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Abstract

Classically, one mean vehicle representative of each category is used by both static and dynamic traffic noise prediction models. The spectrum associated with this mean vehicle is determined from a linear statistical regression analysis based on measurement campaigns on a track or in situ. However, the variability of individual vehicle emissions can influence predictions and hinder comparison between static and dynamic models. In order to estimate the induced bias, statistical analysis of the distributions of sound power levels emitted by the individual passage of vehicles during 82 measurement campaigns was carried out. The results show that 92% of the residual regression distributions are Gaussian and that standard deviations can reach 3.6 dBA. The value of the proposed correction term for this case study could reach 1.4 dBA for light vehicles and 1.2 dBA for heavy vehicles. This analysis also shows that the variability in sound power levels and thus the corresponding corrections are higher at the lowest speeds that correspond to urban driving conditions.

Keywords	sound power level distribution; static prediction model; dynamic prediction model; road traffic noise
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- *Lw* variability is necessary for estimating the emissions of a vehicle flow
- Consideration of *Lw* variability is needed to compare static and dynamic approaches
- *Lw* variability for a given velocity is Gaussian in most cases.
- The standard deviation of *Lw* variability can be used to correct the emission model

Variability in sound power levels: implications for static and dynamic traffic models

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Abstract

Classically, one mean vehicle representative of each category is used by both static and dynamic traffic noise prediction models. The spectrum associated with this mean vehicle is determined from a linear statistical regression analysis based on measurement campaigns on a track or in situ. However, the variability of individual vehicle emissions can influence predictions and hinder comparison between static and dynamic models. In order to estimate the induced bias, statistical analysis of the distributions of sound power levels emitted by the individual passage of vehicles during 82 measurement campaigns was carried out. The results show that 92% of the residual regression distributions are Gaussian and that standard deviations can reach 3.6 dBA. The value of the proposed correction term for this case study could reach 1.4 dBA for light vehicles and 1.2 dBA for heavy vehicles. This analysis also shows that the variability in sound power levels and thus the corresponding corrections are higher at the lowest speeds that correspond to urban driving conditions.

Keywords: sound power level distribution; static prediction model; dynamic prediction model; road traffic noise.

1. Introduction

Road traffic is the main source of noise annoyance in urban areas [1,2]. Accurate road traffic prediction models are important to design suitable actions and interventions to mitigate urban noise. Two modelling approaches exist to estimate the sound power level of vehicles: static and dynamic. Static models, such as the CNOSSOS-EU method [3], determine the sound power level of a vehicle flow as a function of its average speed, flow rate and percentage of heavy vehicles, in addition to field data such as slope and road surface type [4]. Therefore, the values of the variables input in the noise model do not vary for a certain period of time. CNOSSOS-EU method is sometimes called semi-dynamic model because it considers the average speed and the overall line source [5]. Other static models do not consider vehicle speed to estimate sound levels [6, 7]. Dynamic models determine the sound power level of each vehicle in the network at each time step (typically 1 s) from its instantaneous speed and acceleration [8-10]. These dynamic models differ from dynamic noise maps based on measurements and interpolations [11, 12]. The two modelling approaches can rely on the same noise emission models and therefore differ only in the calculation method.

Static models are used to compute the spatial distribution of sound levels over large areas with a limited amount of input data [13]. Their limitation mainly concerns their poor description of traffic dynamics [8]. Dynamic models outperform static models for local applications as they better capture the variability of vehicle kinematics [8]. However, to obtain the vehicles' trajectories, they generally require in counterpart the calibration of a traffic microsimulation tool that can be tedious. Dynamic models additionally make it possible to estimate time series of noise levels, which gives access to the estimation of advanced indicators [9, 10], and opens the door to the estimation of noise indicators related to annoyance and awakenings such as peaks of noise and the number of events [14, 15].

Both static and dynamic models aggregate by default the emissions of a fleet of vehicles into one representative vehicle, through statistical regressions carried out from measurement campaigns recorded on a track or pas. The sound power laws are constructed from linear statistics and consider only one average sound power level per vehicle category. When the variability of sound power level between vehicles is high, the following should be taken into account:

- In dynamic models, this variability can be taken into account explicitly when calculating the sound power level of each vehicle. This should make it possible to estimate specific indicators such as noise peaks, which can result from the noisiest vehicles, as some studies suggest [16-18];
- In static models, Barry and Reagan have demonstrated that if sound power level variability follows a Gaussian distribution, the difference between the arithmetical and energetic average of a set of individual sound power levels is $0.115 \times \sigma^2$ where σ is the standard deviation [19]. This difference should therefore be added to the sound power level determined by static models as a correction term [20].

Not considering the variability of sound power levels can be problematic in three respects:

- It biases the sound power level of a vehicle flow estimated by static models;
- It hinders comparison of the results provided by static and dynamic models for an identical case study;
- High variability in the sound power levels of a vehicle fleet can mask the potential benefits of noise control actions.

A better knowledge and understanding of the variability of sound power levels on site is thus required. Brown and Tomerini measured the distribution of sound power levels generated by the pass-by of vehicles at ten measurement sites with a posted speed limit ranging from 60 to 100 km/h [21]. The standard deviations of sound levels measured for this experiment extended from 4.0 to 7.5 dBA depending on the mean speed and vehicle category. Following the equation proposed by Barry and Reagan [19], the corresponding correction term can reach 6.5 dBA. Although useful, this first study considered the posted speed limit as a reference, thus a large part of the variance can be explained by the variability in vehicle speeds and accelerations on the road sections studied, which hides the relative influence of kinematic variables and fleet composition on emission variability.

In this paper, a statistical analysis of 82 measurement campaigns, during which the kinematics and sound power level of each vehicle were recorded as it passed-by, is proposed. The part of the variance due to speed variability is excluded from the analysis, and the case studies presented incorporate very little variability in acceleration. For each of these campaigns, the sound power level of an average vehicle is calculated and then the distribution of the vehicle fleet's sound power levels around this average value is analysed. The impact of the width of this distribution on the correction to be applied is calculated and discussed, as well as the impact of taking into account a Gaussian approximation as the distribution shape. A discussion on the consequences in terms of predicting road traffic sound levels then follows.

2. Material and methods

2.1. Databases

Two sound emission databases for light and heavy vehicles registered on different roads in France were used for the present study. One of the databases consisted of measurements made on tracks (2001–2006) and the other of on-site measurements on public roads (2007–2013). Light vehicles were monitored in 57 locations (3 on track and 54 on public roads) and heavy vehicles in 25 locations (2 on track and 23 on public roads), constituting a set of 82 measurement campaigns (see Tables 1 and 2 – Supplementary Material). On-track measurements were made in controlled conditions (controlled pass-by procedure NF S 31 119-

2 [22]), and on-site measurements were made in real traffic conditions (statistical pass-by procedure NF S 31 119 [23] and ISO 11819-1 [24]). Pass-by methods are based on noise levels measured at the far field. These methods are used when a large number of different types of vehicles are analysed. There are also methods to measure vehicle radiated noise in the near field [25-27].

