for CO, CO_2 and FC is ~64% and drops down to 19% for N_2O. For CH_4, hot and cold emission factors explain equal portions of the variance (36% each). Analytically:

- VOC: 91% of the VOC emissions variance is explained by single contributions of the 16 variables; 78% of the VOC emissions variance is explained by the single contribution of the eEF. The sum of all the S_i's is very close to 1 indicating that the model behaves almost additively (with respect to the input parameters).
- NO_x: the eEF (83%) and the milHDV (8%) are influencing more the uncertainty of the NO_x emissions. The single contributions of the 16 variables explain the 95% of the NO_x emissions. Like VOC, the model behaves almost additively (with respect to the input parameters).
- PM: the results are similar with those of NO_x. 93% of the PM emissions variance is explained by single contributions of the 16 variables. Likewise, 88% of the PM emissions variance is explained by single contributions of only 2 variables, the eEF (81%) and the milHDV (7%). The model behaves almost additively (with respect to the input parameters).
- CO: 78% of the CO emissions variance is explained by single contributions of the 16 variables. A big fraction of the variance (specifically, 69%) is explained by single contributions of the hot (64%) and cold (5%) emission factors. The CO emissions are influenced by some high-order interactions, as seen by the sum of S_{Ti}, which is quite greater than 1.
- N_2O: only half (i.e. 50%) of the N_2O emissions variance is explained by single contributions of the 16 variables. The eEF explains 19% of the N_2O emissions variance followed by eEFratio (4%) while all the other variables contribute equally by 2%. The interaction effects of second and higher-order in the N_2O emissions are as high as the contributions of the 16 uncertain input variables taken singularly. The low explanation of variance by the 16 variables and the high uncertainty of the N_2O calculation is rather an artefact of the method, based on the selection of the range of the input variables. This is corrected in the subsequent sections.
- CH_4: uncertainty in the CH_4 emissions is mostly influenced by the emission factors, which taken singularly explain 72% of the variance (36% by the eEF and 36% by the eEFratio). The single contribution of all the uncertain inputs explains 78% of the CH_4 emissions variance.
- CO_2: 88% of the CO_2 emissions variance is explained by single contributions of the 16 variables. The single contribution of four variables [eEF (63%), milHDV (8%), eEFratio (5%) and milPC (3%)], explain 81% of the CO_2 emissions variance.

- FC: 87% of the FC variance is explained by single contributions of the 16 variables. Similarly, 82% of the FC variance is explained by single contributions of only 4 variables, namely eEF (64%), milHDV (8%), eEFratio (5%) and milPC (3%).

We now restrict the analysis to the subset of the simulations with predicted fuel consumption within a range of one standard deviation (i.e. 10%). This is done as the PRIMES output is based on the statistical fuel consumption, which is generally known with good confidence. Therefore, it is interesting to limit the analysis of uncertainty to these runs only that come with realistic fuel consumption figures. The annual fuel consumption for Italy (2005) according to EC4MACS (PRIMES) is 14,203,743 tonnes for gasoline and 22,860,081 tonnes for diesel. Therefore, we summed up the predicted by COPERT 4 fuel consumption of gasoline and diesel cars at each Monte Carlo simulation and kept only the runs for which both predicted values were within 10% of the reported value.

The statistical distribution of the filtered fuel consumption is presented in Figure 3-3b while for all other output variables it is shown in Figure 3-4. The corresponding descriptive statistics are given in Table 3-3. The normal distribution represents quite well the emissions of CO_2, VOC, NO_x and PM. Apart from CH_4, all distributions exhibit lower skewness. The coefficient of variation has been reduced by a factor of 5 for N_2O, by a factor of 1.6 for CH_4 and approximately by a factor of 2.5 for all the others. The new coefficient of variation is 4% for CO_2, on the order of 10-13% for NO_x, VOC, $PM_{2.5}$, PM_{10} and non-exhaust PM, on the order of 21-25% for CO and N_2O and 32% for CH_4.

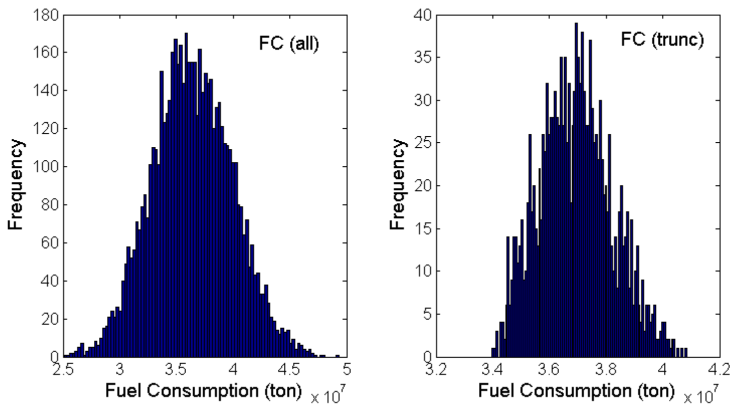

Figure 3-3: Uncertainty Analysis of the annual fuel consumption from road transport for Italy resulted from: (a) all simulations (left), (b) simulations within 10% of the officially reported fuel consumption.

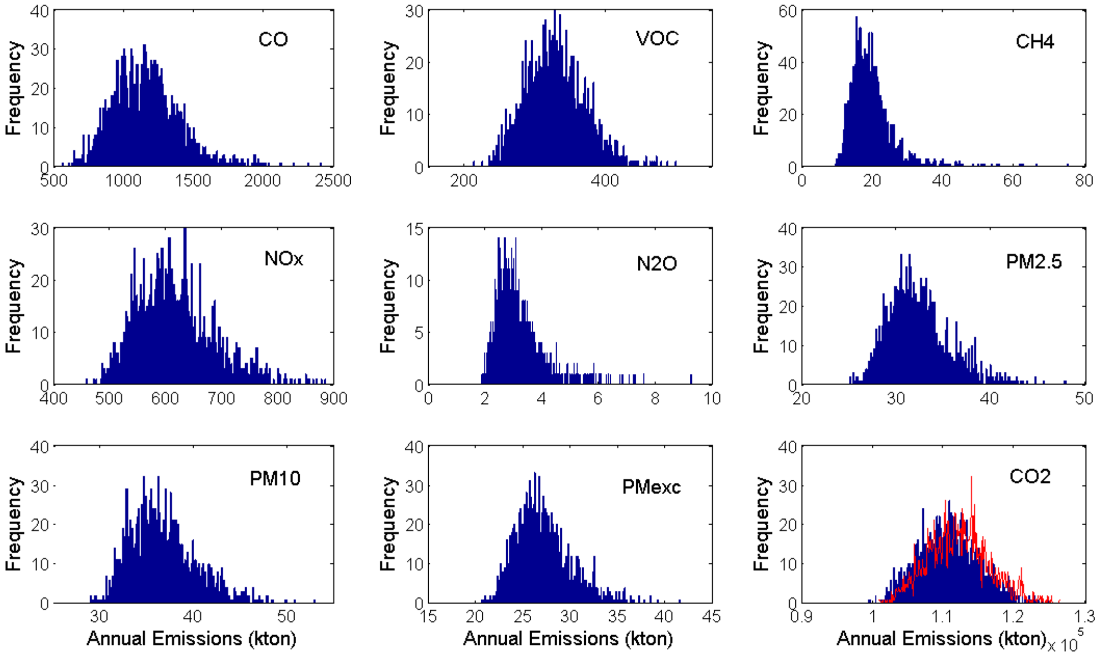

Figure 3-4: Uncertainty Analysis of the annual emissions from road transport for Italy (year 2005) for the simulations with predicted fuel consumption within a small range of the official value.

Table 3-3: Descriptive statistics of the histograms presented in Figure 3-4. Values are in ktonnes.

	CO	VOC	CH_4	NO_x	N_2O	$PM_{2.5}$	PM_{10}	PM_{exh}	FC	CO_2	CO_{2e}
Mean	1,161	329	20	617	3	32	37	27	36,929	110,689	112,061
Median	1,140	327	19	607	3	32	36	27	36,924	110,600	111,957
St. Dev.	245	41	6	69	1	3	4	3	1,285	4,194	4,310
Coef. Var. (%)	21	13	32	11	25	10	10	11	3	4	4

3.1.2Corrected Data Sample

The updated scheme for the emission factors and the mileage, in order to respect the limitation of the fuel consumption resulted to a significant reduction of the output uncertainty. The uncertainty of the annual emissions of CO, VOC, CH_4, NO_x, N_2O, $PM_{2.5}$, PM_{10}, non-exhaust PM and CO_2 is presented in Figure 3-5 while their descriptive statistics are given in Table 3-4. Apart from CO, CH_4 and N_2O that are best fit by a log-normal distribution, all the others are better represented by a normal distribution. Among them, the most skewed are CH_4 and N_2O followed by CO. The coefficient of variation is 7% for FC and CO_2, 13% for $PM_{2.5}$, PM_{10} and non-exhaust PM, 15% for NO_x, 18% for VOC, on the order of 30-33% for CO and N_2O and 44% for CH_4. The reduction of the output uncertainty compared with the previous setting ranged from 17% (CH_4) to 70% (N_2O) and resulted in a normally distributed output uncertainty for most of the emissions.

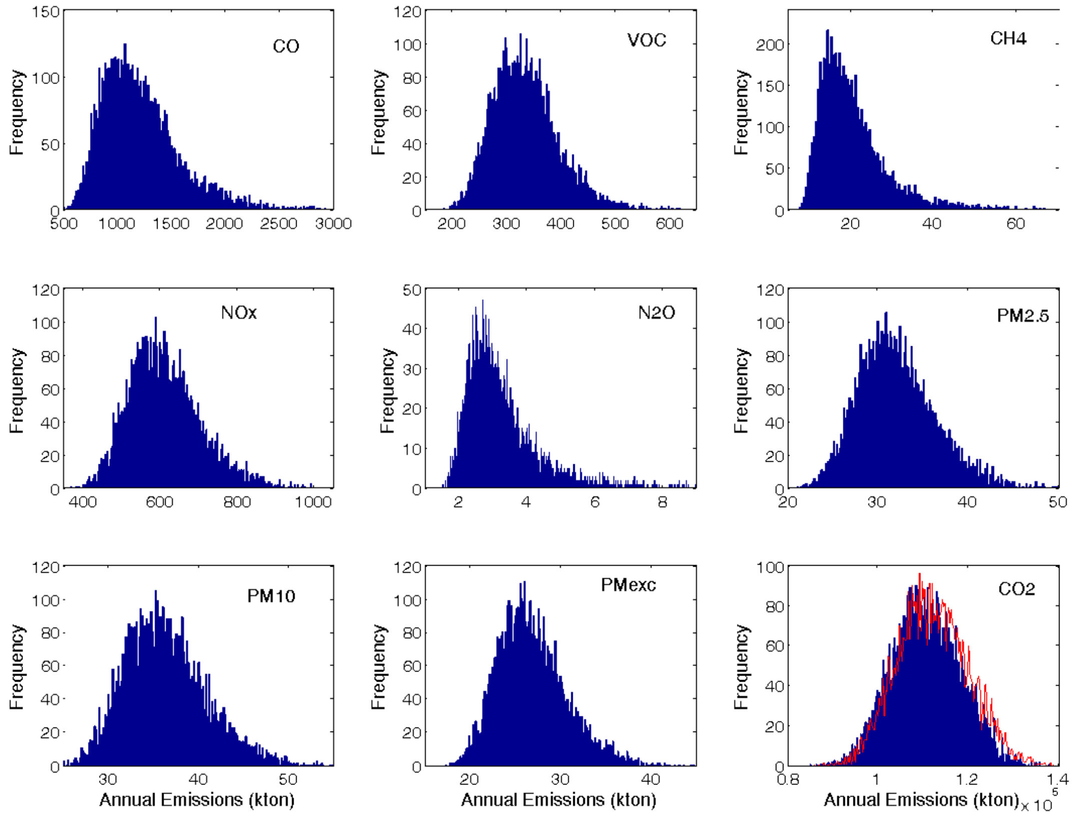

Figure 3-5: Uncertainty analysis of the annual emissions from road transport for Italy (year 2005).

