Atmospheric Pollution Research 4 (2013) 282-289

Atmospheric Pollution Research

www.atmospolres.com

Impact of the dropping activity with vehicle age on air pollutant emissions

Stefano Caserini [1], Cinzia Pastorello [1,2], Pietro Gaifami [1,3], Leonidas Ntziachristos [4]

[1] *DIIAR – Sezione Ambientale, Politecnico di Milano – Piazza L. da Vinci, 32 – 20133 Milano, Italy*
[2] *Present address: EEA – European Environment Agency, Kongens Nytorv 6, 1050 Copenhagen, Denmark*
[3] *Present address: Redecam Group, Piazza Montanelli, 20 20099 Sesto S. Giovanni, Italy*
[4] *Laboratory of Applied Thermodynamics, Aristotle University, PO BOX 458, GR 54124 Thessaloniki, Greece*

ABSTRACT

Road transport is a major source of air pollution especially in cities. Detailed calculations are needed to support road transport emission inventories due to the variance of technologies and operating conditions encountered on the roads. The annual distance driven by cars in relation to their characteristics is an important variable in such calculations. In this work, a large amount of mileage data were collected from second–hand car sellers in Italy and were then analyzed in order to understand the influence of vehicle age on annual mileage driven. The available data enabled the development of dropping functions of annual mileage with vehicle age. It was found that the average mileage of 10 year old cars is only approximately 40% of the mileage driven on year one. This drops to approximately only 10% for 20–year old cars. The findings are of paramount importance in environmental calculations as road transport NO_X and PM emissions drop by more than 20% when the corrected functions are used compared to using a constant mileage. Not introducing such a correction may result to an approximately 8% higher nation–wide NO_X emissions with negative implications towards meeting the national emission ceilings. In terms of policy implications, the dropping activity with age results to a decrease in the importance of accelerated scrappage schemes and of environmental zones in air quality.

Keywords: *Air quality, emissions, NO_X, road transport, vehicle activity*

Corresponding Author:
Cinzia Pastorello
☎ : *+45-3336-7298*
🖷 : *+45-3336-7128*
✉ : *cinzia.pastorello@eea.europa.eu*

Article History:
Received: 07 February 2013
Revised: 24 April 2013
Accepted: 07 May 2013

doi: 10.5094/APR.2013.031

1. Introduction

Road transport is one of the main sources of pollution in urban areas in Europe, accounting for 39%, and 15% of total NO_X and $PM_{2.5}$ emissions, respectively (EEA, 2010). During the last years, benefits from the progressive replacement of uncontrolled gasoline cars with new ones equipped with three way catalysts are counterbalanced by the increasing penetration of diesel cars and their higher emission levels, in particular NO_X, compared to their gasoline counterparts. Urban sprawling and the general association of personal mobility with quality of life and economic development (Uherek et al., 2010) have increased the mean annual distance travelled by cars (EC, 2012) until 2008; then a slight decrease has been visible due to the economic crisis.

Emission models are used to calculate emissions from road transport. Examples of such models in Europe include HBEFA used in German–speaking countries (Hausberger et al., 2009), VERSIT+ used in the Netherlands (Smit et al., 2007), LIPASTO in Finland (lipasto.vtt.fi), and COPERT 4 which is used in 22 out of the 27 European Union member states (Ntziachristos et al., 2009). In such models vehicle activity is multiplied with emission factors to calculate total emissions. Vehicle activity is estimated as the number of fleet vehicles per type distinguished in each model times the annual mileage driven by each vehicle type. Vehicle fleet data are readily available in several countries. For example, official statistics in Italy (ACI, 2011) provide the number of vehicles distinguished per fuel type used, engine capacity, and emission control regulation (EURO categories).

With regard to mileage estimates, Andre et al. (1999) pointed out the importance and the difficulties of estimating annual mileage and its trend as a function of various factors (such as vehicle age) for different vehicle categories. On the basis of inspection and maintenance monitoring programs, Beydoun and Guldmann (2006), Washburn et al. (2001), and Bin (2003) demonstrated that the total mileage of a vehicle is strongly associated to emission and test failure rates. Finally, Sawyer et al. (2000) underlined the importance of having accurate activity data for obtaining an improved transport emission inventory.

Despite its significance though, annual mileage is usually available as an average value for the entire gasoline or diesel car fleet, without distinguishing into more emission–relevant criteria, such as type of road or length of service that affect the emission assessment (Ntziachristos et al., 2008). Often, mileage values used in national emission inventories are not based on measured data but are just calibrated values, estimated so as to achieve a balance between the fuel consumption calculated by the model and official statistics on fuel sold. Although this produces an inventory which is consistent with total energy statistics, it does not guarantee a correct allocation of consumption to the different vehicle types, neither that total activity is correctly disseminated to the various vehicle types and ages.

An estimate of the mileage of different vehicle types as a function of age is therefore an important input to road transport environmental models, in order to accurately estimate the total emissions produced. It is also necessary in order to accurately predict the real–world impact of policy measures targeting specific vehicle technologies. For example, implementing policies targeting the removal (scrappage) or ban of travelling (environmental zones) of old vehicle types will be less effective than planned in case that a decreasing function of mileage with vehicle age is established.