In statistical pass-by (SPB) measurements, the maximum sound level (LAFmax (dBA)) and speed of individual vehicles passing-by were recorded, as shown in Fig. 1. A temporal recording of broadband sound levels every 125 ms was carried out to identify the vehicle pass-bys and their LAFmax. Background noise levels were at least 10 dBA below the LAFmax during pass-bys according to ISO 11819-1 [24]. The sound power level, Lw (dBA), of a vehicle was obtained from its measured LAFmax, using the ISO 9613 propagation model [28], assuming free field propagation conditions, default meteorological conditions and a hard surface throughout the simulated area. Previous studies have carried out a similar procedure [17, 21, 29]. The following restrictions were considered in SPB measurements, in order to eliminate sound power variations not due to the variability in the vehicle fleet: constant vehicle speed, flat road, dry road surface and homogeneous pavement in good condition. The sound measurements were conducted using a portable PULSE System (type 3560C, Brüel & Kjaer) with a microphone (type 4188-A-021, Brüel & Kjaer) protected by a windscreen. A speedometer (MESTA 208) was also used in the measurements.

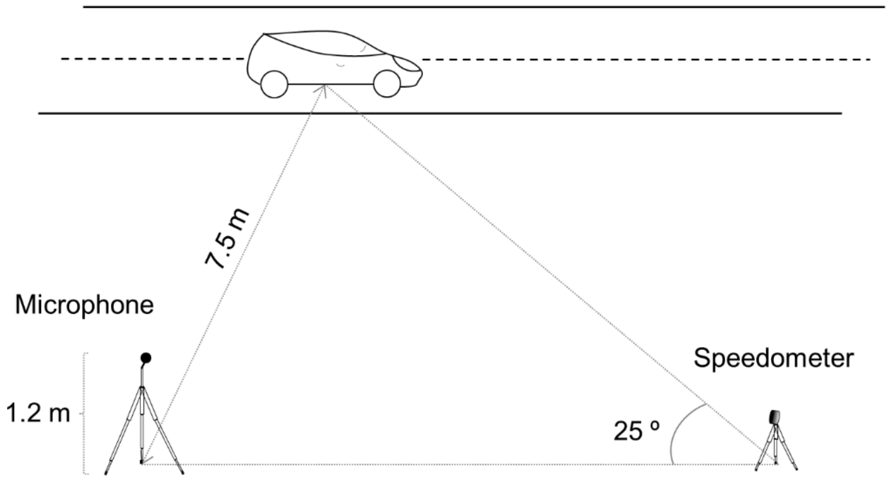

Fig. 1. Schematic diagram of the experimental protocol according to ISO 11819-1 [24]

The controlled pass-by (CPB) procedure is similar to the SPB procedure, but specified vehicles with specified sets of tyres are used. Thus, the following vehicle characteristics are known: vehicle model, engine, speed, acceleration, engine speed, gear ratio and tyre type. From this information, only vehicles with diesel or gasoline engines were selected. Hybrid and electric engines were eliminated because these vehicle categories are not yet defined in the noise prediction models. Furthermore, these vehicles were only recorded on track measurements and they passed very few times. Two filters were also applied to ensure that vehicles on the track had a constant speed. The first filter was to select acceleration in the range between −0.1 and 0.1 m/s^2. Secondly, measurements of vehicles with an engine speed higher than 3000 r.p.m. were eliminated. However, not all data recorded acceleration and engine speed. In such cases, the engine speed was computed from the ratio between speed and the gearbox of the registered vehicles. A total of 33 models of light vehicles with 14 tyre types, and seven models of heavy vehicles with three configurations (without trailer, with trailer and with loaded trailer) and two types of tyres were analysed on test tracks.

The number of light vehicles recorded was, on average, 106 for each on-site and 806 for each on-track measurement campaign, giving a total of 8177 registered vehicles (see Table 1 – Supplementary Material). The number of heavy vehicles registered was, on average, 79 for each on-site and 200 for each on-track measurement campaign, giving a total of 2195 registered vehicles. (see Table 2 – Supplementary Material).

2.2. Estimation of average sound power levels

A model linking the sound power level of an average vehicle to its speed was calibrated for each of the 82 experimental campaigns *i*, in order to highlight the importance of the variations in sound power levels within a given site. As in many standard models [3, 30, 31], the model used takes into account: (i) the rolling noise produced by the tyre/road interaction and aerodynamic noise, and (ii) the propulsion noise generated by the driveline of the vehicle. Those two sound power levels sum to form the sound power level of a vehicle as a function of its speed v:

$$Lw_i = 10 \times lg\left(10^{\frac{A_{R,i} + B_{R,i} \times lg\left(\frac{v}{v_{ref}}\right)}{10}} + 10^{\frac{A_{P,i} + B_{P,i} \times \left(\frac{v - v_{ref}}{v_{ref}}\right)}{10}}\right), \quad (1)$$

where v_{ref} is a reference speed set to 70 km/h.

The four coefficients $A_{R,i}$, $B_{R,i}$, $A_{P,i}$ and $B_{P,i}$ are calibrated for each measurement campaign i, based on the sound power levels and speeds collected. Some examples of the fit of Eq. (1) to the sound power levels generated by the light and heavy vehicle pass-bys at different speeds are shown in Fig. 2. The coefficient of determination for each of the measurement campaigns is shown in Tables 1 and 2 – Supplementary Material.

a) **b)**

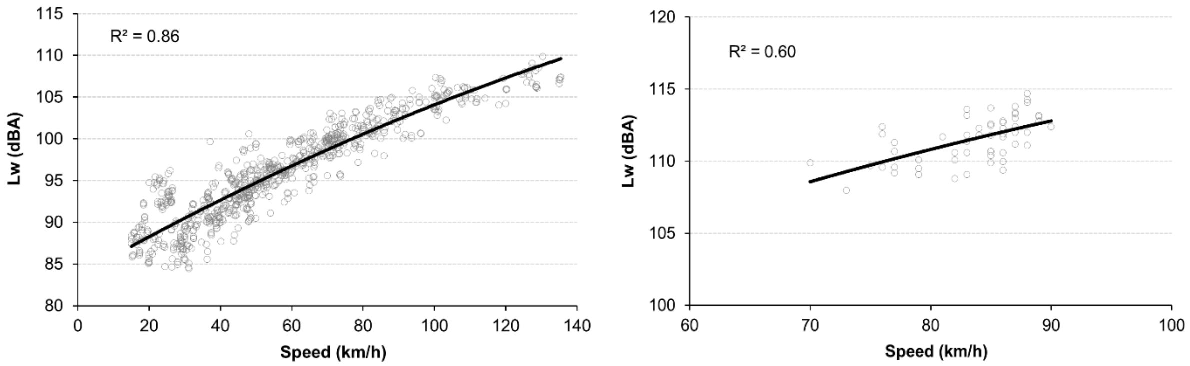

Fig. 2. Relationship between sound power level (dBA) and speed (km/h) for light and heavy vehicle pass-bys registered in the France_2006 (a) and Erstein (b) campaigns, respectively.