Table 3-4: Descriptive statistics of the histograms presented in Figure 3-5.

Values are in ktonnes. CO_{2e} stands for total uncertainty of GHG equivalent.

	CO	VOC	CH_4	NO_X	N_2O	$PM_{2.5}$	PM_{10}	PM_{exh}	FC	CO_2	CO_{2e}
Mean	1,215	335	21	613	3.2	32	36	27	36,885	110,570	111,999
Median	1,150	329	19	603	2.9	32	36	26	36,828	110,357	111,751
St. Dev.	371	60	9	92	1.1	4	5	4	2,484	7,596	7,902
Coef. Var. (%)	30	18	44	15	33	13	13	14	7	7	7

Table 3-5: First and Total Order Sensitivity Indices (extended-FAST) for VOC, NO_X, $PM_{2.5}$, PM_{10}, PMexhaust, CO, N_2O, CH_4, CO_2 and FC (2005).

VOC	**S_I**	**S_{TI}**	**NO_X**	**S_I**	**S_{TI}**	**PM2.5**	**S_I**	**S_{TI}**	**PM_{10}**	**S_I**	**S_{TI}**	**PMexh**	**S_I**	**S_{TI}**
eEF	0.63	0.78	eEF	0.76	0.85	eEF	0.72	0.86	eEF	0.72	0.84	eEF	0.72	0.86
ltrip	0.08	0.22	milHDV	0.12	0.22	milHDV	0.08	0.22	milHDV	0.08	0.21	milHDV	0.09	0.23
eEFratio	0.05	0.15	HDV	0.01	0.08	ltrip	0.01	0.13	ltrip	0.01	0.13	ltrip	0.01	0.14
milMO	0.05	0.17	PC	0	0.08	HDV	0.01	0.12	HDV	0.01	0.11	HDV	0.01	0.14
VUPC	0.02	0.16	ltrip	0	0.08	eEFratio	0.01	0.13	milPC	0.01	0.12	eEFratio	0.01	0.14
O2C	0.02	0.15	LDV	0	0.08	LDV	0.01	0.12	LDV	0.01	0.11	LDV	0.01	0.12
HDV	0.01	0.13	VHPC	0	0.1	milPC	0.01	0.13	eEFratio	0.01	0.13	milPC	0.01	0.14
MOP	0.01	0.14	VUPC	0	0.08	PC	0	0.13	PC	0.01	0.13	milMO	0.01	0.12
milHDV	0.01	0.14	O2C	0	0.08	milMO	0	0.11	milMO	0.00	0.10	PC	0.00	0.14
LDV	0.01	0.12	milPC	0	0.08	milLDV	0	0.12	milLDV	0.00	0.12	milLDV	0.00	0.13
PC	0	0.15	UPC	0	0.08	VHPC	0	0.13	VHPC	0.00	0.12	VHPC	0.00	0.14
VRPC	0	0.15	MOP	0	0.09	MOP	0.00	0.13	MOP	0.00	0.12	MOP	0.00	0.15
milPC	0	0.14	eEFratio	0	0.1	O2C	0	0.11	O2C	0	0.1	O2C	0	0.12
VHPC	0	0.13	milMO	0	0.07	UPC	0	0.12	UPC	0	0.11	UPC	0	0.13
milLDV	0	0.14	VRPC	0	0.1	VUPC	0	0.12	VRPC	0	0.12	VRPC	0	0.13
UPC	0	0.14	milLDV	0	0.08	VRPC	0	0.12	VUPC	0	0.11	VUPC	0	0.13
ΣS_i	**0.91**	**3.03**		**0.91**	**2.27**		**0.87**	**2.78**		**0.87**	**2.69**		**0.88**	**2.96**

CO	**S_I**	**S_{TI}**	**N_2O**	**S_I**	**S_{TI}**	**CH_4**	**S_I**	**S_{TI}**	**CO_2**	**S_I**	**S_{TI}**	**FC**	**S_I**	**S_{TI}**
eEF	0.44	0.56	eEFratio	0.59	0.76	eEFratio	0.61	0.76	eEF	0.40	0.51	eEF	0.43	0.54
eEFratio	0.19	0.29	ltrip	0.06	0.37	eEF	0.13	0.29	eEFratio	0.10	0.22	eEFratio	0.11	0.24
ltrip	0.05	0.21	VUPC	0.06	0.23	ltrip	0.03	0.26	milHDV	0.09	0.2	milHDV	0.09	0.21
O2C	0.03	0.16	eEF	0.04	0.16	VUPC	0.01	0.19	milPC	0.05	0.17	milPC	0.05	0.17
VUPC	0.03	0.17	milHDV	0.01	0.14	HDV	0	0.16	ltrip	0.04	0.21	ltrip	0.04	0.21
milMO	0.01	0.13	milPC	0.01	0.13	milMO	0	0.13	O2C	0.04	0.16	HDV	0.02	0.13
HDV	0.01	0.15	HDV	0	0.13	LDV	0	0.16	HDV	0.02	0.13	VUPC	0.01	0.11
LDV	0	0.12	MOP	0	0.18	MOP	0	0.18	VUPC	0.01	0.11	PC	0.01	0.12
VHPC	0	0.15	LDV	0	0.13	VHPC	0	0.21	PC	0.01	0.12	LDV	0.01	0.13
VRPC	0	0.17	milLDV	0	0.11	milHDV	0	0.16	LDV	0.01	0.12	UPC	0.01	0.14
MOP	0	0.17	milMO	0	0.11	VRPC	0	0.2	UPC	0.01	0.14	MOP	0.00	0.12
UPC	0	0.15	VRPC	0.00	0.18	UPC	0	0.16	MOP	0.00	0.12	milLDV	0.00	0.12
PC	0	0.14	UPC	0	0.13	PC	0	0.2	milLDV	0	0.12	VHPC	0	0.12
milHDV	0	0.12	VHPC	0	0.25	milLDV	0	0.13	VHPC	0	0.11	O2C	0	0.12
milPC	0	0.15	O2C	0	0.24	milPC	0	0.16	milMO	0	0.14	milMO	0	0.14
milLDV	0	0.1	PC	0	0.17	O2C	0	0.21	VRPC	0	0.12	VRPC	0	0.12
ΣS_i	**0.79**	**2.94**		**0.79**	**3.44**		**0.80**	**3.58**		**0.78**	**2.68**		**0.79**	**2.72**

The first and total order sensitivity indices (*extended-FAST*) are presented in Table 3-5. The emission factors influences most the variability of the emissions; this characteristic is common for all the outputs. The hot emission factors are driving the uncertainty of all the emissions except for N_2O and CH_4 that are influenced primarily from the cold emission factors. Specifically, 72-76% of the emissions variance of NO_X, $PM_{2.5}$, PM_{10} and $PM_{exhaust}$ is explained by the single contribution of the hot emission factors. The fraction of explained variance from hot emission factors for VOC is 63% and drops down to ~40-44% for CO,

CO_2 and FC. On the other hand, for CH_4 and N_2O, the cold emission factors explain 59-61% of the output variance. Analytically:

- VOC: 91% of the VOC emissions variance is explained by single contributions of the 16 variables; 81% of the VOC emissions variance is explained by the single contribution of only four variables, namely eEF (63%), ltrip (8%), eEFratio (5%) and milMO(5%). The sum of all the S_i's is very close to 1 indicating that the model behaves almost additively (with respect to the input parameters).
- NO_x: two variables, the eEF (76%) and the milHDV (12%), are influencing more the uncertainty of the NO_x emissions. The single contributions of the 16 variables explain the 91% of the NO_x emissions. Like VOC, the model behaves almost additively (with respect to the input parameters).
- PM: the results are similar with those of NO_x. 87% of the PM emissions variance is explained by single contributions of the 16 variables. Likewise, 80% of the PM emissions variance is explained by single contributions of only 2 variables, the eEF (72%) and the milHDV (8%). The model behaves almost additively (with respect to the input parameters).
- CO: 79% of the CO emissions variance is explained by single contributions of the 16 variables. A big fraction of the variance (specifically, 63%) is explained by single contributions of the hot (44%) and cold (19%) emission factors.
- N_2O: 79% of the N_2O emissions variance is explained by single contributions of the 16 variables. The eEFratio explains most of the N_2O emissions variance (59%) followed by ltrip and VUPC (6% each) and eEF (4%). The interaction effects of second and higher-order in the N_2O emissions are quite high as can be seen from the sum of the total indices. However, N_2O variance has been greatly reduced compared to the initial sample used and most of the uncertainty is now explained.
- CH_4: uncertainty in the CH_4 emissions is mostly influenced by the emission factors, which taken singularly explain 74% of the variance (61% by the eEFratio and 13% by the eEF). The single contribution of all the uncertain inputs explains the 80% of the CH4 emissions variance.
- CO_2: 78% of the CO_2 emissions variance is explained by single contributions of the 16 variables. The single contribution of six variables [eEF (40%), eEFratio (10%), milHDV (9%), milPC (5%), ltrip (4%), O2C (4%)], explain 72% of the CO2 emissions variance.
- FC: 79% of the FC variance is explained by single contributions of the 16 variables. Similarly, 72% of the FC variance is explained by single contributions of only five variables, namely eEF (43%), eEFratio (11%), milHDV (9%), milPC (5%) and ltrip (4%).

Furthermore, the parameter that contributes most to the output uncertainty by means of higher order interactions is *ltrip*. In addition, N_2O and CH_4 demonstrate significant interactions of second and higher order while for NO_X, the higher order interactions are of minor importance.

Like the previous section, we performed also an analysis for the subset of the simulations with predicted fuel consumption within a range of one standard deviation (i.e. 7%). In this way we would like to demonstrate that the statistical distribution of output uncertainty is correct. The statistical distribution of the filtered fuel consumption is presented inFigure 3-6b while for all other output variables it is shown in Figure 3-7. The corresponding descriptive statistics are given in Table 3-6. We clearly observe a homogeneous reduction in the output uncertainty of all emissions by ~30%.

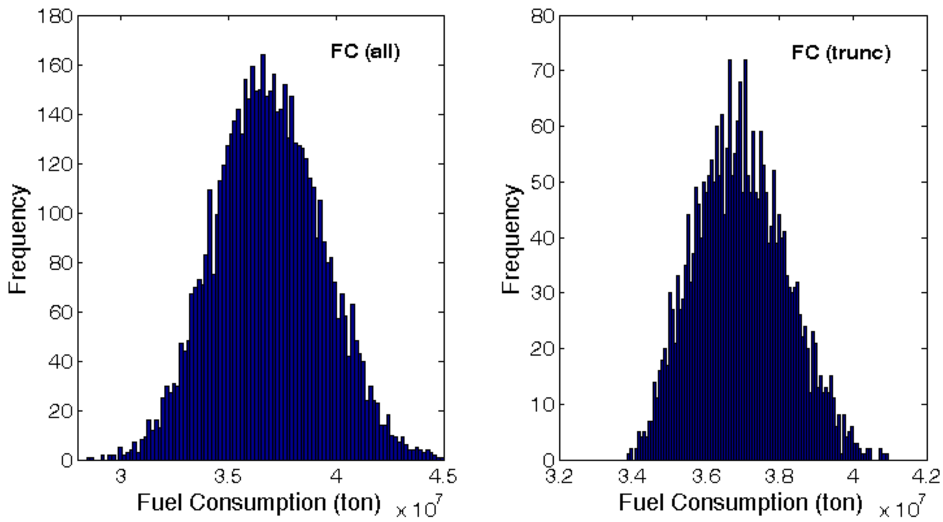

Figure 3-6: Uncertainty Analysis of the annual fuel consumption from road transport for Italy resulted from: (a) all simulations (left), (b) simulations within 10% of the officially reported fuel consumption.

Table 3-6: Descriptive statistics of the histograms presented in Figure 3-4. Values are in ktonnes.