In this study we are proposing a methodology for precise mileage estimation as a function of vehicle age that can be introduced to emission models for improving the quality of the calculations. As an example case, we apply the method in the case of Italy to demonstrate the extent by which mileage misallocation between different vehicle classes may affect emissions estimates. This can also serve as a measure of the uncertainty of an inventory, when mileage values are not based on measured data.

2. Material

Real–world data on passenger car mileage was collected by visiting 32 950 individual second–hand passenger car sales on the internet (see the Supporting Material, SM, Table S1). The collection and analysis of the data took place in the period between June and September 2010. The final dataset consisted of 18 652 gasoline cars registered in the period from 1994 to 2010 and 14 298 diesel cars, registered between 1996 and 2010. Older vehicles were practically not for sale as they are not allowed to circulate in several Italian regions during the winter, due to air–quality limitations. The dataset constructed included fuel used, year of first registration and odometer reading. Table S2 (see the SM) shows some key statistics of the dataset.

Data collected represent about 1.1% of the 2.8–3.0 million of used cars sold in Italy every year. This was as much as could be collected from the second hand market with complete information on age and mileage. No particular criteria were set to select the vehicles in the sample. Hence, we expect them to make a representative sample of the actual vehicle stock. This is also verified by the fact that the distribution of vehicles in the different age classes is quite similar to the distribution of the complete stock of vehicles registered in Italy. This is demonstrated in Table 1 which compares the age distribution of the sample used in the current study with the Italian stock distribution, based on data taken from the Italian car association database (ACI, 2011). The frequency distributions are quite similar between the two datasets. One might expect that the ratio of cars being sold vs. cars in operation would increase as the age increases. This was partly visible in the case of diesel but not for gasoline cars. Several reasons could contribute to these different trends, such as generally longer lifetime for diesel cars, scrappage and exporting of vehicles vs. second hand sale within the country, etc. Anyway, the differences in the ratio between sold and registered car in every year are low (from 0.08% to 0.2% for diesel and from 0.09% to 0.13% for gasoline) and the sample size per age class is satisfactory, with the minimum number per class still above 400 vehicles (diesel, 14 years old).

Questions may arise on the reliability of the odometer reading as a method to infer the mileage driven by each vehicle. This is only reported by the owner and suspicions may arise regarding the effect of clocking of the cars, i.e. the fraudulent winding back of the odometer reading to make the car appear younger than it really is and negotiate a better price with the potential buyer. A recent study on the impact of mileage fraud with used cars (EREG, 2010) identified mileage fraud as a serious problem, but no data were made available to define how much this issue could affect the variation of average mileage with time. In this work, we have assumed that the distortion effect is proportional to the length of service. That is, we have assumed that car clocking takes place at the same frequency for new and old cars and that the mileage correction is proportional to the odometer reading. In other words, the assumption is that the intention to improve the selling price of the vehicle is the same, regardless of the actual age of the car, which tends to be a reasonable approach. Hence, this will have an impact on the total mileage reported but will not affect the relative relation between mileage and age, which is of importance to this study. All data collected were pooled together and a statistical analysis was conducted. The results of this statistical analysis and the methods used are presented in the following section.

Table 1*. Frequency distribution of vehicles in the available dataset and of vehicles registered in Italy, according to their age*

Gasoline					Diesel				
Vehicle age	Data available		Vehicles registered in Italy		Vehicle age	Data available		Vehicles registered in Italy	
	Number	(%)	Number	(%)		Number	(%)	Number	(%)
1	1 142	6.1%	1 069 212	6.1%	1	1 170	8.2%	937 819	7.3%
2	1 260	6.8%	1 268 172	7.2%	2	1 184	8.3%	952 648	7.4%
3	1 123	6.0%	1 080 342	6.2%	3	1 143	8.0%	1 118 239	8.7%
4	1 148	6.2%	1 115 822	6.4%	4	1 184	8.3%	1 425 176	11.1%
5	1 183	6.3%	982 559	5.6%	5	1 103	7.7%	1 375 719	10.7%
6	1 103	5.9%	928 070	5.3%	6	1 107	7.7%	1 309 433	10.2%
7	1 175	6.3%	935 830	5.3%	7	1 089	7.6%	1 306 260	10.1%
8	1 188	6.4%	1 128 497	6.4%	8	1 069	7.5%	1 058 484	8.2%
9	1 170	6.3%	1 246 925	7.1%	9	1 107	7.7%	899 656	7.0%
10	1 191	6.4%	1 403 895	8.0%	10	1 084	7.6%	756 601	5.9%
11	1 177	6.3%	1 379 962	7.9%	11	1 062	7.4%	660 656	5.1%
12	1 183	6.3%	1 211 130	6.9%	12	991	6.9%	494 371	3.8%
13	1 307	7.0%	1 222 049	7.0%	13	595	4.2%	346 132	2.7%
14	1 291	6.9%	1 198 861	6.8%	14	412	2.9%	242 833	1.9%
15	1 150	6.2%	705 916	4.0%					
16	861	4.6%	666 246	3.8%					
Total	18 652	100%	17 543 488	100%	Total	14 300	100%	12 884 027	100%
16<age<30			5 298 935		14<age<30			1 016 079	

3. Calculation and Results

3.1. Cumulative and annual mileages

The average cumulative mileage (ACM_k) refers to the total distance covered on average by each car of the same age, or in a more technical way, with the same length of service (k–in years).