2.3. Statistical analysis of the residuals

Once the noise emission model was calibrated for a given measurement campaign *i*, the residuals were calculated for each individual pass-by *j*. As the shape of the residuals distributions could eventually depend on the speed, analysis by speed interval *k* was performed. These residuals ($R_{i,j,k}$) are the difference between the observed sound power level $Lw_{i,j,k}$ and the sound power level $\widehat{Lw}_{i,k}$ calculated with the model.

Twelve speed intervals of 10 km/h were considered, with the exception of the first and last intervals, which ranged between 0 and 20 km/h (although most speeds exceeded 10 km/h), and included speeds above 120 km/h, respectively. Kolmogorov–Smirnov and Shapiro–Wilk tests were used to test the hypothesis that the residuals followed a normal distribution.

2.4. Correction term

As the sound power level of an average vehicle is calculated through a statistical regression analysis of a set of *n* pass-by measurements in dBA, it differs from the equivalent value of the sound energy as shown in Eq. 2.

$$\Delta Lw_{i,k(vehicles)} = 10 \times lg\left(\frac{\sum_{j=1}^{n} 10^{\frac{Lw_{i,j,k}}{10}}}{n}\right) - \widehat{Lw_{i,k}} \quad (2)$$

Eq. 2 defines the difference in sound power level between the one estimated by the model and the one that should be used to ensure that the equivalent pressure level incorporates the variability in sound power levels of the vehicle fleet. Due to the energetic average, the contribution of vehicles with higher sound power levels is higher than the contribution of other vehicles.

If a normal distribution of the residuals from the regression models is assumed, $\Delta Lw_{vehicles}$ can be written as [13]:

$$\Delta Lw_{i,k(vehicles,\ Gauss)} = 0.115 \times \sigma_{R_{i,j,k}}^{2} \quad (3)$$

where $\sigma_{R_{i,j,k}}$ corresponds to the standard deviation of the estimated gaussian distribution.

The standard deviation of the residuals ($R_{i,j,k}$) is equivalent to the standard deviation of the sound power level $Lw_{i,j,k}$, if they follow a normal distribution.

3. Results

3.1. Descriptive analysis

For each on-site measurement campaign, the standard deviation of the sound power levels was calculated for all the pass-bys. The standard deviations ranged between 1.0 and 2.6 dBA with an average of 1.7 dBA for light vehicles (see Table 1 – Supplementary Material), and between 0.9 and 2.0 dBA with an average of 1.5 dBA for heavy vehicles (see Table 2 – Supplementary Material). Since speed was not controlled for on-site measurements, this variability is due to both the variability in vehicle characteristics and the variability in vehicle speed.

The average speed for on-site measurement campaigns ranged between 65 and 117 km/h for light vehicles with a standard deviation of 9.0 km/h (see Table 1 – Supplementary Material), and between 49 and 88 km/h for heavy vehicles with a standard deviation of 3.5 km/h (see Table 2 – Supplementary Material). The speed range recorded in each on-site measurement campaign generally covered three or four intervals of 10 km/h for light vehicles and one or two intervals for heavy vehicles. On the contrary, the track measurements covered all the speed intervals.

The standard deviation of sound power levels increased at low speeds for both light and heavy vehicles, as shown in Table 3, exceeding for example 2 dBA for light vehicles for speeds below 50 km/h. This suggests a greater variability in sound power levels under urban driving conditions than on interurban roads, even when ignoring vehicles' acceleration phases.

Table 3. Average standard deviation of sound power level, and number of light and heavy vehicles for the different speed ranges.

Speed (km/h)	Light vehicles		Heavy vehicles	
	Average σ_{Lw} (dBA)	No.	Average σ_{Lw} (dBA)	No.
0–20	2.40	169	1.74	31
20–30	3.56	351	2.68	42
30–40	2.79	258	2.06	58
40–50	2.46	337	1.35	98
50–60	1.84	364	1.46	82
60–70	1.28	848	2.50	74
70–80	1.23	1395	1.54	185
80–90	1.16	1329	1.56	1408
90–100	1.19	781	1.54	217
100–110	1.09	958	–	–
110–120	1.08	730	–	–
> 120	1.07	657	–	–

3.2. Distribution of the residuals

An example of the distribution of residuals (R_{ij}) for the different speed intervals is shown in Fig. 3 for the example of the Satolas campaign, in which light vehicle pass-bys were registered in all speed ranges. The distributions shown in Fig. 3 are Gaussian except in the ranges from 0 to 30 km/h and from 40 to 70 km/h. The increase in variability of the residuals with a decrease in speed is also shown in Fig. 3.

Adjustment of the residuals distribution to normal distributions was analysed for the complete dataset. Kolmogorov–Smirnov (with Lilliefors significance correction) and Shapiro–Wilk tests show that 92% of the residuals analysed at the different speed intervals follow a normal distribution ($p > 0.05$), for which Eq. 3 provides $\Delta Lw_{vehicles\text{-}Gauss}$ with the standard deviation as a single parameter.

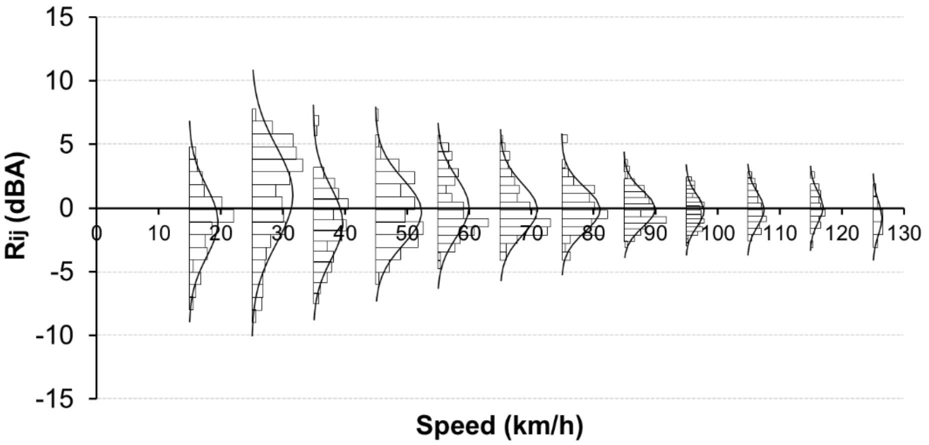

Fig. 3. Distribution of the residuals at different speeds in the Satolas campaign (France).