	CO	**VOC**	**CH_4**	**NO_x**	**N_2O**	**$PM_{2.5}$**	**PM_{10}**	**PM_{exh}**	**FC**	**CO_2**	**CO_{2e}**
Mean	1,134	325	19	614	3.1	32	37	27	36,945	110,735	112,094
Median	1,118	324	18	608	2.9	32	36	27	36,901	110,622	111,941
St. Dev.	218	38	7	59	0.8	3	3	3	1,241	4,079	4,203
Variation (%)	19	12	34	10	26	9	8	9	3	4	4

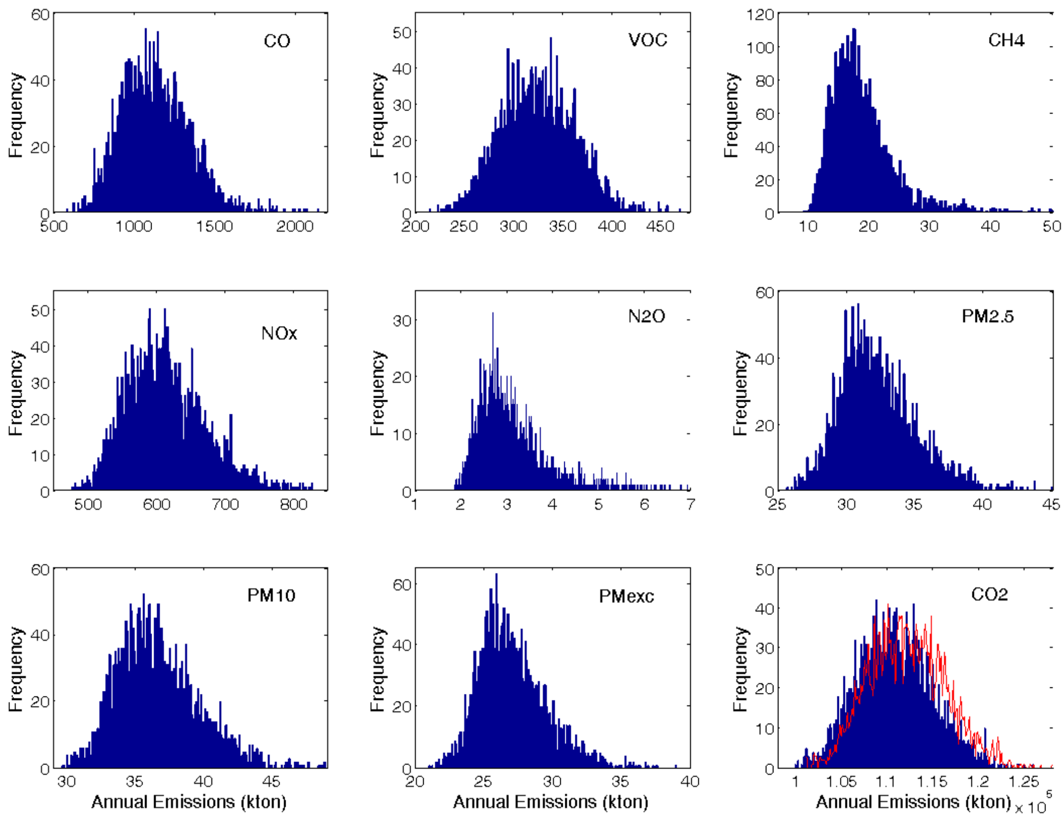

Figure 3-7: Uncertainty Analysis of the annual emissions from road transport for Italy (year 2005) for the simulations with predicted fuel consumption within a small range of the official value.

3.2 Case study 2: Uncertainty & sensitivity for Poland

3.2.1 Initial Data Sample

The methodological procedure adopted for Italy is repeated hereafter for Poland. The difference of Poland with Italy is that the former has a very weak description of the stock allocation to the different vehicle technologies (emission standards). This is expected to increase uncertainty. On the other hand, Italy has a very large and poorly described stock of small power two wheelers which increase uncertainty. Hence, it is interesting to compare how the different national circumstances affect the result.

Therefore, the differences in the statistical distributions of the uncertain inputs with the run conducted for Italy were mostly in the vehicle populations and in the temperature time series. In addition, a slightly modified module in the fleet breakdown model, from total population down to the sub-sector level, has been implemented due to the different type of available information (i.e. the stochastic fleet breakdown model was conditional on different restrictions). The screening analysis with the *method of Morris* (Figure 3-8) identified the following influential variables:

- the total population of light duty vehicles and heavy duty vehicles (LDV, HDV)
- the parameters of the fleet breakdown model (delta, sigma, tau)
- the annual mileage of passenger cars, light duty vehicles, heavy duty vehicles and urban buses-coaches (milPC, milLDV, milHDV, milUB, eM0)
- the urban driving cycle velocity of the passenger cars, the light duty vehicles and the urban buses (VUPC, VULDV, VUUB)
- the average trip length (ltrip)
- the oxygen to carbon ratio in the fuel (O2C)
- the hot and cold emission factors (eEF, eEFratio)

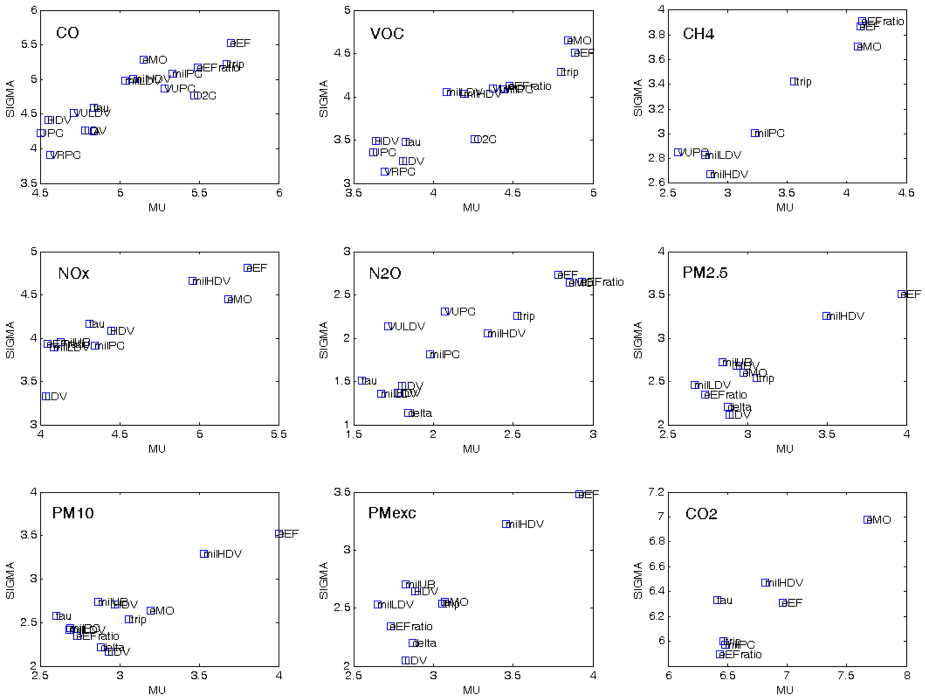

Figure 3-8: Morris results for Poland (year 2005)

The 17 most influential parameters identified from the screening analysis were used next in a quantitative sensitivity analysis. The sample was created with FAST sampling and required 6273 Monte Carlo simulations. The uncertainty of the annual emissions of CO, VOC, CH_4, NO_x, N_2O, $PM_{2.5}$, PM_{10}, non-exhaust PM and CO_2 is presented in Figure 3-9 while their descriptive statistics are given in Table 3-7. The red line in the histogram of CO_2 corresponds to the cumulative uncertainty of the greenhouse gases (N_2O, CH_4, CO_2) and is presented as equivalent CO_2. Apart from CO_2 and FC (Figure 3-10a) that are best fit by a normal distribution, all the others are better represented by a log-normal distribution. Among them, the most skewed are N_2O followed by CO and CH_4. The coefficient of variation is 13% for CO_2, on the order of 20-30% for NO_x, VOC, $PM_{2.5}$, PM_{10}, non-exhaust PM and CO, 66% for CH_4 and almost 200% for N_2O.

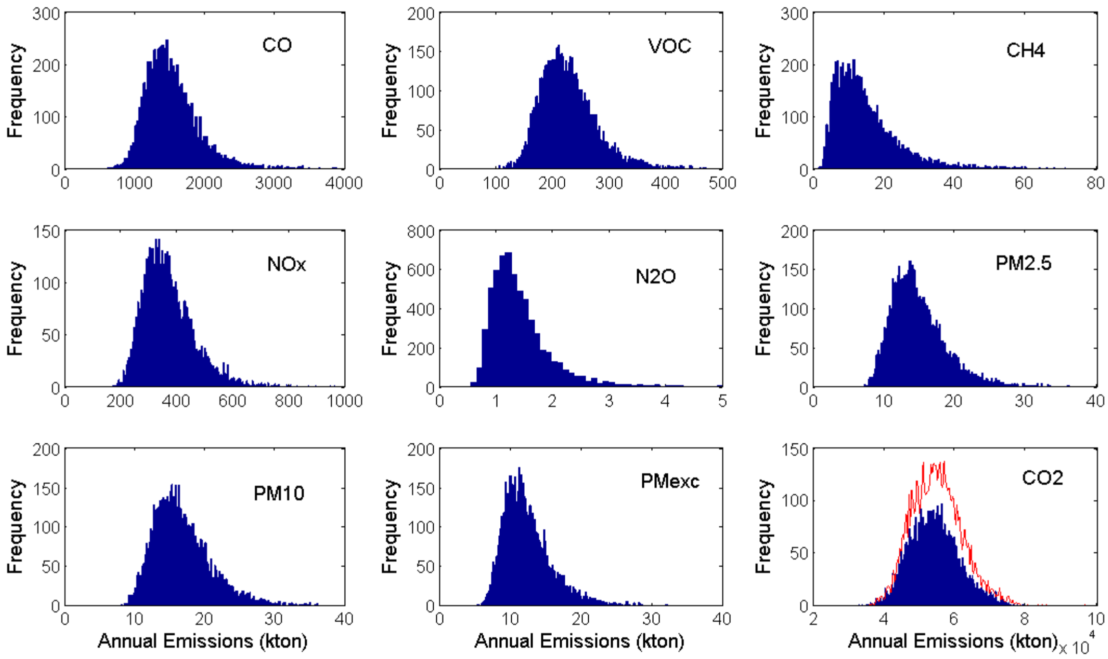

Figure 3-9: Uncertainty Analysis of the annual emissions from road transport for Poland (year 2005).

Table 3-7: Descriptive statistics of the histograms presented in Figure 3-9. Values are in ktonnes.

	CO	**VOC**	**CH_4**	**NO_x**	**N_2O**	**$PM_{2.5}$**	**PM_{10}**	**PM_{exh}**	**FC**	**CO_2**	**CO_{2e}**
Mean	1,553	228	15	369	1.75	15	17	13	17,865	54,029	54,891
Median	1,470	220	13	354	1.31	14	16	12	17,762	53,763	54,509
St. Dev.	459	52	10	91	3.48	4	4	4	2,273	6,889	7,324
Coef. Var.(%)	30	23	66	25	199	27	26	29	13	13	13

The first and total order sensitivity indices (*extended-FAST*) are presented in Table 3-8. The hot emission factors influence most the variability of the emissions; they are ranked first in all the outputs except for FC and CO_2 where the mileage parameter M0 is dominant. Specifically, 73-75% of the emissions variance of NO_x, $PM_{2.5}$, PM_{10} and non-exhaust PM is explained by the single contribution of the hot emission factors. The fraction of explained variance from hot emission factors for VOC and CO is 51% and 44% respectively and drops down to 8% for N_2O. For CH_4, hot and cold emission factors explain equal portions of the variance (36% each). Finally, for CO_2 and FC, although the emission factors were ranked in 2nd place, they explain 25% of the variance. Analytically:

- VOC: 95% of the VOC emissions variance is explained by single contributions of the 17 variables. Similarly, 91% of the VOC emissions variance is explained by single contributions of only 4 variables, namely eEF (51%), eM0 (20%), ltrip (13%) and eEFratio (7%). The sum of all the S_i's is very close to 1 indicating that the model behaves almost additively (with respect to the input parameters).
- NO_x: 96% of the NO_x emissions variance is explained by single contributions of the 17 variables. Likewise, 89% of the NO_x emissions variance is explained by single contributions of only 2 variables, namely eEF (73%) and eM0 (16%). Like VOC, the model behaves almost additively (with respect to the input parameters).
- PM: the results are similar with those of NO_x. 95% of the PM emissions variance is explained by single contributions of all the uncertain inputs while 87% of the variance is explained by single contributions of only 2 variables, namely eEF (74%) and eM0 (13%). The model behaves almost additively (with respect to the input parameters).
- CO: 86% of the CO emissions variance is explained by single contributions of the 17 variables. Most of the explained variance (~75%) arises from single contributions of only 4 variables, namely eEF (44%), eM0 (12%), eEFratio (10%) and ltrip (9%). The CO emissions are influenced by some high-order interactions, as seen by the sum of S_{TI}, which is quite greater than 1.
- N_2O: less than half (44%) of the N_2O emissions variance is explained by single contributions of the 17 variables. The eEF explains 8% of the N_2O emissions variance followed by eEFratio (3%) while all the other variables contribute equally by 2%. The interaction effects of second and higher-order in the N_2O emissions are higher than the contributions of the 17 uncertain input variables taken singularly. The same problem of the N_2O variance with the Italy case is also shown here.
- CH_4: 82% of the CH_4 emissions variance is explained by single contributions of the 17 variables. The emission factors taken singularly explain 75% of the CH_4 emissions variance (37% by the eEF and 38% by the eEFratio).
- CO_2: 94% of the CO_2 emissions variance is explained by single contributions of the 17 variables. The single contribution of two variables [eEF (25%), eM0 (56%)], explain 81% of the CO_2 emissions variance. CO_2 emissions seem to behave almost additively (with respect to the input parameters).
- FC: 94% of the FC variance is explained by single contributions of the 17 variables. Similarly, 82% of the FC variance is explained by single contributions of only 4 variables, namely eM0 (56%) and eEF (26%). FC emissions seem to behave almost additively (with respect to the input parameters).