The relationship between ACM_k and vehicle age is shown in Figure 1 as an average for all gasoline and diesel passenger cars in our sample. The figure shows that *ACM* increases with vehicle age almost in a linear fashion up to 4–5 years of age. Beyond this point, the rate of increase in *ACM* drops, denoting a decrease of the annual mileage conducted. After 14 years and approximately 126 thousand kilometers for gasoline vehicles and 13 years and approximately 180 thousand kilometers for diesel cars, there is only limited (if any) increase in the cumulative mileage.

When looking at single vehicles only, total mileage can only monotonically increase with vehicle age. Hence, the stabilization of mileage after a certain age cannot be explained on a single vehicle basis. The reason for mileage stabilization in Figure 1 is that vehicles with excessive mileage are removed earlier from the stock, even if their age – measured in years – does not justify this. Hence, as the frequency of vehicles being scrapped increases with age, the rate of increase of mileage with age gradually drops at a fleet – wide level and a saturation point is reached. After this point, increasing the mean vehicle age does not cause any significant increase in the mileage. Actually, a drop in the mileage would also be theoretically possible.

The mileage stabilization is of importance to road transport emission models. For example, as an input in functions which correct emission factors according to the mileage covered. Figure 1 shows that, despite to general belief, the actual average mileage of a fleet of passenger cars does not increase beyond a certain point as they grow older, hence emission factors should not degrade above a certain level.

By dividing the *ACM* value with the length of service, one obtains the average annual mileage (AAM_k) which is the average annual distance covered by each car of the same length of service. That is,

$$AAM_k = \frac{ACM_k}{k} \tag{1}$$

AAM only depends on vehicle age and it is the same for each year during the lifetime of the vehicle. AAM_k values as a function of vehicle age are shown in Figure 2. This shows that the average mileage driven per year generally drops while the vehicles become older. The function does not drop monotonically for diesel cars but cars of one year of age appear to be driven less than cars of two and three years of age. We have no evidence that this is a sample artifact, however a satisfactory number of more than 1 000 diesel vehicles was available for each age class in our dataset.

If vehicle age is not taken into account, then the average mileage of our gasoline car sample is 10 636 km and 18 685 km for diesel cars. However, as shown in Figure 2, the true average will depend on the average age of the vehicles considered. This is not always taken into account in relevant studies.

3.2. Mileage to be used for emission modeling

Just because cars are used differently throughout their lifetime, the maximum length of service, *j*, i.e. the age in years at which the vehicle is removed from the stock, may vary from vehicle to vehicle. The maximum length of service will have an impact on the increase rate of *ACM* with age. That is, vehicles which are scrapped from the stock early (short length of service) should be expected to accumulate mileage faster than vehicles with a longer maximum length of service. Therefore, the maximum length of service is a parameter that has to be taken into account when expressing the function of mileage with vehicle age.