Fig. 4 shows the value of the standard deviation of the residuals for the 82 experimental campaigns. For the Satolas example, the standard deviation decreased as speed increased in the case of light vehicles. This decrease was less pronounced for heavy vehicles. Fig. 4 shows that the average variability of vehicle emissions at constant speed was between 1.0 and 3.6 dBA for light vehicles and 1.3 and 2.3 dBA for heavy vehicles.

a) **b)**

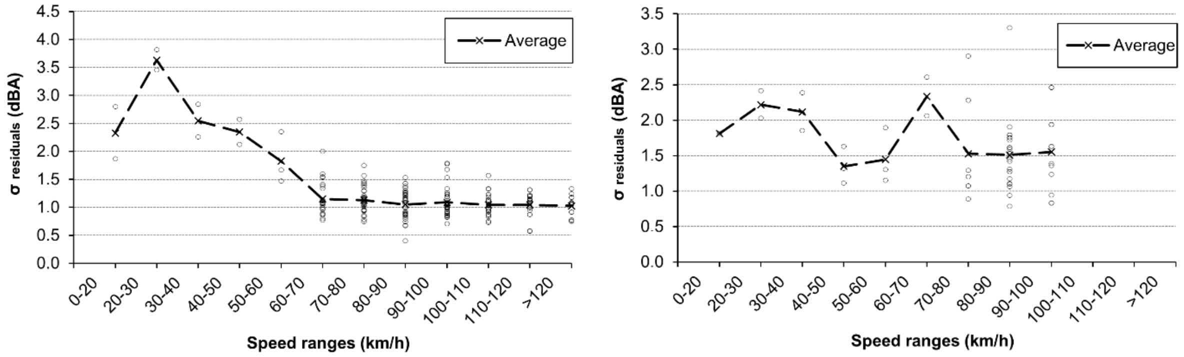

Fig. 4. Standard deviation of regression residuals for light (a) and heavy (b) vehicles in the different speed ranges (82 measurement campaigns).

3.3. Correction term calculation.

As presented in section 2.4, a correction term should be used within static models to include the variability in sound power levels. It can be calculated directly from the actual distribution of the measurements around the mean sound power level, but also from its Gaussian approximation, which provides the correction term in a simple manner with the standard deviation as a single descriptive parameter. To observe the potential error made by considering that all the distributions of residuals are Gaussian, the correction term $\Delta Lw_{vehicles}$ is calculated using Eq. 2 and Eq. 3. Fig. 5 shows the relationship between $\Delta Lw_{vehicles}$ and the standard deviation of residuals for all of the measurement campaigns.

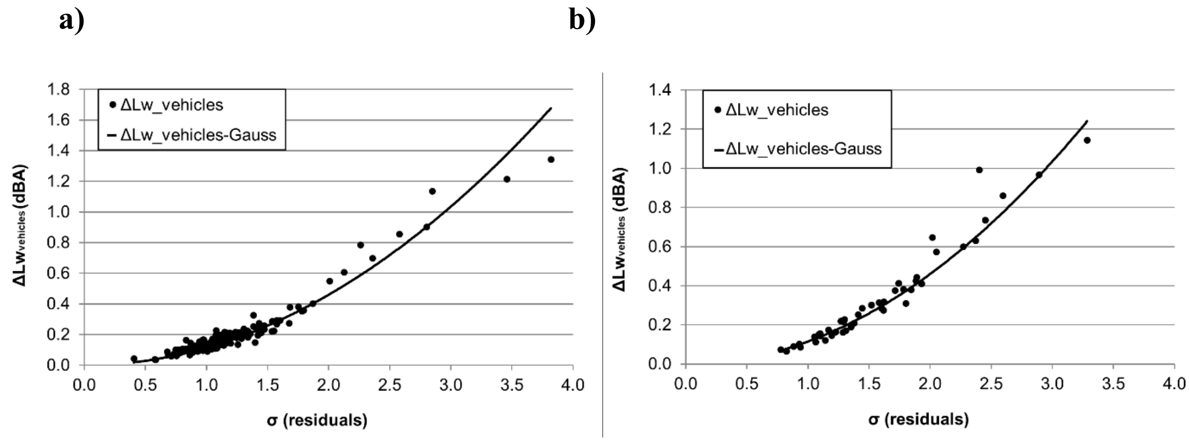

Fig. 5. Relationship between the correction term and regression residuals for light (a) and heavy (b) vehicles.

As the residual distribution does not differ significantly from a normal distribution (see Section 3.2), the differences between $\Delta Lw_{vehicles}$ and $\Delta Lw_{vehicles\text{-}Gauss}$ are small. Following Fig. 5, the observed variability of sound power levels implies a correction $\Delta Lw_{vehicles}$ on the emission model of 0.1 to 1.4 dBA for light vehicles and 0.1 to 1.2 dBA for heavy vehicles. This justifies the approximation of the residuals distributions by Gaussian functions under static modelling.

4. Discussion

4.1. General comments

This study gives insight into the distribution of sound power levels within a vehicle car fleet. However, most of the 82 measurement campaigns covered traffic conditions more fluid and with higher speeds than urban ones. Additional measurement campaigns, specifically addressing urban areas, are now required to better understand the distribution of sound power levels at the lowest speeds. The locations also presented different types of pavement and although the variability of sound power levels was analysed for each measurement campaign, the measurement campaigns did not permit a specific variability per road pavement to be highlighted, which could be done with a dedicated experimental campaign.

The variability of sound power levels between vehicles is greater at low speeds. Propulsion noise is predominant at low speeds and its variability between vehicles will be influenced when electric or hybrid vehicles are registered. Hamet et al. also showed greater variability in the use of different gears at low speeds [29].

4.2. Introducing kinematic variability in static modelling

Static road traffic prediction models generally rely on the mean vehicle speed to estimate the sound power level of a vehicle flow on a road segment. Accounting for the distribution in speed values improves this estimation [32]. In addition, the variability in both speed and acceleration between vehicles contributes to the overall variability of sound power levels.

In this study, the distribution of the speed values has a standard deviation of 9 km/h for light vehicles and 3.5 km/h for heavy vehicles. This speed variability introduces an additional variability of sound power levels (ΔLw_{speed}). The sound power level of a set of vehicles travelling at a given average speed can be calculated from usual noise emission models. The sound power level of a set of vehicles with different individual speeds is the energetic average of each individual sound power level computed at the individual vehicle speed. ΔLw_{speed} is the difference between both. For example, a ΔLw_{speed} of 0.9 and 0.55 dB is obtained for light vehicles at an average speed of 30 and 50 km/h, respectively. Both ΔLw_{speed} and $\Delta Lw_{vehicles}$ should be considered.

4.3. Comparison with previous studies

Fig. 6 compares the results of previous studies with those obtained in this study for light and heavy vehicles, taking into account standard deviations of the sound power level in each speed range [20, 21].

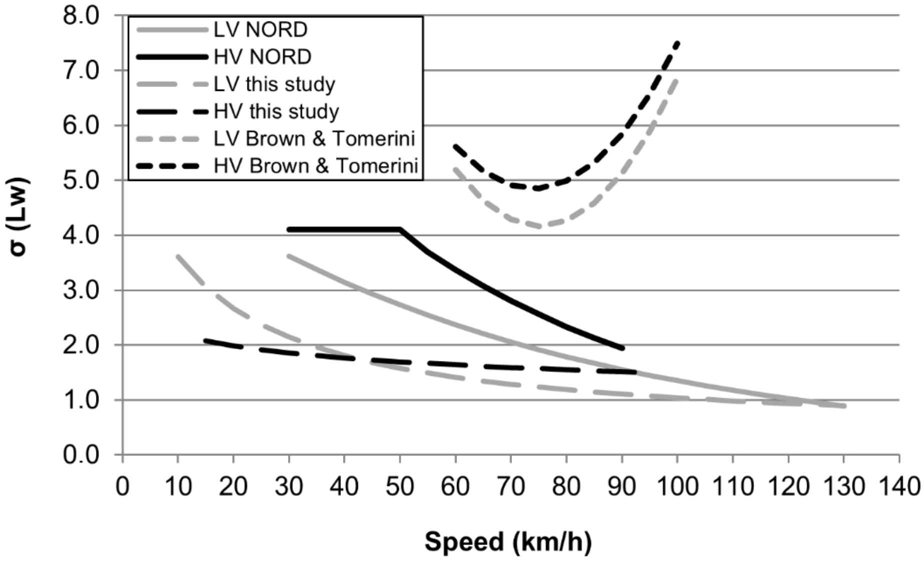

Fig. 6. Standard deviation of sound power levels from heavy (HV) and light vehicles (LV) obtained by NORD [20], Brown and Tomerini [21] and this study.