Table 3-8: First and Total Order Sensitivity Indices (extended-FAST) for VOC, NO_x, $PM_{2.5}$, PM_{10}, non-exhaust, CO, N_2O, CH_4, CO_2 and FC (2005).

VOC	S_I	S_{TI}	***NO_X***	S_I	S_{TI}	***PM2.5***	S_I	S_{TI}	***PM10***	S_I	S_{TI}	***PMexh***	S_I	S_{TI}
eEF	0.51	0.65	eEF	0.73	0.80	eEF	0.74	0.81	eEF	0.73	0.79	eEF	0.75	0.82
eM0	0.20	0.33	eM0	0.16	0.26	eM0	0.13	0.24	eM0	0.15	0.25	eM0	0.11	0.23
ltrip	0.13	0.23	milHDV	0.04	0.12	milHDV	0.04	0.13	milHDV	0.04	0.12	milHDV	0.04	0.14
eEFratio	0.07	0.19	eEFratio	0.01	0.09	ltrip	0.01	0.07	ltrip	0.01	0.07	Ltrip	0.01	0.08
VUPC	0.02	0.15	HDV	0.01	0.06	HDV	0.01	0.07	HDV	0.01	0.06	HDV	0.01	0.07
O2C	0.01	0.11	delta	0.00	0.06	delta	0.01	0.07	delta	0.00	0.07	delta	0.01	0.08
milPC	0.00	0.12	tau	0.00	0.07	LDV	0.00	0.08	LDV	0.00	0.07	eEFratio	0.00	0.10
VULDV	0.00	0.10	VUUB	0.00	0.06	eEFratio	0.00	0.09	milLDV	0.00	0.07	LDV	0.00	0.09
VUUB	0.00	0.11	milPC	0.00	0.07	milLDV	0.00	0.08	eEFratio	0.00	0.09	milLDV	0.00	0.09
milHDV	0.00	0.12	ltrip	0.00	0.06	VUUB	0.00	0.07	VUUB	0.00	0.07	milUB	0.00	0.09
milUB	0.00	0.12	LDV	0.00	0.07	milUB	0.00	0.08	milUB	0.00	0.08	VUUB	0.00	0.08
LDV	0.00	0.12	sigma	0.00	0.06	milPC	0.00	0.06	milPC	0.00	0.06	O2C	0.00	0.06
HDV	0.00	0.07	milLDV	0.00	0.06	O2C	0.00	0.06	O2C	0.00	0.06	sigma	0.00	0.07
delta	0.00	0.08	milUB	0.00	0.08	sigma	0.00	0.06	sigma	0.00	0.06	milPC	0.00	0.07
sigma	0.00	0.12	O2C	0.00	0.06	tau	0.00	0.06	tau	0.00	0.06	VUPC	0.00	0.07
milLDV	0.00	0.10	VUPC	0.00	0.06	VUPC	0.00	0.07	VUPC	0.00	0.06	tau	0.00	0.07
tau	0.00	0.11	VULDV	0.00	0.05	VULDV	0.00	0.06	VULDV	0.00	0.05	VULDV	0.00	0.07
ΣS_i	**0.95**	**3.84**		**0.96**	**3.10**		**0.95**	**3.15**		**0.95**	**3.09**		**0.95**	**3.27**

CO	S_I	S_{TI}	***N2O***	S_I	S_{TI}	***CH4***	S_I	S_{TI}	***CO2***	S_I	S_{TI}	***FC***	S_I	S_{TI}
eEF	0.44	0.72	eEF	0.08	0.88	eEFratio	0.38	0.61	eM0	0.56	0.63	eM0	0.56	0.63
eM0	0.12	0.39	eEFratio	0.03	0.80	eEF	0.37	0.58	eEF	0.25	0.30	eEF	0.26	0.30
eEFratio	0.10	0.33	VULDV	0.02	0.75	eM0	0.03	0.18	milHDV	0.04	0.07	milHDV	0.04	0.07
ltrip	0.09	0.26	milUB	0.02	0.82	ltrip	0.02	0.18	eEFratio	0.02	0.09	eEFratio	0.02	0.09
O2C	0.04	0.24	eMO	0.02	0.85	VUPC	0.00	0.17	ltrip	0.02	0.06	ltrip	0.02	0.06
VUPC	0.02	0.31	VUUB	0.02	0.81	tau	0.00	0.17	tau	0.01	0.05	tau	0.01	0.05
VULDV	0.01	0.18	tau	0.02	0.82	VUUB	0.00	0.19	milPC	0.01	0.04	milPC	0.01	0.04
milUB	0.01	0.25	LDV	0.02	0.81	LDV	0.00	0.22	O2C	0.01	0.06	LDV	0.01	0.05
LDV	0.00	0.25	milLDV	0.02	0.78	milPC	0.00	0.16	LDV	0.01	0.05	HDV	0.01	0.05
VUUB	0.00	0.21	O2C	0.02	0.72	milUB	0.00	0.16	HDV	0.01	0.05	VUPC	0.01	0.05
milPC	0.00	0.23	milPC	0.02	0.79	VULDV	0.00	0.16	VUPC	0.01	0.05	sigma	0.00	0.04
milHDV	0.00	0.24	delta	0.02	0.76	HDV	0.00	0.14	sigma	0.00	0.05	milLDV	0.00	0.05
milLDV	0.00	0.21	VUPC	0.02	0.83	O2C	0.00	0.15	milLDV	0.00	0.05	delta	0.00	0.04
tau	0.00	0.25	milHDV	0.02	0.79	milHDV	0.00	0.15	delta	0.00	0.04	VUUB	0.00	0.04
delta	0.00	0.15	HDV	0.02	0.70	delta	0.00	0.13	VUUB	0.00	0.03	O2C	0.00	0.05
sigma	0.00	0.21	sigma	0.02	0.72	milLDV	0.00	0.15	VULDV	0.00	0.03	VULDV	0.00	0.03
HDV	0.00	0.14	ltrip	0.02	0.70	sigma	0.00	0.17	milUB	0.00	0.05	milUB	0.00	0.05
ΣS_i	**0.86**	**5.59**		**0.40**	**14.3**		**0.82**	**4.68**		**0.94**	**2.69**		**0.94**	**2.68**

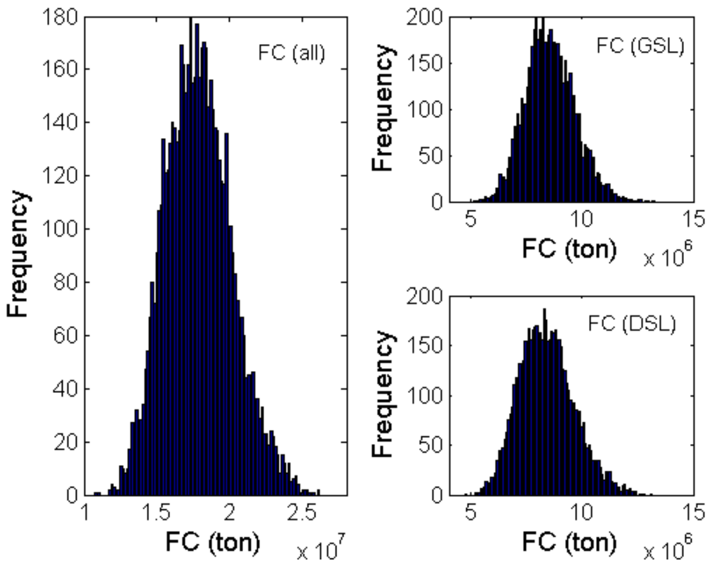

Figure 3-10: Uncertainty Analysis of the annual fuel consumption from road transport for Poland: (a) Cumulative fuel consumption (left), (b) Gasoline fuel consumption (right, top row), (c) Diesel fuel consumption (right, bottom row).

We now restrict the analysis to the subset of the simulations with predicted fuel consumption within a range of one standard deviation (i.e. 13%) from the known fuel consumption. The annual fuel consumption for Poland (2005) according to EC4MACS (PRIMES) is 4,140,256 tonnes for gasoline and 5,445,725 tonnes for diesel. Therefore, we summed up the predicted by COPERT 4 fuel consumption of gasoline and diesel cars at each Monte Carlo simulation and kept only the runs for which both predicted values were within 13% of the reported value.

The statistical distribution of the gasoline and diesel fuel consumption is presented in Figure 3-10b,c). We clearly observe that the simulated fuel consumption is much above the official values. The big difference between calculated and statistical fuel consumption may be derived either from a large black market or from an erroneous M0 value, which was based on data from other countries. In any case, the significant difference between the two does not allow focussing the discussion only around values of the statistical fuel consumption. However, we still corrected the sample removing some outliers that were identified in the case of Italy. We also used a corrected M0 value that was 56% of its original value for gasoline and 74% of its original value for diesel, just to bring the calculated fuel consumption in the range of the statistical one. These corrections did not affect the uncertainty of the calculation, they only shifted the distribution to a more realistic range for Poland.

3.2.2Corrected Data Sample

The uncertainty of the annual emissions of all pollutants is presented in Figure 3-11 while their descriptive statistics are given in Table 3-9. CH_4 and N_2O are best fit by a log-normal distribution, FC and CO_2 are better represented by a normal distribution while the others are log-normally distributed with small sigma though (quasi normal). Among them, the most skewed are CH_4 and N_2O followed by CO. The coefficient of variation is 11% for FC and CO_2, 17-20% for $PM_{2.5}$, PM_{10}, non-exhaust PM, NO_x, VOC and CO, 28% for N_2O and 57% for CH_4. The reduction in the output uncertainty compared with the previous setting ranged from 14% (CH_4, FC, CO_2) to 86% (N_2O).