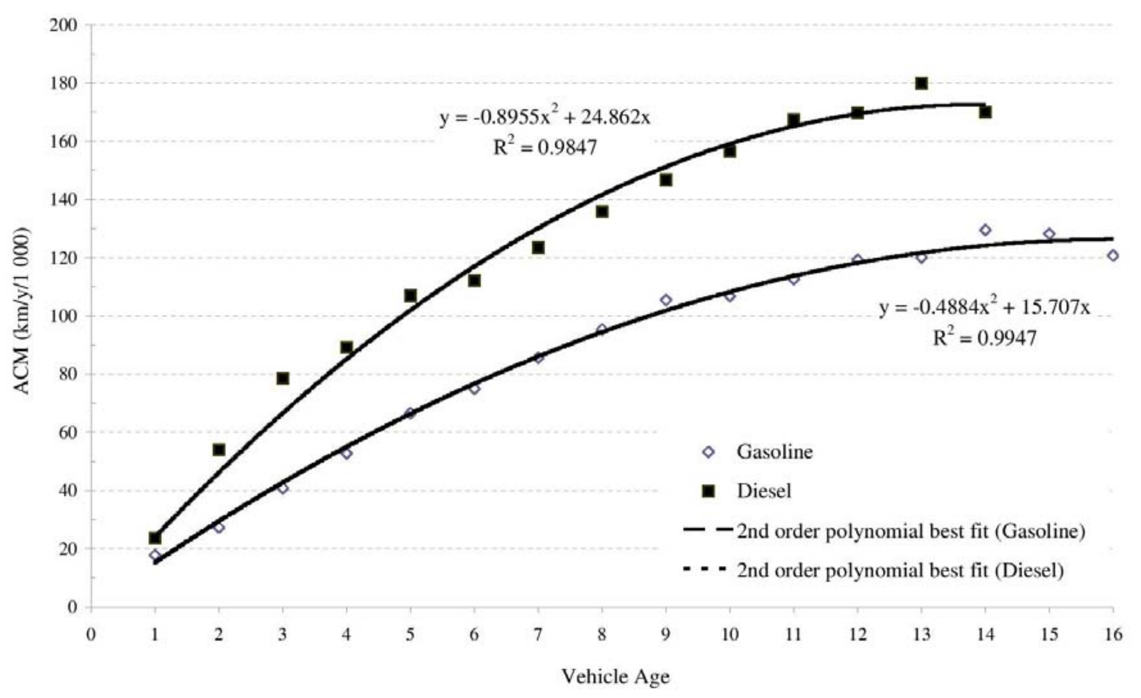

Figure 1. *Average cumulative mileage (ACM) for diesel and gasoline passenger cars, as a function of their age. Fitted parabolas passing though the axes origin have been drawn for both datasets.*

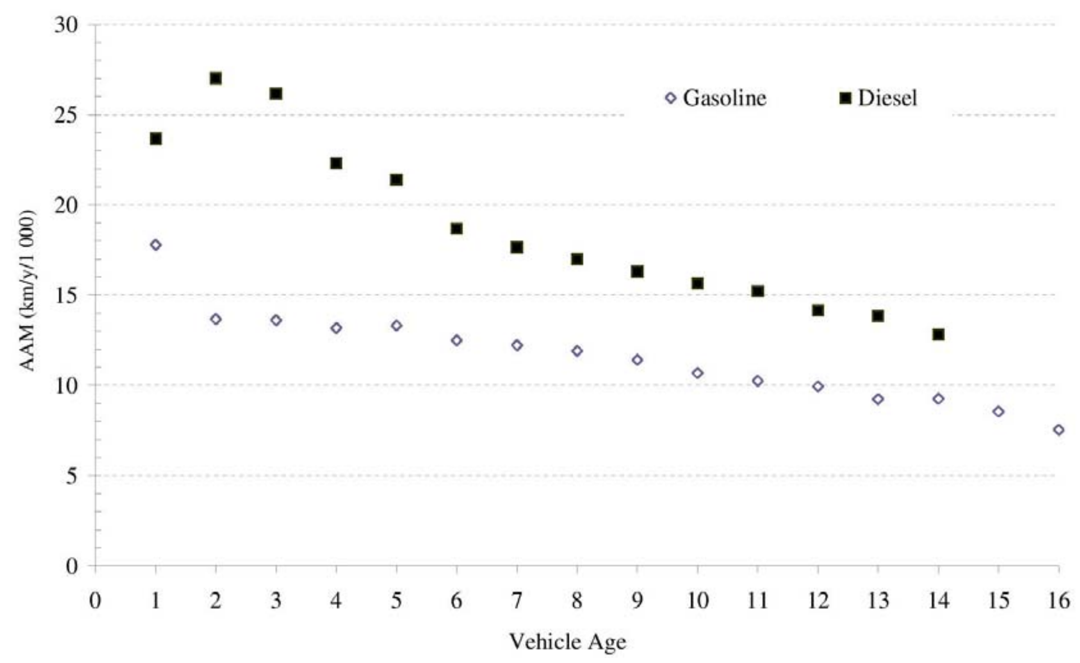

Figure 2. *Average annual mileage (AAM) driven by vehicles of different age.*

In order to introduce the maximum length of service (j) in the calculation, one may start by observing that the mileage values in Figure 1 seem to follow a parabolic function with age. Hence, *ACM* can be approached by a binomial function passing through the axes origin, i.e. a function of the type shown in Equation (2):

$$ACM_k = a\,k^2 + b\,k \tag{2}$$

The binomial curves that best fit the data result to the a and b parameters are shown in Figure 1 for both diesel and gasoline passenger cars. This equation can be considered representative for a stock of vehicles with an average end–of–life age at the point where the binomial equation becomes level. This is mathematically expressed by the function:

$$\left.\frac{dACM}{dk}\right|_{k=j} = 0 \tag{3}$$

For such a curve, parameters a and b can be easily calculated by Equations (2) and (3) as:

$$a = \frac{-ACM_j}{j^2} \tag{4}$$

$$b = -2\,a\,j \tag{5}$$

Using Equations (4) and (5) and the best fit parameters for diesel and gasoline cars, this method results to j values of 16 (years of service) for gasoline cars and 14 years of service for diesel cars, with corresponding *ACM* values of 126 300 km and 172 600 km, respectively. These values are very close the ones estimated in the previous section which means that the binomial function very well describes the evolution of the *ACM* as a function of vehicle age.

Having established a parabolic development of mileage with age, with parameters defined in Equation (4) and (5), this can be used to estimate the evolution of the mileage of vehicles that have a maximum useful life more than what is shown in Figure 1 (see also the SM, Figures S1 and S2, for gasoline and diesel cars, respectively). The maximum average mileage remains constant, as this was the evidence from the experimental data in Figure 1; hence, the evolution of mileage along the life of the vehicle can be predicted having the end–of–life age of the vehicle as the only independent parameter. All gasoline cars which are younger than 16 years old and diesel cars which are younger than 14 years old are expected on average to follow the original curve.