The standard deviations of the sound power levels recorded in this study are lower than those of the NORD study [20]. This difference may be due to the fact that the NORD results integrate the variability of speed into the global variability.

Another example of on-site measurement of the distribution of noise levels from the pass-by of vehicles was carried out by Brown and Tomerini [21]. The standard deviations of the measured sound levels for their experiment extend from 4.0 to 7.5 dBA depending on the road speed limit and vehicle class. But again, this variability includes acceleration and speed-related variabilities that were not taken into account in the present study. For this case study, the measured variabilities could result in combined corrections ($\Delta Lw_{vehicles} + \Delta Lw_{speed}$) of more than 2 dBA on the static modelling results.

4.4. Dynamic prediction of noise emissions

Dynamic models would benefit from taking into account the distribution of sound power levels in the vehicle fleet for a given kinematics scenario. A small proportion of noisy vehicles could mask the expected benefits when evaluating traffic strategies such as the introduction of Intelligent Transportation Systems or the promotion of eco-driving whose interest in reducing speed variations has been demonstrated in the field of airborne pollutants [33,34].

Understanding the distribution in sound power levels is also crucial for the estimation of specific indicators such as noise peaks. However, it is not certain that distributing speeds, accelerations and sound power levels would be sufficient to assess noise peaks. For instance, it is likely that the conditions ‘noisy vehicle’ and ‘high acceleration’ are not independent: sport vehicles are for instance prone to reach high accelerations while being noisier.

5. Conclusion

Static and dynamic traffic noise prediction models suffer from a lack of knowledge about the distribution of sound power levels within a car fleet. This information is crucial since: (i) it can bias the estimates of static models, which are based on linear regressions despite the logarithmic behaviour of the decibel, and (ii) it makes it impossible to compare results between static and dynamic models. In the present study, the kinematics and sound levels of individual pass-bys recorded in 82 measurement campaigns carried out on public roads and tracks in France were analysed. The following conclusions can be drawn:

- The distributions of the regression residuals obtained at speed intervals of 10 km/h for each measurement campaign follow a normal distribution in most cases. Consequently, the noise emission levels calculated through usual static noise prediction models should be corrected using the following equation: $\Delta Lw_{vehicles,\,Gauss} = 0.115 \times \sigma_{residuals}^{2}$.
- The variability of sound power levels was between 1.0 and 3.6 dBA for light vehicles and between 1.3 and 2.3 dBA for heavy vehicles after correction with speed, implying a correction ΔLw on the emission model of 0.1 to 1.4 dBA for light vehicles and 0.1 to 1.2 dBA for heavy vehicles for a static modelling use. However, greater variabilities can be found in the literature, up to 7.5 dBA, which would result in corrections of 6.5 dBA.
- Speed variation is a factor that should also be considered in sound emission levels. The mean speed standard deviation in this study was 9 km/h for light vehicles and 3.5 km/h for heavy vehicles. Therefore, the effect of speed would be accounted for by addition of between 0.5 and 1 dBA to the $\Delta Lw_{vehicles}$ under usual urban driving mean speeds.

These conclusions imply that for a study that would seek to compare static approaches to in situ measurement or dynamic approaches using the same input data, the $\Delta Lw_{vehicles}$ and ΔLw_{speed} corrections should be taken into account.

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Supplementary material

Table 1

Characteristics of the locations where light vehicle pass-bys were recorded.

Location	Road type	Road surface type	Average$_{speed}$ (km/h)	σ_{speed} (km/h)	σ_{Lw} (dBA)	$\sigma_{residuals}$ (dBA)	R^2	No. vehicles
France_2006	Track	Dense Asphalt Concrete	-	-	-	2.09	0.86	805
Nantes	Track	Dense Asphalt Concrete	-	-	-	1.71	0.87	46
Satolas	Track	Dense Asphalt Concrete	-	-	-	2.57	0.80	1598
Boofzheim	Regional	Surface Dressing 6/10	78.08	10.03	2.60	1.32	0.74	89
DianeCapelle	Regional	Cold-applied Slurry Surfacing	81.76	9.19	2.35	1.15	0.76	99
Diebolsheim	Regional	Surface Dressing 6/10	77.67	9.91	2.31	1.02	0.80	92
Duttlenheim	Regional	Surface Dressing 6/10	79.39	8.12	1.99	1.30	0.57	100
Kogenheim	Regional	Very Thin Asphalt Concrete 0/6 class 2	65.84	5.46	1.36	1.00	0.68	104
Krautegersheim	Regional	Surface Dressing 4/6	79.78	9.41	1.99	1.04	0.73	88
Moernach	Regional	Very Thin Asphalt Concrete 0/4	77.06	8.47	1.56	1.25	0.59	95
Schnersheim	Regional	Surface Dressing 6/10	79.62	10.78	2.32	1.29	0.69	97
Erstein	Regional	Stone Mastic Asphalt 10(EB10)	98.72	7.51	1.34	0.96	0.49	121
Erstein	National	Stone Mastic Asphalt 10 (EB10)	100.06	7.98	1.35	0.83	0.63	105
Erstein	National	Stone Mastic Asphalt 10 (EB10)	98.98	6.87	0.99	0.83	0.30	107
Marainviller	National	Bituminous Bound Macadam 0/10	97.60	9.69	1.41	0.79	0.69	115
Marainviller	National	Surface Dressing 10/14	102.26	7.26	1.75	0.98	0.69	102
Moncel-les-Luneville	National	Surface Dressing 10/14	105.87	8.12	1.74	1.22	0.51	104
Moncel-les-Luneville	National	Dense Asphalt Concrete 0/10	101.53	9.27	1.59	0.94	0.65	128
Durlinsdorf	Regional	Very Thin Asphalt Concrete 0/4	78.14	11.18	1.93	1.42	0.68	105
Weiterswiller	Regional	Surface Dressing 4/6	75.40	7.17	1.68	1.06	0.60	104
Hohengoeft	Regional	Surface Dressing 6/10	84.37	10.27	2.16	1.11	0.74	107
Reitwiller	Regional	Surface Dressing 10/14	81.77	7.48	2.11	1.21	0.67	102
Stutzheim	Regional	Dense Asphalt Concrete 0/10	77.22	6.47	1.43	0.70	0.76	116
Cutrellles	Regional	Cold-applied Slurry Surfacing	82.18	8.26	1.72	0.92	0.71	97
Cutrelles	Regional	Cold-applied Slurry Surfacing	75.17	7.22	1.75	0.85	0.76	113
Lutzelhouse	Regional	Surface Dressing 4/6	65.32	7.72	1.88	1.22	0.58	98
Arcis-sur-Aube	Regional	Cold-applied Slurry Surfacing	79.27	9.89	2.07	0.99	0.77	101
Kogenheim	Regional	Very Thin Asphalt Concrete 0/6 - type 2	70.58	7.26	1.44	1.00	0.52	109
Dorlisheim	Regional	Very Thin Asphalt Concrete 0/6 - type 2	79.02	5.91	1.19	0.86	0.48	103
Moernach	Regional	Very Thin Asphalt Concrete 0/4	80.33	9.90	1.74	1.37	0.61	108
Voulangis	Regional	Very Thin Asphalt Concrete 0/6 - type 1	74.33	8.85	1.59	0.75	0.78	112
Cutrelles	Regional	Cold-applied Slurry Surfacing	75.41	8.56	1.89	0.88	0.79	111