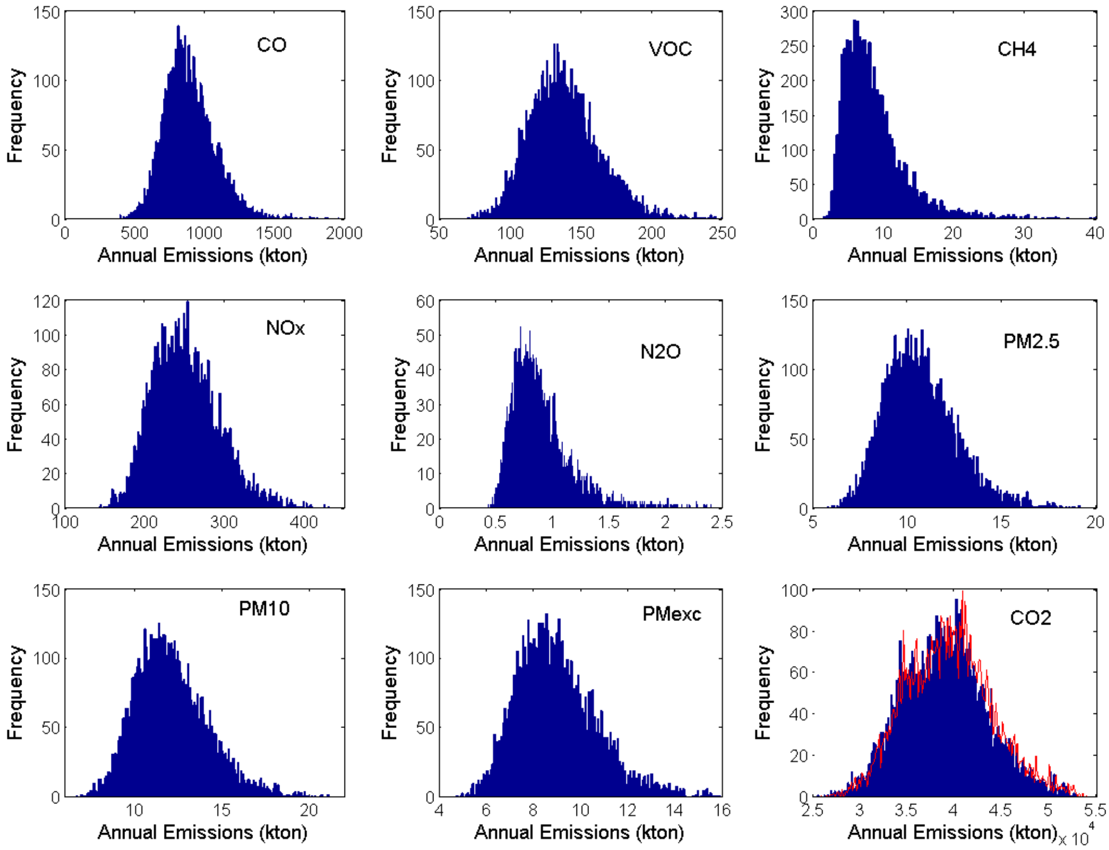

Figure 3-11: Uncertainty analysis of the annual emissions from road transport for Poland (year 2005).

Table 3-9: Descriptive statistics of the histograms presented in Figure 5-13.
Values are in ktonnes. CO_{2e} stands for total uncertainty of GHG equivalent.

	CO	**VOC**	**CH_4**	**NO_X**	**N_2O**	**$PM_{2.5}$**	**PM_{10}**	**PM_{exh}**	**FC**	**CO_2**	**CO_{2e}**
Mean	892	139	8.8	251	0.9	11	12	9.0	12,895	38,912	39,370
Median	873	136	7.7	247	0.8	10	12	8.8	12,846	38,839	39,277
St. Dev.	183	25	5.0	42	0.2	1.9	2.1	1.7	1,465	4,447	4,531
Poland	20	18	57	17	28	18	17	19	11	11	12

Table 3-10: First and Total Order Sensitivity Indices (extended-FAST) for VOC, NO_X, $PM_{2.5}$, PM10, PMexhaust, CO, N_2O, CH_4, CO_2 and FC (2005).

VOC	**S_I**	**S_{TI}**	**NO_X**	**S_I**	**S_{TI}**	**PM2.5**	**S_I**	**S_{TI}**	**PM10**	**S_I**	**S_{TI}**	**PMexc**	**S_I**	**S_{TI}**
eM0	0.27	0.40	eEF	0.49	0.56	eEF	0.54	0.60	eEF	0.52	0.58	eEF	0.55	0.61
ltrip	0.23	0.37	eMO	0.35	0.43	eMO	0.28	0.37	eMO	0.31	0.39	eMO	0.25	0.34
eEF	0.20	0.34	milHDV	0.07	0.12	milHDV	0.05	0.12	milHDV	0.05	0.11	milHDV	0.06	0.14
VUPC	0.10	0.23	HDV	0.02	0.08	ltrip	0.02	0.07	ltrip	0.02	0.07	ltrip	0.02	0.08
eEFratio	0.08	0.18	eEFratio	0.01	0.08	HDV	0.02	0.07	HDV	0.01	0.07	HDV	0.02	0.08
delta	0.01	0.09	LDV	0.00	0.07	LDV	0.01	0.07	LDV	0.01	0.07	LDV	0.01	0.08
O2C	0.01	0.14	ltrip	0.00	0.07	eEFratio	0.01	0.08	eEFratio	0.01	0.08	delta	0.01	0.06
tau	0.01	0.10	VUPC	0.00	0.06	milLDV	0.01	0.07	milLDV	0.01	0.06	eEFratio	0.01	0.09
LDV	0.00	0.12	VUUB	0.00	0.05	delta	0.01	0.05	delta	0.00	0.05	milLDV	0.01	0.08
milPC	0.00	0.11	O2C	0.00	0.06	tau	0.00	0.05	tau	0.00	0.04	tau	0.00	0.05
HDV	0.00	0.07	tau	0.00	0.05	milUB	0.00	0.07	milUB	0.00	0.06	milUB	0.00	0.08
milUB	0.00	0.09	milPC	0.00	0.06	VUUB	0.00	0.05	VUUB	0.00	0.05	VUUB	0.00	0.06
VULDV	0.00	0.10	milLDV	0.00	0.06	O2C	0.00	0.05	O2C	0.00	0.05	O2C	0.00	0.05
sigma	0.00	0.13	milUB	0.00	0.07	VULDV	0.00	0.05	milPC	0.00	0.04	VUPC	0.00	0.06
milHDV	0.00	0.10	VULDV	0.00	0.05	sigma	0.00	0.06	VULDV	0.00	0.05	sigma	0.00	0.07
VUUB	0.00	0.11	sigma	0.00	0.06	VUPC	0.00	0.06	sigma	0.00	0.06	VULDV	0.00	0.06
milLDV	0.00	0.10	delta	0.00	0.05	milPC	0.00	0.05	VUPC	0.00	0.06	milPC	0.00	0.05
ΣS_i	**0.93**	**2.80**		**0.96**	**1.97**		**0.95**	**1.94**		**0.95**	**1.89**		**0.95**	**2.04**

CO	**S_I**	**S_{TI}**	**N2O**	**S_I**	**S_{TI}**	**CH4**	**S_I**	**S_{TI}**	**CO2**	**S_I**	**S_{TI}**	**FC**	**S_I**	**S_{TI}**
eM0	0.22	0.35	eEFratio	0.48	0.70	eEFratio	0.56	0.80	eMO	0.67	0.74	eMO	0.68	0.74
ltrip	0.20	0.36	eMO	0.14	0.28	eEF	0.12	0.35	eEF	0.09	0.13	eEF	0.10	0.14
eEFratio	0.15	0.28	eEF	0.11	0.39	eMO	0.03	0.11	delta	0.03	0.06	delta	0.03	0.06
eEF	0.15	0.31	VUPC	0.06	0.25	ltrip	0.03	0.25	milHDV	0.03	0.05	milHDV	0.03	0.05
O2C	0.08	0.24	ltrip	0.04	0.27	VUPC	0.01	0.16	ltrip	0.02	0.06	ltrip	0.02	0.06
VUPC	0.08	0.23	milHDV	0.02	0.20	delta	0.00	0.12	eEFratio	0.02	0.06	eEFratio	0.02	0.07
delta	0.01	0.10	VULDV	0.01	0.18	HDV	0.00	0.18	LDV	0.01	0.06	LDV	0.01	0.05
VULDV	0.01	0.11	HDV	0.01	0.17	milUB	0.00	0.16	O2C	0.01	0.06	HDV	0.01	0.05
LDV	0.01	0.15	delta	0.00	0.11	milPC	0.00	0.14	HDV	0.01	0.05	milPC	0.01	0.04
tau	0.01	0.13	tau	0.00	0.18	LDV	0.00	0.22	milPC	0.01	0.04	VUPC	0.01	0.05
milUB	0.00	0.11	LDV	0.00	0.20	VUUB	0.00	0.18	VUPC	0.01	0.05	milLDV	0.00	0.04
HDV	0.00	0.09	milPC	0.00	0.14	O2C	0.00	0.13	milLDV	0.00	0.04	sigma	0.00	0.04
sigma	0.00	0.16	milLDV	0.00	0.16	tau	0.00	0.15	sigma	0.00	0.04	tau	0.00	0.04
milPC	0.00	0.13	milUB	0.00	0.20	milLDV	0.00	0.15	tau	0.00	0.04	VUUB	0.00	0.04
VUUB	0.00	0.12	O2C	0.00	0.20	VULDV	0.00	0.14	VUUB	0.00	0.04	VULDV	0.00	0.03
milLDV	0.00	0.12	VUUB	0.00	0.16	milHDV	0.00	0.13	VULDV	0.00	0.03	milUB	0.00	0.03
milHDV	0.00	0.12	sigma	0.00	0.14	sigma	0.00	0.15	milUB	0.00	0.04	O2C	0.00	0.05
ΣS_i	**0.92**	**3.11**		**0.89**	**3.96**		**0.77**	**3.55**		**0.91**	**1.58**		**0.92**	**1.58**

The first and total order sensitivity indices (*extended-FAST*) are presented in Table 3-10. The emission factors, the mileage parameter M0 and the average trip length influences mostly the variability of the emissions. The hot emission factors are driving the uncertainty of NO_X and PM, the cold emission factors influence primarily the emissions of N_2O and CH_4 and the mileage parameter M0 is the key uncertainty factor for FC and CO_2. For VOC and CO, all the above mentioned factors contribute to the output uncertainty. The fraction of explained variance from the single contributions of the emission factors and the mileage parameter M0 ranges between 52% and 85%. Analytically:

- VOC: 93% of the VOC emissions variance is explained by single contributions of the 17 variables; 88% of the VOC emissions variance is explained by the single contribution of only five variables, namely eM0 (27%), ltrip (23%), eEF (20%), VUPC (10%) and eEFratio (8%). The sum of all the S_i's is very close to 1 indicating that the model behaves almost additively (with respect to the input parameters).
- NO_x: two variables, the eEF (49%) and the eM0 (35%), are influencing more the uncertainty of the NO_x emissions. The single contributions of the 17 variables explain the 96% of the NO_x emissions. Like VOC, the model behaves almost additively (with respect to the input parameters)
- PM: the results are similar with those of NO_x. 95% of the PM emissions variance is explained by single contributions of the 17 variables. Likewise, 81-84% of the PM emissions variance is explained by single contributions of only 2 variables, the eEF (52-55%) and the eM0 (25-31%). The model behaves almost additively (with respect to the input parameters).
- CO: 92% of the CO emissions variance is explained by single contributions of the 17 variables. The biggest fraction of the variance (specifically, 88%) is explained by single contributions of only six variables, namely eM0 (22%), ltrip (20%), eEFratio (15%), eEF (15%), O2C (8%) and VUPC (8%).
- N_2O: 89% of the N_2O emissions variance is explained by single contributions of the 17 variables. The eEFratio explains most of the N_2O emissions variance (48%) followed by eM0 (14%) and eEF (11%). The interaction effects of second and higher-order in the N_2O emissions are quite high as can be seen from the sum of the total indices.
- CH_4: uncertainty in the CH_4 emissions is mostly influenced by the emission factors, which taken singularly explain 68% of the variance (56% by the eEFratio and 12% by the eEF). The single contribution of all the uncertain inputs explains the 77% of the CH4 emissions variance.
- CO_2: 91% of the CO_2 emissions variance is explained by single contributions of the 17 variables. The single contribution of two variables [eM0 (67%), eEF (9%)], explain 78% of the CO_2 emissions variance.
- FC: 92% of the FC variance is explained by single contributions of the 17 variables. Similarly, 80% of the FC variance is explained by single contributions of only two variables, namely eM0 (68%) and eEF (10).

Furthermore, the parameter that contributes more to the output uncertainty by means of higher order interactions is *ltrip*. In addition, N_2O and CH_4 demonstrate significant interactions of second and higher order while for CO_2 and FC, the higher order interactions are of minor importance.