The parabolic functions defined can in turn be used to model how the annual mileage of cars drops with their age. This was not possible by subtracting the *ACM* values of two consecutive years as this stabilized after a certain age and would result to zero, or even negative values. With the model developed, if one specifies the end–of life age of vehicles (j), then the actual average annual mileage (*AAAM*) that these vehicles conducted when at age k will be:

$$AAAM_{k,j} = \left(a_j\,k^2 + b_j\,k\right) - \left[a_j\,(k-1)^2 + b_k\,(k-1)\right] \tag{6}$$

The parameters a and b in this function differ for gasoline and diesel passenger cars. The model developed in Equation (6) can be applied to predict the evolution of mileage of the Italian passenger car stock. The distribution of vehicles according to year of registration is available at national level in the Italian car association database (ACI, 2011). This database shows that there are very few vehicles registered above 30 years of age, which is considered as the maximum end of life age in our analysis. The probability of vehicles to reach a certain end of life age is required in order to apply Equation (6) on the Italian stock data. However, this is not known a–priori. We can assume that this probability is equal to the percentage of vehicles in the particular age bin registered in Italy in 2010. This approximation is actually also theoretically accurate if the number of vehicles registered in Italy is constant throughout the years. In reality, in the period 2000–2011, the Italian new passenger car registrations have been falling with an average rate of 2%. This is a very mild change which means that our approximation is very close to the theoretical accurate and can be safely used in our calculations.

With this assumption, and the fact that all vehicles below a certain age (*J**=16 for gasoline cars and *J**=14 for diesel cars) follow the same *ACM* curve, the *AAAM* value of all vehicles registered in Italy as a function of their age can be calculated by means of:

$$AAAM_k = \frac{\sum_{j=J*}^{30} AAAM_{k,j} f_j}{\sum_{j=J*}^{30} f_j} \qquad (7)$$

where f_j is the probability of cars to reach an end of life age j.

The graphical representation of Equation (7) is shown in Figure 3. The $AAAM_k$ values drop with vehicle age and practically reach zero at an age of 30 years. Regression curves split in different regions have been drawn that allow using these trends in different applications. A quadratic fit has been assumed until the 22nd year of age and then a linear fit to the minimum of mileage in the 30th year. This has been selected in order to maximize the fitting of the curves with the data. Several attempts have been done and the split <22 and >22 year of age resulted as the best one.

3.3. Comparison to other studies

Despite its significance for emission calculations, information on vehicle mileage as a function of age is rather scarce in the literature. Few data are available, mostly estimated on the assumption that vehicles are driven for the same annual distance during their whole lives. As already said, this assumption does not correctly represent the known dependence of mileage on vehicle age which is described by *AAAM*. On the other hand, not taking into account the drop of annual mileage with age likely results to an overestimation of total emissions as the contribution of older vehicle technologies is overstated.

A dataset of mileage data has been developed at European level in the framework of the TREMOVE (EC, 2005) and MEET (Andre, 1999; Andre et al., 1999) activities. TREMOVE is a policy assessment tool that provides the background calculations for impact assessment studies in the area of transport policy interventions. In the MEET project, the dependence of mileage on vehicle age was also collected from a few national data, without offering distinction to vehicle categories (Andre et al., 1999). For example, for Sweden the dependence of mileage on vehicle age (Figure 4) was calculated using data sets from two consecutive years (1987–1988) and matching car with the registration number. Although no information is available on the amount of data processed, in this case the result is the actual annual mileage defined previously.

Vehicle survivability and mileage for passenger cars were also developed on the basis of 1977 to 2002 registrations and 2001 mileage survey data (NHTSA, 2006) in US. This analysis shows that a typical passenger car travels for a total distance of approximately 150 000 miles, reached after 25 years, while in the present study the lifetime mileage for gasoline and diesel vehicles was respect-tively 126 300 km (after 14 years) and 172 600 km (after 16 years). As it is shown in Figure 4, the decrease of *AAAM* mileage in the first years of service is higher than for the other curves.

The comparison of the data generated in this work with results from other studies generally shows that the *AAM* values generated are close to the maximum of the range of the data collected. Actually, the relative increase of diesel cars up to 3 years of age is unique in our dataset. On the other hand, the *AAAM* values – which should closer reflect the actual drop in mileage with age – are at the low end of the range collected, and comparable to data from US. It has not been possible to exactly identify which method has been used by other studies for estimating the mileage function with age. However, the values obtained in this work with two different methods are generally within the range of values reported elsewhere.

This comparison shows that the definition of the mileage function with age is important and that different dropping mileage rates can be obtained, depending on the definition. This leads to two important conclusions. First, the method used to estimate the function of mileage with age has to be reported and, second, the environmentally relevant calculations will depend on which method has been used for the assessment.