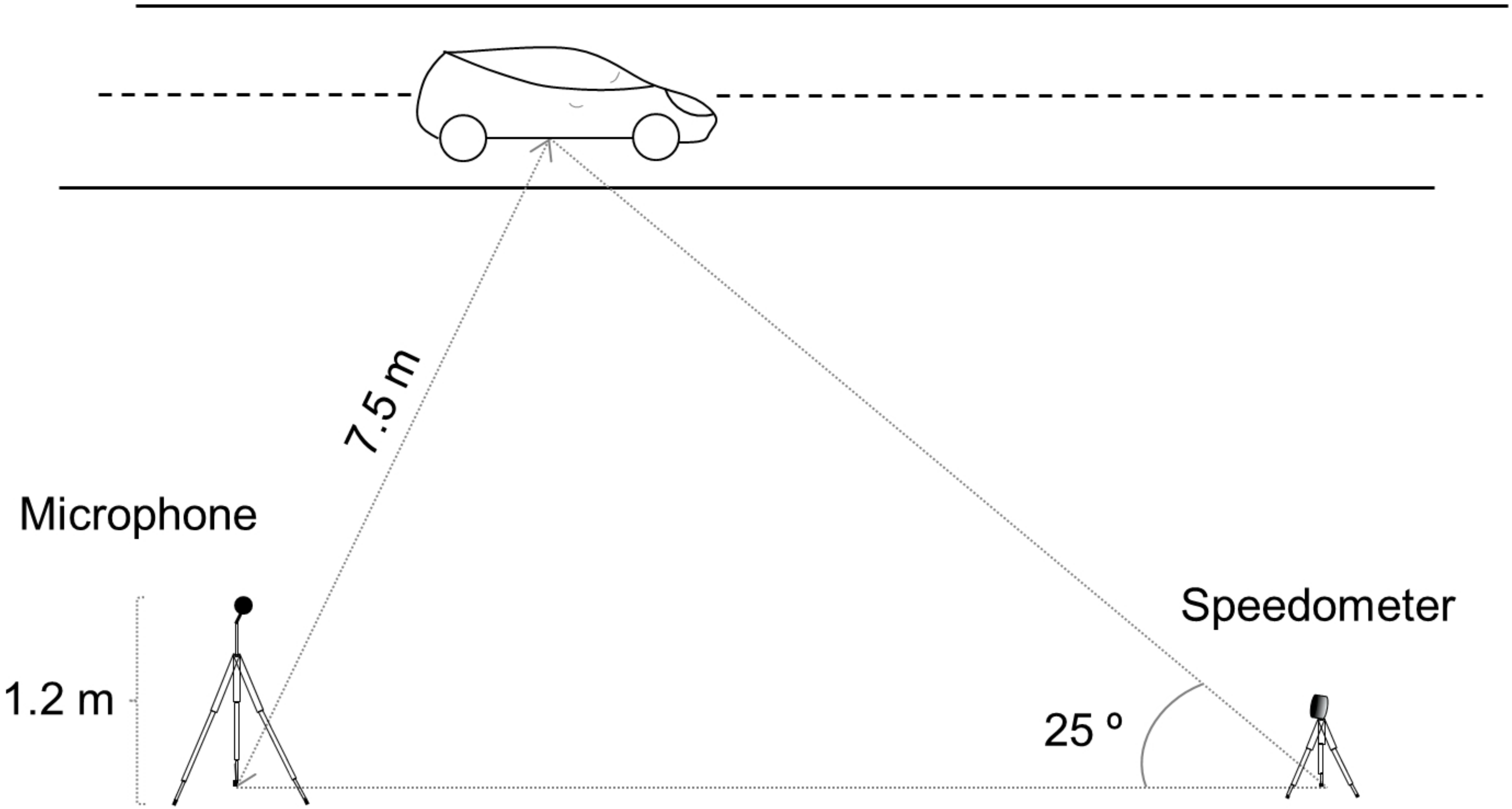
Voulangis	Regional	Very Thin Asphalt Concrete 0/4	80.07	10.29	2.06	1.17	0.68	103
Dachstein	Regional	Surface Dressing 4/6	73.59	9.73	2.30	0.93	0.84	96
Dachsetin	Regional	Surface Dressing 4/6	75.96	9.32	2.27	0.94	0.83	98
Nantes_RD30	Regional	Surface Dressing 4/6	81.09	9.43	2.22	1.05	0.78	87
Nantes_RD30	Regional	Surface Dressing 4/6	79.49	10.17	2.20	1.16	0.72	83
Dachstein	Regional	Surface Dressing 4/6	75.29	8.62	1.94	1.15	0.65	80
Dachstein	Regional	Surface Dressing 4/6	80.60	8.41	1.83	1.08	0.65	87
Dachstein	Regional	Surface Dressing 4/6	83.58	11.61	2.22	1.33	0.64	101
Dachstein	Regional	Surface Dressing 4/6	83.73	8.90	1.86	1.24	0.55	97
Molsheim	Regional	Surface Dressing 4/6	75.71	7.84	1.78	1.05	0.65	103
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	110.45	11.88	1.28	0.90	0.51	110
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	115.93	9.08	1.13	0.89	0.61	112
Nantes	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	116.26	10.26	1.41	1.19	0.54	107
Nantes A35	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	112.44	9.71	1.49	1.24	0.55	99
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	117.15	8.87	1.17	1.04	0.47	125
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	115.93	9.72	1.38	1.19	0.51	147
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	111.89	9.55	1.45	1.16	0.61	139
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	112.40	10.50	1.37	1.11	0.59	135
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	114.92	10.06	1.29	1.03	0.60	99
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	108.77	10.54	1.24	0.88	0.71	106
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	117.15	8.87	1.17	1.04	0.47	125
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	111.89	9.55	1.45	1.16	0.61	139
Nantes A35	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	116.26	10.26	1.41	1.19	0.54	107
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	114.92	10.06	1.29	1.03	0.60	99
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	115.93	9.08	1.13	0.89	0.61	112