Like the previous section, we performed also an analysis for the subset of the simulations with predicted fuel consumption within a range of one standard deviation (i.e. 11%). In this way we would like to demonstrate that the statistical distribution of output uncertainty is correct. The corresponding descriptive statistics of this analysis are given in Table 3-11. We clearly observe a homogeneous reduction in the output uncertainty of most emissions by ~40% (~20% for CO, VOC and N2O; only 5% for CH4).

Table 3-11: Descriptive statistics of the histograms presented in Figure 5-15. Values are in ktonnes.

	CO	VOC	CH_4	NO_x	N_2O	$PM_{2.5}$	PM_{10}	PM_{exh}	FC	CO_2	CO_{2e}
Mean	793	124	7.2	222	0.8	9.4	10.7	7.9	11,772	35,520	35,907
Median	783	123	6.3	218	0.7	9.2	10.5	7.7	11,666	35,199	35,569
St. Dev.	134	18	3.9	26	0.2	1.2	1.3	1.1	934	2,891	2,933
Variation (%)	17	15	54	12	24	13	12	14	8	8	8

3.2.3 Uncertainty in emission projections

The analysis preceding in this chapter refers to the year 2005, i.e. a historic year where, in principle, all input data to emission calculation are available. Several of key data required for emission calculation though were not readily available. For example, the actual mileage driven as a function of age is a statistic figure which cannot be precisely determined (let alone be determined for each year). Moreoever, the uncertainty in the emission factors is a large component of the total uncertainty, which cannot be easily curtailed.

For this reasons, the uncertainty in the projections is not expected much larger than the uncertainty in the historic estimates, for as long as a fixed fuel consumption development is assumed. This has to be clarified: Road transport projections take into account a fixed fuel consumption development that comes from PRIMES. This has its own uncertainty, related to the elasticities of demand assumed in PRIMES. However, this is external to our projection. If a fixed fuel consumption development has been assumed, we will have to respect this and as a result the uncertainty in the emission projection will be controlled. If total uncertainty has to be assessed, the alternative fuel consumption projections will have to be derived and a new emission projection has to be done for each alternative fuel consumption development. This would be a good indication of the total projected uncertainty.

However, once a fixed fuel consumption uncertainty is agreed, the degrees of freedom that an emission projection are more or less equal to the degrees of freedom for a historic emission calculation. For some, this may be counter-intuitive. That is, the question automatically rising is "is it possible that we know the future with the same degree of confidence that we have observed the past?". But this question is irrelevant to the current analysis. It should be clearly recognized that our work in EC4MACS is not to make a forecast of how emissions will develop in the future regardless of whatever the development of the macroeconomic and demographic data. The objective is to calculate how emissions will develop, once we have agreed how we expect economy and activity data to have evolved. In other words, the aim is to make a projection, not a prediction.

In such a projection, the additional components of uncertainty are the emission and consumption factors of future technologies and the rate of introduction of new technologies. The emission factors of future vehicle technologies are assumed to be decreased proportionally to what the emission standard reduction aims for. Therefore, in our analysis we have considered that the coefficient of variation of the emission factors of future vehicle technologies will be equal to the coefficient of variation of the last available technology. Such an assumption is realistic, assuming that the emission standards deliver the reductions that they should. In the next chapter we identify cases that emission standards have been ineffective in introducing expected reductions. However, again, this cannot be part of an uncertainty analysis – rather an objective of a forecast of what the most possible scenario is. In a projection we have to assume that the emission standards will be effective.

Therefore, the only true component in an emissions projection that increases the degrees of freedom in an uncertainty analysis, compared to a historic emission estimate, is the rate of technological replacement and the vehicle choices which can be made available. This is difficult to quantify – not from a modeling perspective – but because PRIMES fuel consumption projection has already assumed a certain replacement rate of new vehicle technologies in order to achieve a fuel consumption projection, assuming a gradual improvement of vehicle efficiency. Our projection is consistent to the PRIMES assumption. We have also assumed identical marginal efficiency improvements for new vehicle technologies introduced in the stock. Therefore, to a certain extent, the problem boils down again to determining the uncertainty of the PRIMES projection. Of course, in our projection one may assume that the improvement in the average energy efficiency may be achieved in a multitude of ways. For example, the same average efficiency improvement may be achieved by introducing smaller vehicles or a mix of heavier vehicles and hybrids. Despite they would lead to the same average efficiency, the two options would have led to different average emission. Hybrid vehicles offer a comparatively much better emission performance than fuel efficiency performance, relative to conventional vehicles. Therefore, the latter option would lead to lower emissions than introducing smaller conventional vehicles, for the same mean efficiency.

This can be quantified by an uncertainty analysis. However, we argue that the impact of such vehicle choice options in total uncertainty are comparatively lower than the uncertainty introduced by the emission factors and the main PRIMES assumptions. As a result, this analysis was not conducted.

3.2.4 Conclusions from this work

This work enabled to draw some conclusions which are of significance in the interpretation of the EC4MACS results:

1. The calculation of emissions from the main pollutants is linked to an uncertainty in the order of (expressed as coefficient of variance) 20% for CO, 15% for VOC, 10% for NOx and PM. The exact uncertainty changes from country to country.

2. Most of the uncertainty originates from the uncertainty in the emission factor values. It is very difficult to decrease this uncertainty as this originates from the inherent variance in the emission levels of vehicles which, otherwise, fulfill exactly the same criteria (size, fuel, emission standard, etc.). The only foreseen ways that emission factor variability can be decreases is by performing tests on an even larger number of vehicles and that the ageing effects are even better modeled.

3. Input data which are responsible for a large part of the variance are the allocation of vehicles to different technologies, the decrease in annual driven distance with age and the trip distribution. They explain up to 50% of total uncertainty for some of the pollutants. Better statistics are required to reduce uncertainty.

4. Calibrating results to a fixed fuel consumption, which is known with good confidence from energy statistics, greatly reduces uncertainty. This is good practice for total emission estimates.

5. These estimates of uncertainty are based on historic and not projected data. The uncertainty in the data projection is not much differentiated, if results are again calibrated to a fixed fuel consumption projection. The uncertainty in the fuel consumption projection is not part of the analysis of this work as this is exogenous to our analysis.

6. Calculating total emissions projection uncertainty, including the impact of macroeconomic data, can be performed by simulating alternative scenarios with PRIMES and estimating emissions on the basis of these alternative scenarios.

4 Technology-related uncertainty effects

This chapter discusses in more detail the impact of some emission related issues that are often considered as major sources of uncertainty in road transport emission estimates.

4.1 The impact of high emitters

High-emitters (or super emitters or ultra emitters) are vehicles which emit several times above their emission limit, due to malfunctions in the emission control system. Malfunctions may occur for various reasons, i.e defected catalyst, malfunctioning sensor, compromised fuel injection systems, etc. The impact of malfunctions on emission levels depend on vehicle emission control technology, the severity of the malfunction, the pollutant considered, the driving conditions, etc. Superemitters may emit up to two order of magnitudes higher than their emission limit, in particular for pollutants such as CO and HC. The question arising is what is the effect of superemitters on total emissions of a national stock and then, how well this is reflected by emission models.

In EC4MACS we have taken into account the decline in vehicle activity with age. This is based in reported mileage functions of actual vehicles in different countries, as a function of their age. This is important in characterizing the impact of high emitters assuming that the frequency of malfunctions increases with age. For example, the average vehicle of ten years of age is reported to run for approximately 50% of the annual distance of a new vehicle. The average vehicle of 20 years of age is reported to run for only 20% of the annual distance of the average new vehicle. This is important as total emissions per year are a product of the emission factor times the annual distance driven. When the annual distance declines with age, the impact of high emitters – assuming their frequency also increases with age – is proportionally less.

We have also taken into account the degradation of the emission level with age. This is shown for gasoline passenger cars in Figure 4-1. The degradation functions have been derived from tests on hundreds of passenger cars (mainly through inspection and maintenance tests). These degradation functions include both the effect of normal emission control deterioration with age but also the effect of the increasing number of high emitters as vehicles grow older.

We may also argue that the impact of high-emitters in total emissions today is less than what it used to be in the past. The reason is that a number of measures are in place today to control emissions of vehicles through their lifetime. The distance that a Euro 5 vehicle has to comply with its emission limit is 160 000 km. This was 100 000 km at a Euro 4 level, 80 000 km for a Euro 1 through 3 level, while no durability distance was required for older vehicles. As a result, compliance with durability at an increasing distance for current technology passenger cars is a means to protect against the effect of high-emitters.

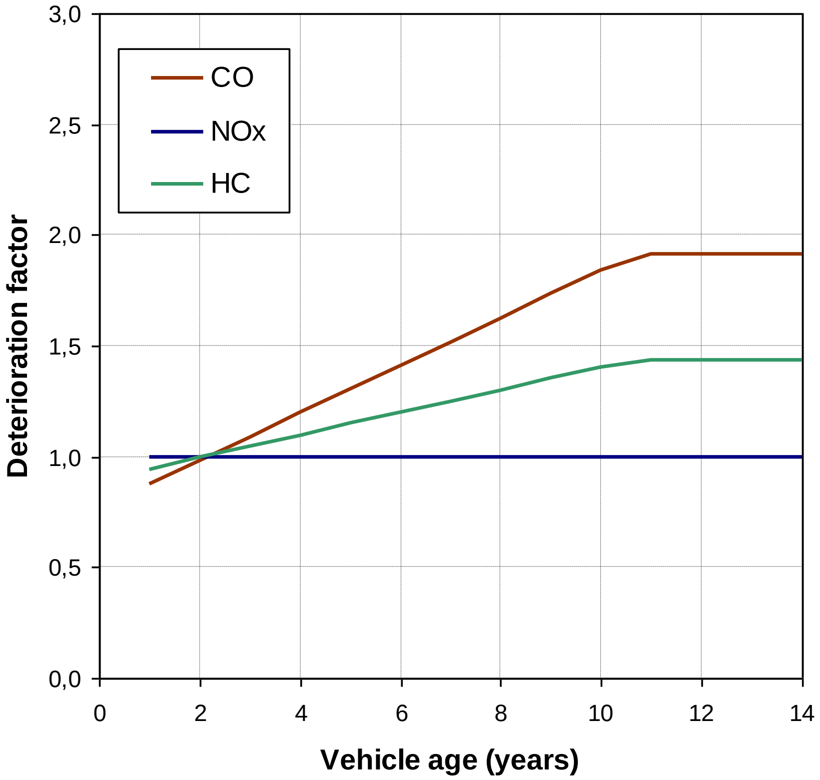

Figure 4-1: Effect of vehicle age on average emission level for gasoline passenger cars.

Current vehicle technologies need also to comply with emission thresholds monitored by on-board diagnostic (OBS) systems. OBD are monitoring systems which are installed on board the vehicle and monitor the operation of the emission control systems. Whenever the operation of a component of the emission control system deviates from the manufacturer specifications, then a malfunction indicator lamp (MIL) lights up on the vehicle dashboard and informs the driver that vehicle maintenance is required. In fact, the OBD should monitor the operation of the systems against an emission threshold which, if exceeded, should lead to a malfunction indication. This threshold is defined as a ratio between the emission level and the emission limit that the vehicle complies with. Figure 4-2 shows the ratio of OBD threshold over emission limit for vehicles with different year of registration. It should be noted that no OBD threshold were established prior to 2000. In addition, the figure shows that OBD thresholds become increasingly stringent (the only exception is PM but this is because PM emission standard was decreased by more than five times in 2010 as an effect of the introduction of particle filters). This is a further confirmation that high emitters will be identified in real-world and so their effect will be reduced.

We do not yet have a clear picture in Europe regarding the effectiveness of OBD systems. However, such data have started to appear in USA. Table 4-1 (Eisinger and Wathern, 2008). The table shows that the effectiveness of the OBD and I/M tests differ. Several vehicles failed the OBD without failing the ASM test and vice versa. In fact, the table shows that OBD is more sensitive than it should as the number of vehicles with OBD failures is higher than the number of vehicles with ASM failures. There is scope for action to streamline the two test procedures.