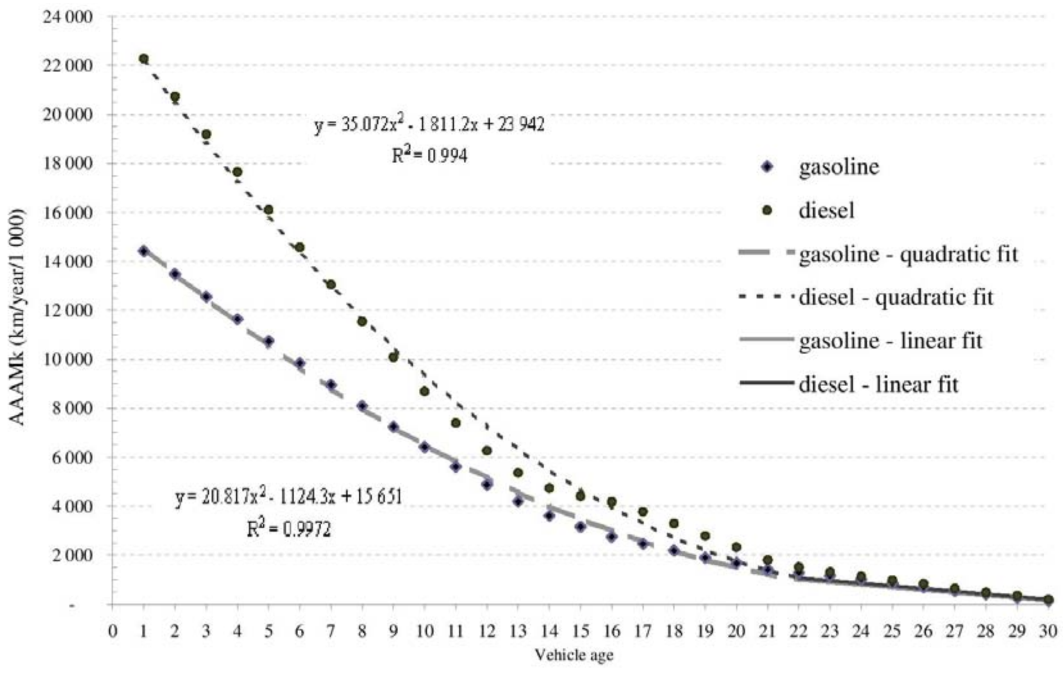

Figure 3. *Actual average annual mileage (AAAM) by diesel and gasoline cars in the Italian vehicle stock. Best-fit curves have been drawn, split in two regions.*

4. Discussion

The relationship between mileage and vehicle age allows the estimation of the average mileage of vehicles that belong to specific legislative (i.e. Euro) classes. This is the standard vehicle classification in all European road transport emission models (e.g. COPERT, HBEFA, VERSIT+). Multiplication of this mean mileage with the number of vehicles in the class and with an appropriate emission factor calculated by the model leads to the estimation of the total emissions produced by the vehicles in the particular class.

The mean mileage per category is derived as the weighted average of vehicles of different age which comply with the same emission limit, as they are registered in the official statistics (ACI, 2011). The percentage distribution of vehicles during different years of age (Table 1) was used in order to estimate average values of *AAAM* separately for the different legislative classes of diesel and gasoline vehicles, from Euro 0 (non–catalytic vehicles) to Euro 5, as well as an average mileage for the whole fleet (Figure 5). It should be noted that the estimate is related to the year in which the estimation of mileage was carried out, that is the year 2010 in our case, and so one year old vehicles are the ones registered during 2009. As would have been expected, the mean mileage for vehicles registered before 1992 (Euro 0) is only a small fraction of new Euro 5 vehicles.