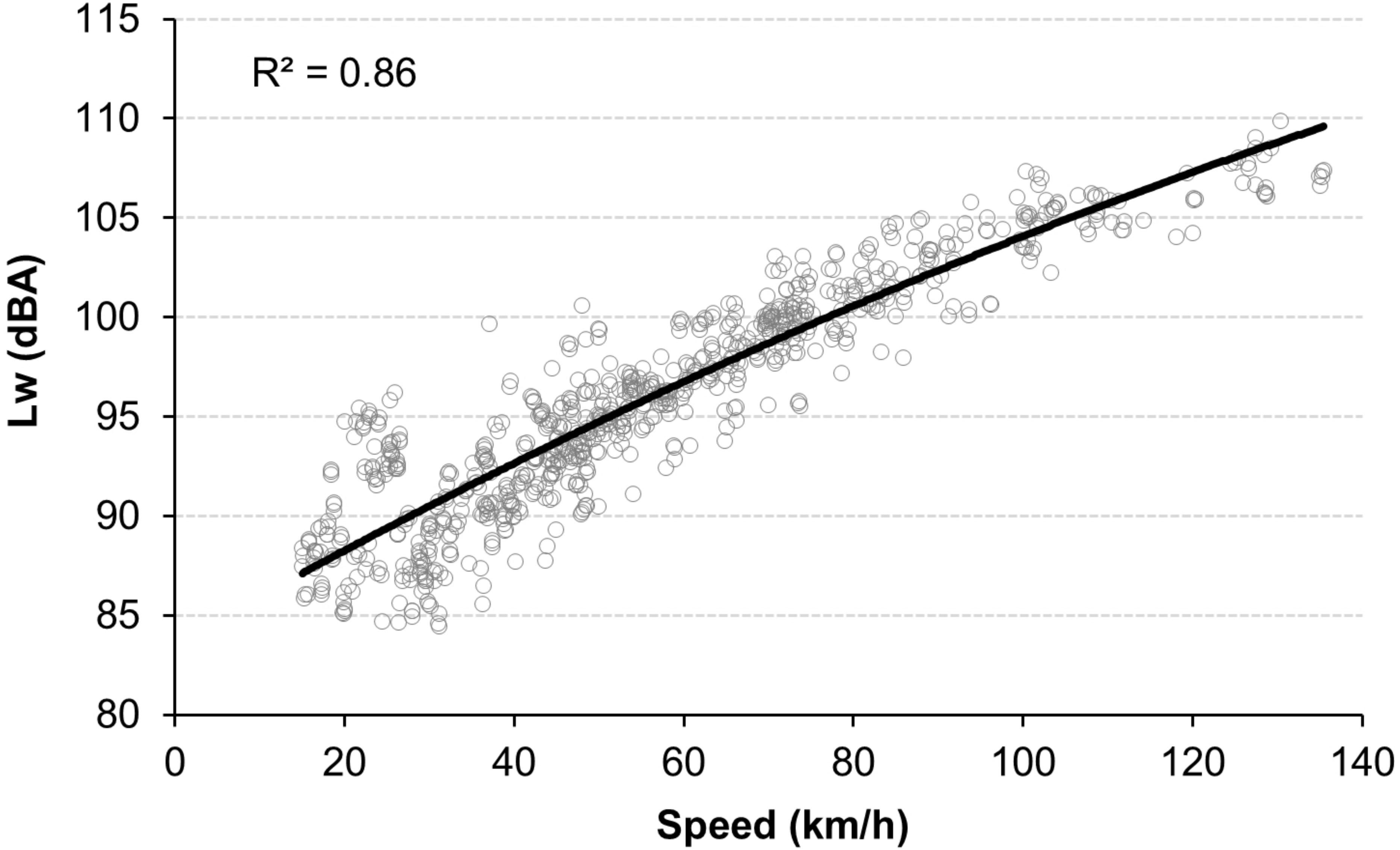
Table 2

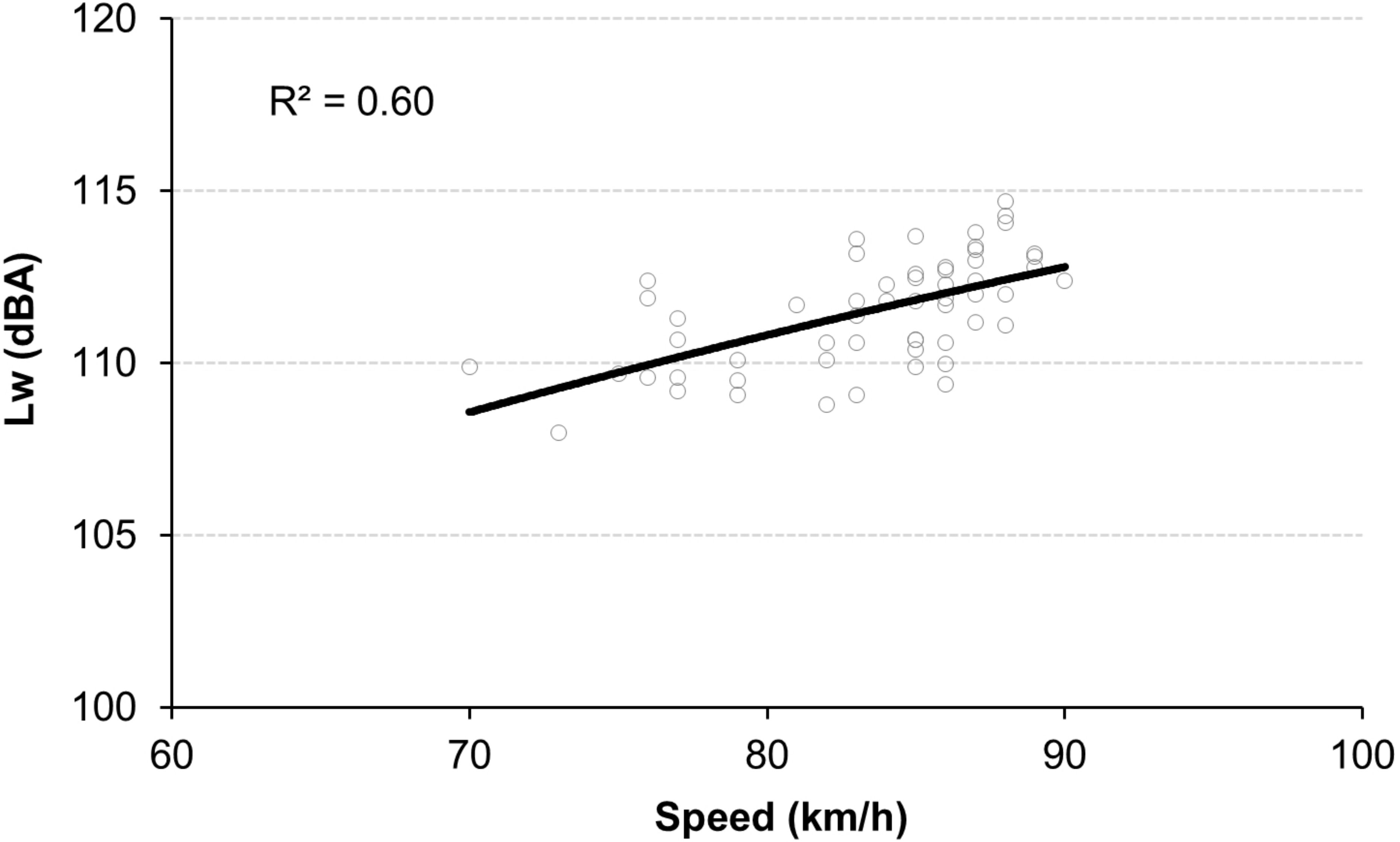
Characteristics of the locations where heavy vehicle pass-bys were recorded.