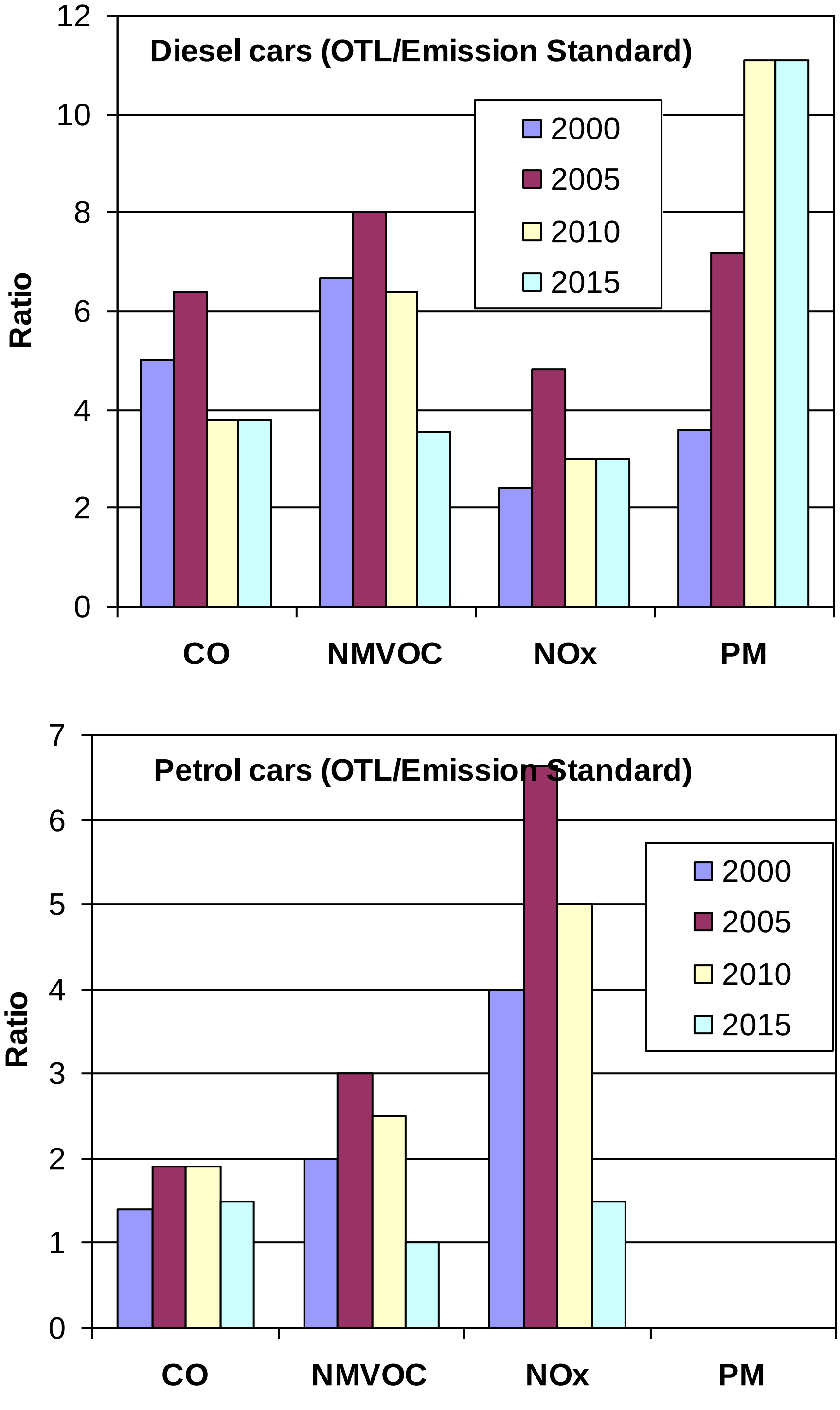

Figure 4-2: Ratio of OBD thresholds over limits for different technology steps (year of registration).

Table 4-1: Effectiveness of OBD compared to inspection and maintenance (ASM) tests. Source: Eisinger and Wathern, (2008).

Model year	Passing vehicles	OBD failures	ASM failures	ASM failures that also failed OBD	% of ASM failures that passed OBD
1996	690,230	87,642	55,157	13,796	75
1997	466,832	52,285	26,855	6683	75
1998	927,701	54,970	24,451	4596	81
1999	506,815	27,204	7856	1522	81
2000	1,198,145	43,172	7398	1254	83
2001	317,379	12,675	1199	203	83
2002	256,352	6686	570	75	87
2003	241,180	5268	373	51	86
2004	148,843	4114	121	20	83
2005	8796	372	2	–	–
ALL	4,762,273	294,388	123,982	28,200	77

Finally, one should consider that the vehicle sample that has been used to derive the emission factors is a sample of vehicle taken from the road, without any exclusion of potentially high emitters. Figure 4-3 shows the cumulative emissions (100% is total emissions) of the vehicle sample used to derive the COPERT 4 emission factors (Gasoline Euro 3 cars in the 10-20 km/h speed range: 140 data points in total). It is clear that only a small fraction of the vehicle sample is responsible for a high share of emissions. For example, in the case of HC, 10% of the vehicles are responsible for 65% of the emissions. This means that the sample used also includes some high-emitters. This trend is compared to the results of Guensler et al. (1994) which are obtained by measuring vehicles on the road by means of remote sensing. The cumulative curves of our sample and of on-road measurements show the same pattern.

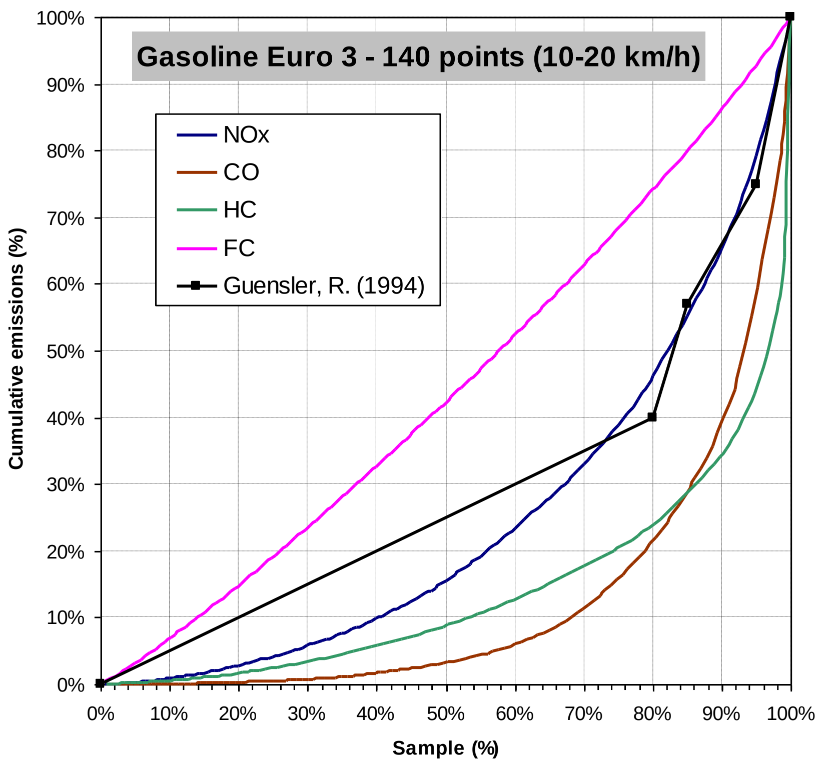

Figure 4-3: Cumulative emissions in the sample of vehicles and real-world data

4.2 Predicting emission reductions of the future

One of the issues associated with a successful emission projection is the prediction of how well future emission standards will manage to control emission levels. Figure 4-4 shows such a comparison.

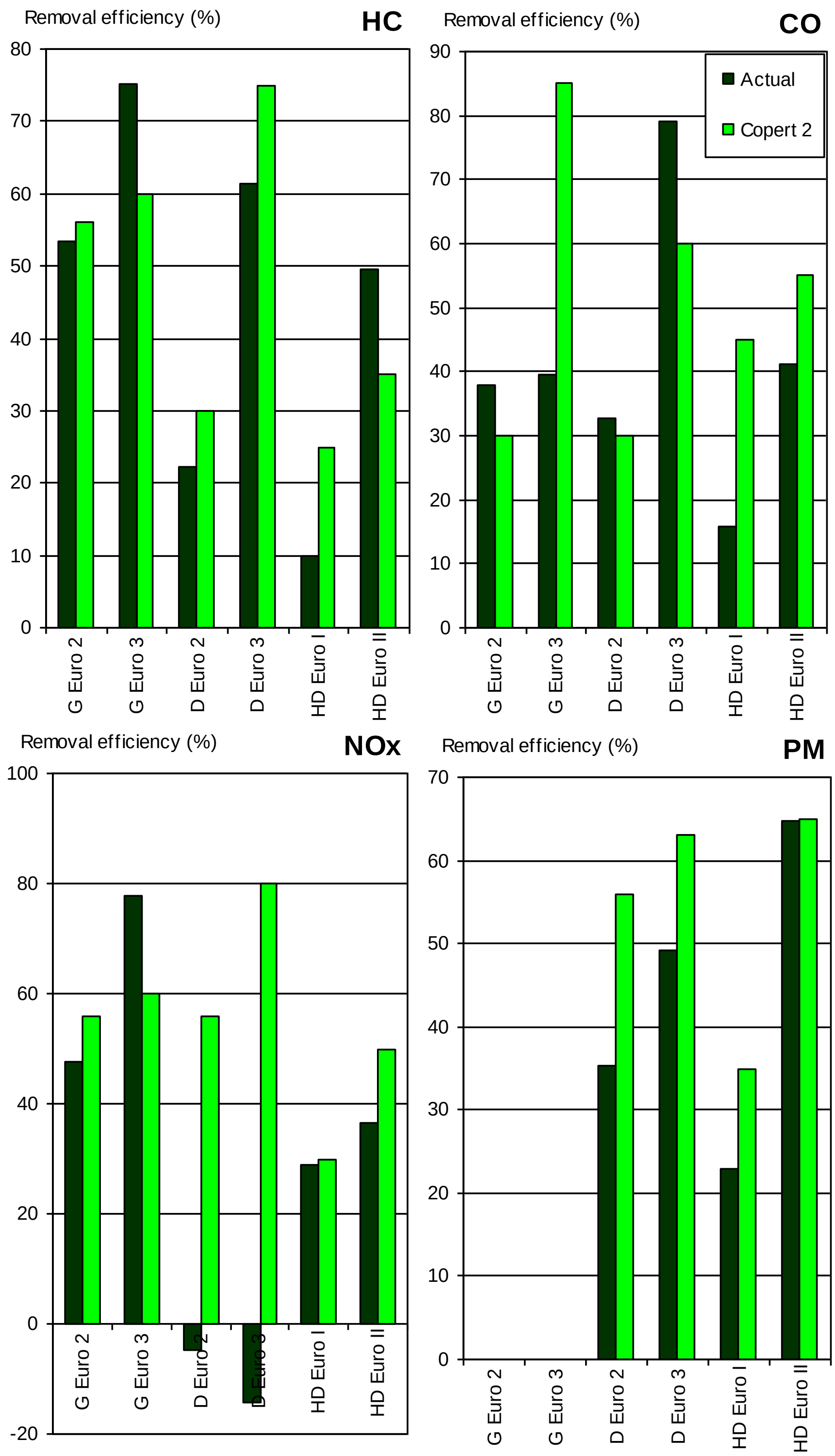

Figure 4-4: Comparison between actual emission reduction and predicted one for various emission standards.

Usually emission models assume that the reduction in the actual emission levels that a future emission standard will bring over an existing emission standard will be equal to the ratio of the emission limits between the two emission standards. However, this is not always case. For example, Figure 4-4 shows in particular for diesel NOx that the Euro 2 and 3 steps not only did not bring a reduction over Euro 1, as their emission limits would call for, but that the actual emission level of Euro 2 and 3 passenger cars was higher than Euro 1. The reason between the inconsistency between emission limit and actual reduction is that the type-approval procedure only controls emissions over a very narrow operation area while the real-world operation extends much beyond this range. Hence, the type-approval procedure is not effective in controlling emissions over the complete vehicle operation range in real-world.