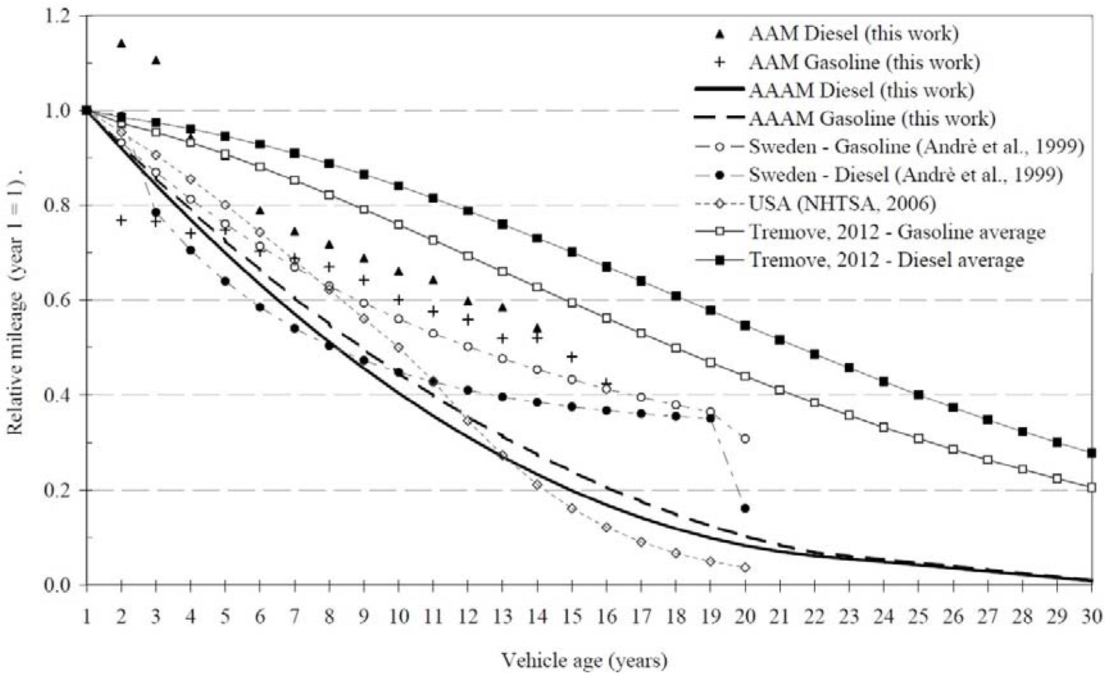

Figure 4. *Comparison between the results of the present study and data from the literature reviews: USA data collected between 1997 and 2002 (NHTSA, 2006), TREMOVE data (EC, 2005) and Swedish data collected between 1987 and 1998 (Andre et al., 1999).*

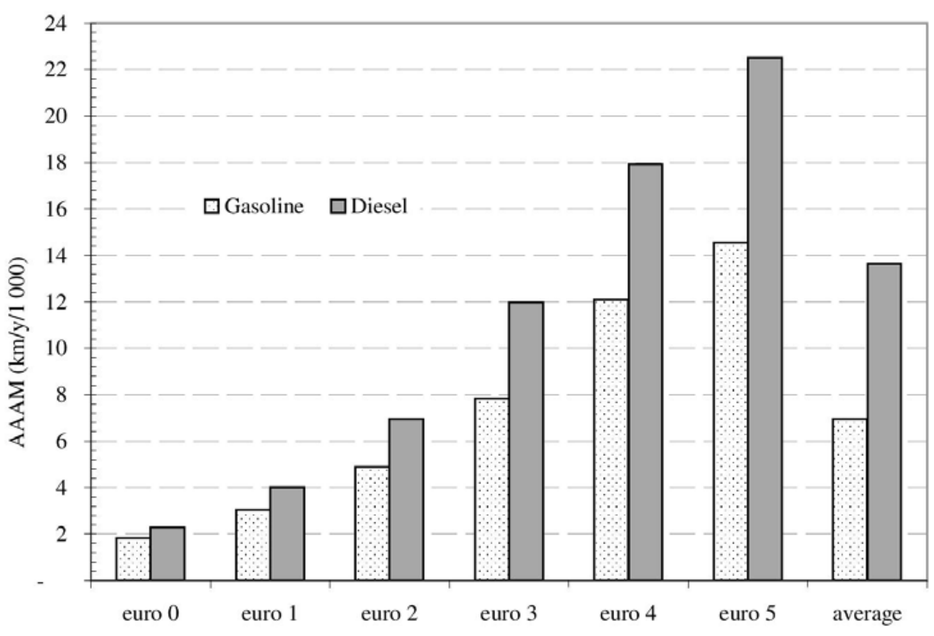

Figure 5. *AAAM (10^3 km/y) for different euro categories and average for the whole fleet in the year 2010.*

The mileage values estimated in Figure 5 can then be used as input to emission models to estimate road transport emissions. We have used COPERT 4 as an example, to demonstrate the impact of the dropping mileage with age on total emission estimates. The main input data used for such a calculation are shown in Table 2. The emission factors for nitrogen dioxide (NO_X) and particulate matter (PM) were derived as aggregates from the detailed COPERT 4 methodology, using detailed activity and environmental information corresponding to the Italian conditions. The number of vehicles split by emission legislation was derived from national statistics, and the relative mileage per technology step was estimated using the approaches described above (constant mileage, *AAM* and *AAAM*). Basically, the mileage values estimated per each class based either on the *AAM* or the *AAAM* methods were proportionally adjusted to lead to the same fuel consumption as the constant mileage case. This is the typical procedure followed in emission inventories, i.e. a relative mileage per technology class is first estimated and then it is proportionally adjusted to meet the fuel consumption reported by the official statistics. With this method, all emission results shown in Table 3 correspond to the same total fuel consumption.

Despite all calculations correspond to the same final energy utilization, there are significant differences in the total emissions calculations for both pollutants. Both NO_X and exhaust PM emissions drop by more than 20% when *AAAM* is used instead of fixed mileage. The difference in NO_X mostly comes from gasoline cars as the true NO_X emission factors (Table 2) of diesel cars do not consistently drop with an improving emission standard. Hence, the allocation of mileage to gasoline vehicles is more important than diesel ones in the case of NO_X. The opposite occurs in case of PM emissions where differences in gasoline vehicle PM emission factors are minimal and the main reductions originate from diesel vehicles only. Relevant differences also occur when the *AAM* estimate of mileage is used.

Such emission differences are not trivial. For example, out of the eleven member states that emitted more than their NO_X targets according to the emission ceilings directive (EEA, 2011), eight of them only exceeded their limits by less than 20%. Taking into account that road transport alone is some 40% of total national NO_X emissions (EEA, 2010) the difference of more than 20% that we calculated due to mileage estimation only in this study would be equivalent of more than 8% of total nation–wide NO_X emissions. Such a difference would bring a number of countries closer or within their allowed limits.

***Table 2**. Aggregated NO_x and PM_{10} emission factors and mileage values used for environmental modeling*

Fuel	Legislative category	NO_X (mg/km)	PM_{10} (mg/km)	Vehicle share (%)	Constant mileage (km/y)	AAM (km/y)	AAAM (km/y)
Gasoline	euro 0	1 958	2.4	18%	6 970	4 219	1 829
	euro 1	426	2.3	8.4%	6 970	5 189	3 038
	euro 2	223	2.2	26%	6 970	6 303	4 909
	euro 3	95	1.1	17%	6 970	7 653	7 854
	euro 4	57	1.1	28%	6 970	9 193	12 088
	euro 5	46	1.1	1.9%	6 970	9 963	14 548
Diesel	euro 0	695	216	4.6%	13 638	6 177	2 267
	euro 1	691	89	2.4%	13 638	8 470	4 023
	euro 2	734	54	13%	13 638	10 984	6 961
	euro 3	804	43	31%	13 638	14 057	11 966
	euro 4	600	36	45%	13 638	16 900	17 922
	euro 5	433	1.8	4.0%	13 638	18 767	22 525

***Table 3.** NO_x and PM_{10} emissions calculated with different average mileage estimates*

		NO_X			PM		
		Constant mileage	AAM	AAAM	Constant mileage	AAM	AAAM
Gasoline	euro 0	73.2%	63.7%	46.6%	24.8%	16.4%	8.1%
	euro 1	7.6%	8.1%	8.0%	11.4%	9.3%	6.1%
	euro 2	12.3%	16.0%	20.9%	34.4%	34.1%	30.0%
	euro 3	3.4%	5.4%	9.3%	10.6%	12.8%	14.8%
	euro 4	3.4%	6.4%	14.2%	17.6%	25.5%	37.8%
	euro 5	0.2%	0.4%	1.0%	1.2%	1.9%	3.1%
	Total (t/y)	67 825	47 160	27 949	243	221	196
Diesel	euro 0	4.6%	2.0%	0.8%	20.2%	9.8%	4.2%
	euro 1	2.4%	1.4%	0.7%	4.4%	2.9%	1.6%
	euro 2	13.9%	10.7%	7.3%	14.4%	12.4%	9.2%
	euro 3	36.9%	36.1%	33.3%	27.9%	30.9%	30.6%
	euro 4	39.6%	46.5%	53.5%	32.9%	43.7%	54.1%
	euro 5	2.5%	3.3%	4.3%	0.1%	0.2%	0.3%
	Total (t/y)	129 219	136 159	125 524	9 230	8 606	7 382

Moreover, it would be interesting to explore what would be the impact of introducing a measure that eliminates non–catalyst vehicles from the road. Such measures could be an incentive–based scrappage scheme or an environmental zone enforced in a part of a city. If one makes the usual assumption that all vehicles are driven for the same distance either annually or on a street network, then elimination of non–catalyst vehicles (Euro 0) would have led to assume that 28% of NO_X and 20% of total PM emissions from gasoline and diesel passenger cars should be reduced with such a measure. However, taking into consideration that older vehicles are driven less, the actual improvement would only be 9% and 4% respectively. This entirely changes the cost–benefit ratios of such measures.

Despite such significant impacts, widespread and robust estimates of mileage as a function of speed are still lacking and our strong recommendation is that such information has to be more reliably and thoroughly assessed and collected.

5. Conclusions

In order to improve traffic emission estimates and, consequently, for defining the strategies aimed to control air pollution events, the present work highlights the importance of increasing our knowledge on vehicle mileage behavior. Basing on an extensive dataset (more than 33 000 data), a relationship between vehicle mileage and age has been defined, both for diesel and gasoline passenger cars, with the example of the Italian stock. A methodology has also been presented which can be applied to the national conditions in other countries. The results of this methodology show that annual mileage drops significantly with mileage age. Both diesel and gasoline cars drive half the annual distance when they have reached an average age of approximately 8 years. Vehicles of 20 years of age only drive approximately 10% of the annual distance they used to drive when they are new.

The impact of the dropping mileage with age is significant in assessing the environmental impacts of transport and the potential impact of environmental policies. NO_X and PM emissions of passenger cars drop by more than 20% when a decreasing function of mileage with age is used, instead of a fixed mileage for each environmental class. Also, the emission contribution from old vehicles decreases which worsens the cost–effectiveness of air quality related policy measures targeting such old vehicles. These findings demonstrate the importance of performing precise estimates of mileage per vehicle class if robust road transport emission inventories need to be produced.

Supporting Material Available

List of websites used to collect data (Table S1); Mean mileage (km) and standard deviation (km) of the vehicle sample per age bin (Table S2); Average cumulative mileage of gasoline cars as a function of end–of–life age (Figure S1); Average cumulative mileage of diesel cars as a function of end–of–life age (Figure S2). This information is available free of charge via Internet at http://www.atmospolres.com.

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