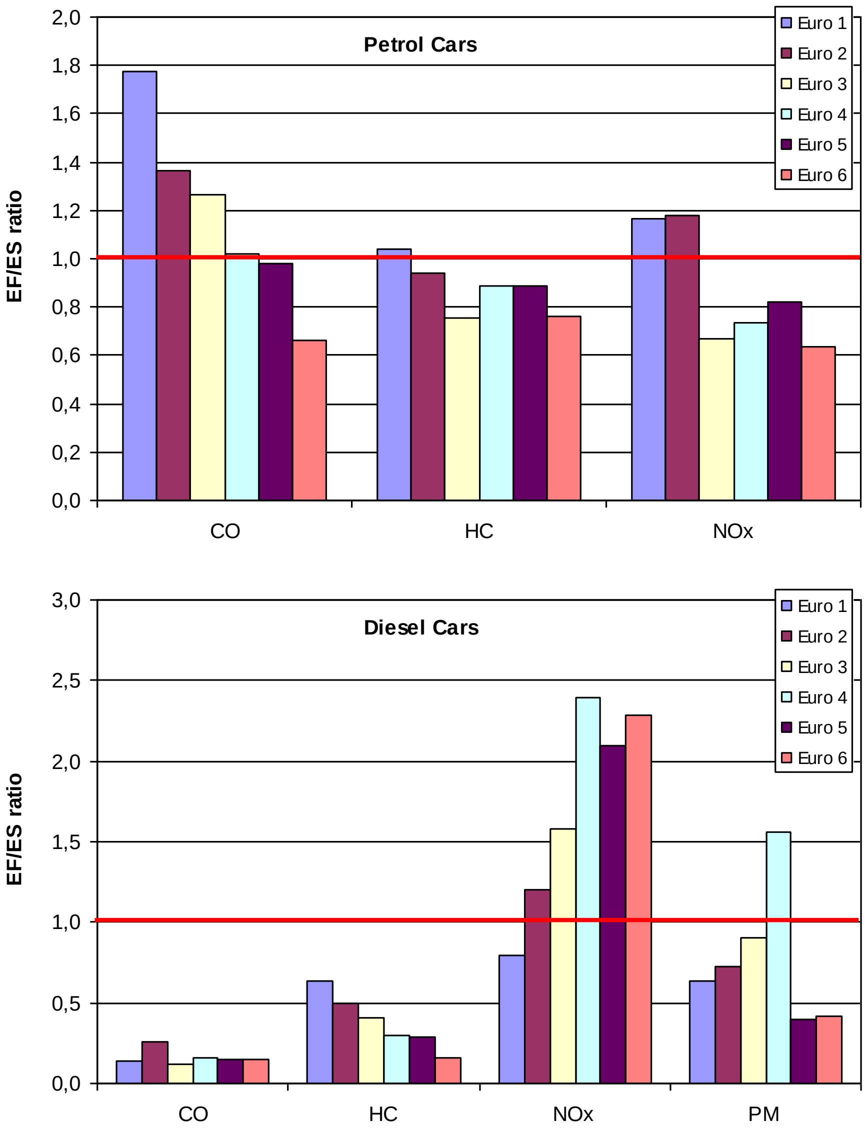

Figure 4-5: Comparison between the emission factor and emission standard per pollutant.

Emission models try to correct for this effect by using emission information collected in real-world and not type-approval driving cycles. Figure 4-5 shows the ratio of COPERT 4 emission factor over the emission standard limit for gasoline and diesel passenger cars. For gasoline passenger cars the emission factors are lower than the emission limit for current and future emission technologies as it is expected that the emission control devices will be effective in controlling emissions. The level is actually lower because the emission factors shown do not include the impact of cold-start (COPERT includes cold-start as a separate procedure). In the case of diesel cars though, and in particular NOx, the emission factor is significantly higher (more than two times) than the emission limit for current and future technologies. Therefore, we try to predict the expected exceedance of the emission limit in this case so that we do not underestimate emissions into the future.

The disparity between emission standard and emission factor is expected to remain as a problem in the future, in particular for diesel NOx. Gasoline emissions seem to be effectively controlled as stoichiometry is by definition the combustion ratio required both for maximum engine and aftertreatment efficiencies. CO and VOC where never and issue from diesel vehicles, while PM has been very effectively addressed by the installation of particle filters. However, NOx will continue to be a problem because high NOx means low fuel consumption. Therefore, NO_x may on purpose be left to rise much beyond emission limit values, in areas not monitored by the type-approval procedure, in an effort to reduce fuel consumption and CO_2 emissions.

It should be made clear that the uncertainty originating from such a behaviour is an issue that cannot be addressed by the modeling community. This is an issue arising from inefficiencies in the regulations, in the sense that the type approval driving cycle of today only covers a small fraction of the engine operation. This driving cycle is currently under review for substitution by a global driving cycle.

4.3 Advanced vehicle technologies

A number of new vehicle technologies are currently being produced and or scheduled to be launched in the near future. The uncertainty associated with predicting the emission levels of such technologies is larger than of conventional vehicle technologies. When simulating such vehicles to predict their emissions one takes into account a physical model of the vehicle powertrain and emission control systems and tries to simulate their operation based on best engineering knowledge of today. Such an example of a simulation is shown in Figure 4-6 where the CO_2 emissions of a conventional diesel passenger car is compared against the operation of a large hybrid, such as a sport utility vehicle. The two points correspond to the CO_2 emissions of the two vehicles over the type-approval NEDC.

A number of different observations can be made from this graph. First, the real world behaviour of various vehicle technologies varies with travelling speed, and following a different shape. Second, the CO_2 emission reduction foreseen by the regulations (e.g. EC 443/2009) over the NEDC will depend on the actual driving conditions of the different vehicles. Third, different technologies may lead to higher or lower emission levels depending on the travelling speed. The variance in the emission behaviour according to the technology increases the uncertainty of the prediction into the future.

It is therefore necessary to have a close look to the market penetration of new vehicle technologies in order to identify which of them obtain significant numbers. Based on these, actual vehicle tests need to be organized as soon as possible, in order to have an early view of their emission behavior. Until such data are obtained, the complete absence of experimental information for some vehicle types increases the uncertainty of the projection.

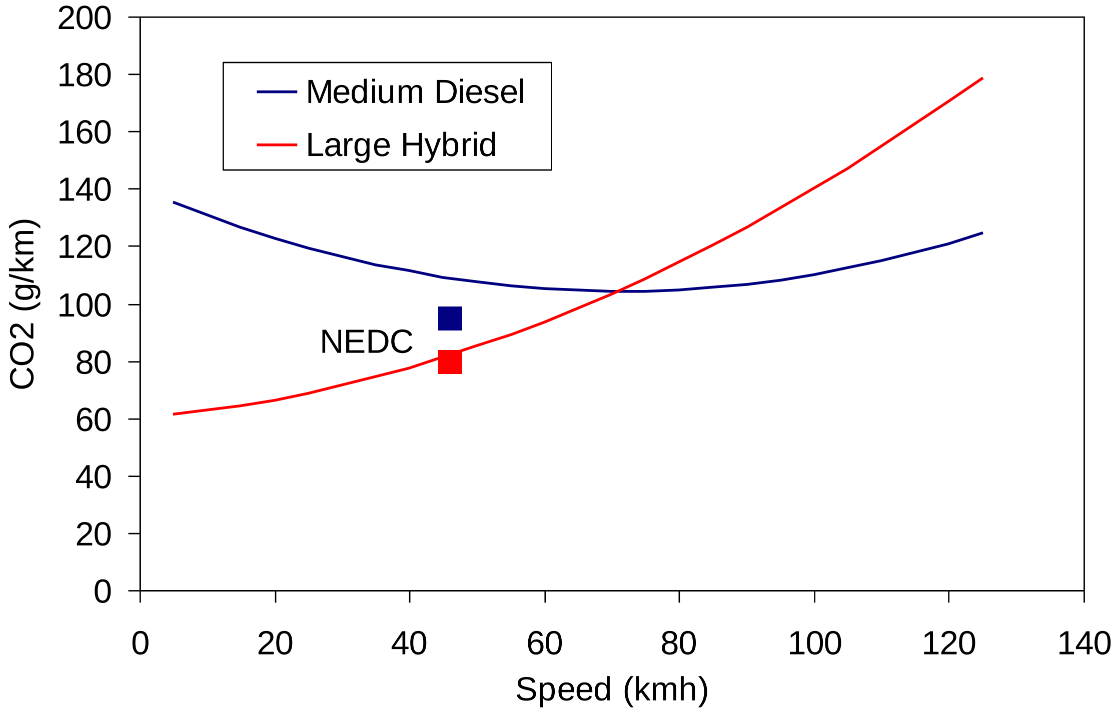

Figure 4-6: Simulations of CO2 emissions as a function of speed for two different vehicle types.

5 Conclusions and Recommendations

This report summarizes our current knowledge about the uncertainty of road transport emission estimations at a national level. Table 5-1 summarizes the uncertainty in total emission estimates for a country at a national level. The coefficient of variance (CV) is the ratio of standard deviation over mean. The uncertainty is very low for fuel consumption and CO_2. This is because total fuel consumption is well known at a country level. Despite the other two greenhouse gases are known with less certainty, the uncertainty of the CO_2 equivalent (CO_{2e}) - taking into account the relevant radiative forcing potential of these species - is still dominated by the uncertainty in direct CO_2. With regard to the other pollutants, the ones dominated by gasoline cars (CO, VOC) appear more variable than the ones dominated by diesel cars (NO_x, PM). This is an effect of the uncertainty in the emission factors between the two different vehicle types. In general terms, this analysis shows that estimates of total road transport emissions are generally known with good confidence.

Table 5-1: Summary of the uncertainty in emission estimates at a national level.

	CO	**VOC**	**CH4**	**NOx**	**N_2O**	**$PM_{2.5}$**	**PM_{10}**	**PM_{exh}**	**FC**	**CO_2**	**CO_{2e}**
Mean [kt]	1,134	325	19	614	3.1	32	37	27	36,945	110,735	112,094
CV(%)	19	12	34	10	26	9	8	9	3	4	4

The sensitivity analysis conducted also reveals that the variance of the emission factors is the dominating source of uncertainty in most pollutants. The total uncertainty due to hot emission factors per pollutant was found: NOx (76%), PM (72%), VOC (63%), CO (44%), FC (43%), CO2 (40%), CH4 (13%). The high contribution of emission factors in total uncertainty may initially sound peculiar, since emission factors for vehicles are based on many tests and measurements of real-world vehicles. In comparison to emission factors from other sources, vehicle emission factors are generally considered to be known with good confidence. On the other hand, there are thousands of individual vehicle types, different environmental and driving conditions, levels of maintenance, driver behaviours, etc., all of which affect the emission level of individual vehicles. The uncertainty in all of these factors is reflected to the uncertainty in the selection of an appropriate emission factor. It is therefore recommended that research in improving emission factors will also improve the quality of projections, and by that, also the quality of political decisions.

Other sources of uncertainties of significant importance are the classification of vehicles in different emission standards, in cases where this is not recorded in the national register, the annual mileage driven and the decrease of mileage with age, and also the mean travelling speed. Better statistics are required to further reduce these uncertainty sources.

Finally, a discussion was made on uncertainty induced by three frequently discussed factors: high emitters, disparity between emission standard and emission factor reductions, and the impact of advanced vehicle technologies:

- With regard to high emitters, the main conclusions are first, that their impact - to a certain extent – is already implemented in the emission factors and second, that the policy measures already taken (durability, OBD, roadworthiness testing) will decrease the frequency of high-emitters in real world. Therefore, high emitters are not considered as much as a problem today as they did in the past.

- The disparity of emission standard and emission factor reduction is potentially an issue that will continue also in the future, for as long as the type-approval test only covers a small part of vehicle operation. This is expected to have an impact on NO_x emissions from both light duty and heavy duty vehicles and does not seem much of problem for other pollutants. This can only be effectively addressed by a new type-approval procedure.

- The expectation for the introduction of many new vehicle technologies increases the uncertainty in the projections, as there is currently very limited or even no experimental information regarding the emission behaviour of such vehicles. Experimental information needs to be collected as soon as possible for these vehicles expected to make it to large market volumes.

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