Location	**Type of road**	**Pavement**	**Average$_{speed}$ (km/h)**	**σ_{speed} (km/h)**	**σ_{Lw} (dBA)**	**$\sigma_{residuals}$ (dBA)**	**R^2**	**No. vehicles**
Lohr	Track	Bituminous Bound Macadam	-	-	-	2.41	0.66	306
Lohr	Track	Bituminous Bound Macadam	-	-	-	2.35	0.76	94
Kogenheim	Regional	Very Thin Asphalt Concrete 0/6 class 2	48.96	3.58	1.22	1.15	0.34	55
Erstein	Regional	Stone Mastic Asphalt 10(EB10)	83.47	4.56	1.59	1.27	0.60	57
Erstein	Regional	Stone Mastic Asphalt 10 (EB10)	84.77	3.87	1.34	1.10	0.60	48
Erstein	Regional	Stone Mastic Asphalt 10 (EB10)	82.56	4.86	1.23	1.16	0.33	45

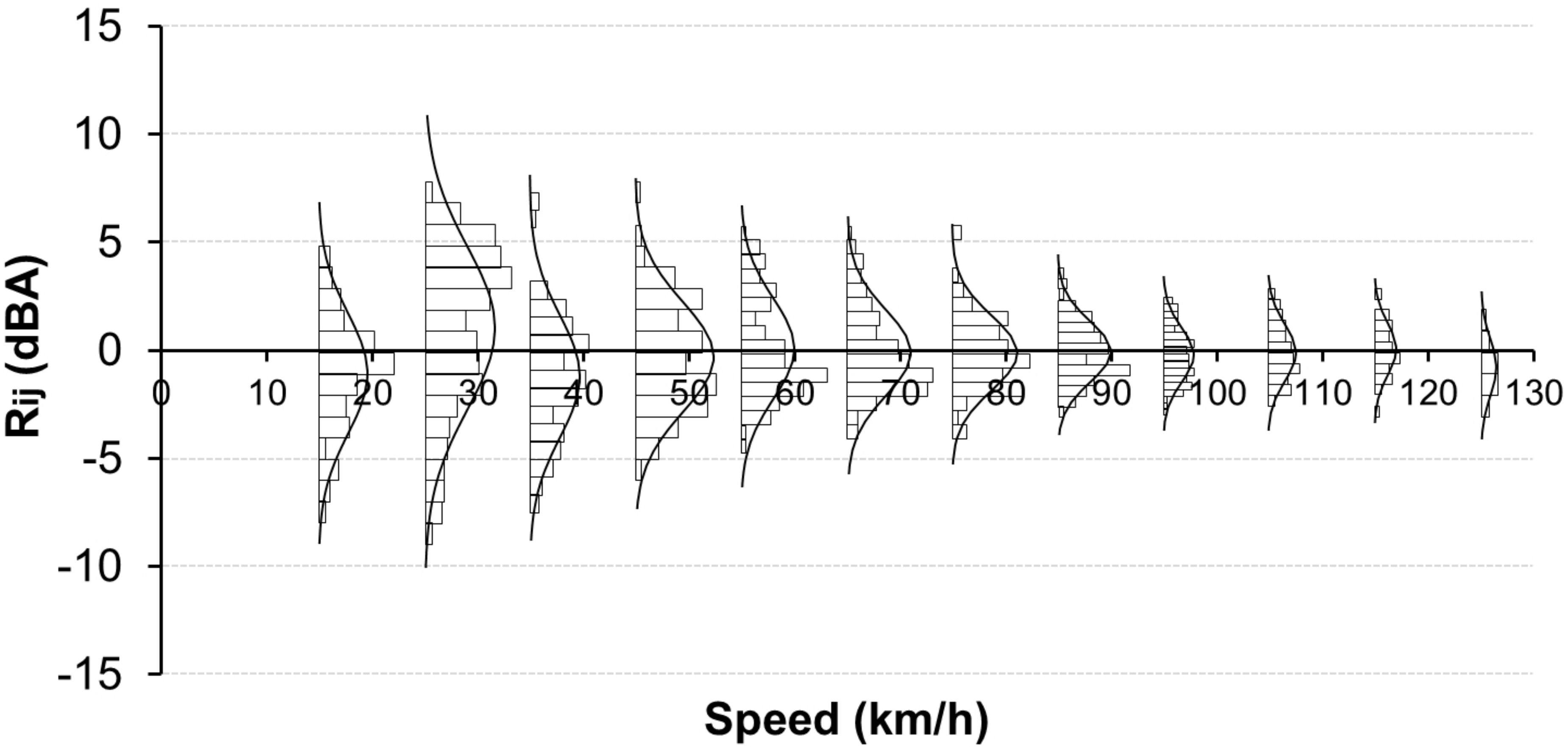
Marainviller	National	Bituminous Bound Macadam 0/10	83.07	3.72	0.91	0.79	0.49	58
Marainviller	National	Surface Dressing 10/14	84.73	3.74	1.06	0.92	0.49	52
Moncel-les-Luneville	National	Surface Dressing 10/14	87.41	2.86	1.16	1.05	0.43	44
Moncel-les-Luneville	National	Dense Asphalt Concrete 0/10	84.79	3.72	1.15	1.02	0.46	57
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	86.08	3.63	1.51	1.41	0.36	83
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	85.79	4.10	1.46	1.19	0.58	84
Nantes A35	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.14	3.53	1.66	1.59	0.29	97
Nantes A35	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.27	2.68	1.60	1.51	0.32	104
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.53	2.37	1.70	1.60	0.34	73
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.37	2.49	1.69	1.64	0.25	73
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	85.95	3.34	1.79	1.76	0.17	99
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	85.47	3.97	1.96	1.92	0.19	115
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	86.23	3.61	1.96	1.85	0.32	113
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	84.63	3.36	1.45	1.41	0.24	72
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.53	2.37	1.70	1.60	0.34	73
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	85.95	3.34	1.79	1.76	0.17	99
Nantes A35	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	87.14	3.53	1.66	1.59	0.29	97
Barr	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	86.23	3.61	1.96	1.85	0.32	113
Stotzheim	Motorway	Very Thin Asphalt Concrete 0/6 - type 2	85.79	4.10	1.46	1.19	0.58	84


7.5 m
Microphone
Speedometer
1.2 m
25 º


R² = 0.86
Lw (dBA)
115
110
105
100
95
90
85
80
0
20
40
60
80
100
120
140
Speed (km/h)



R² = 0.60
Lw (dBA)
120
115
110
105
100
60
70
80
90
100
Speed (km/h)


15
10
5
0
-5
-10
-15
Rij (dBA)
0
10
20
30
40
50
60
70
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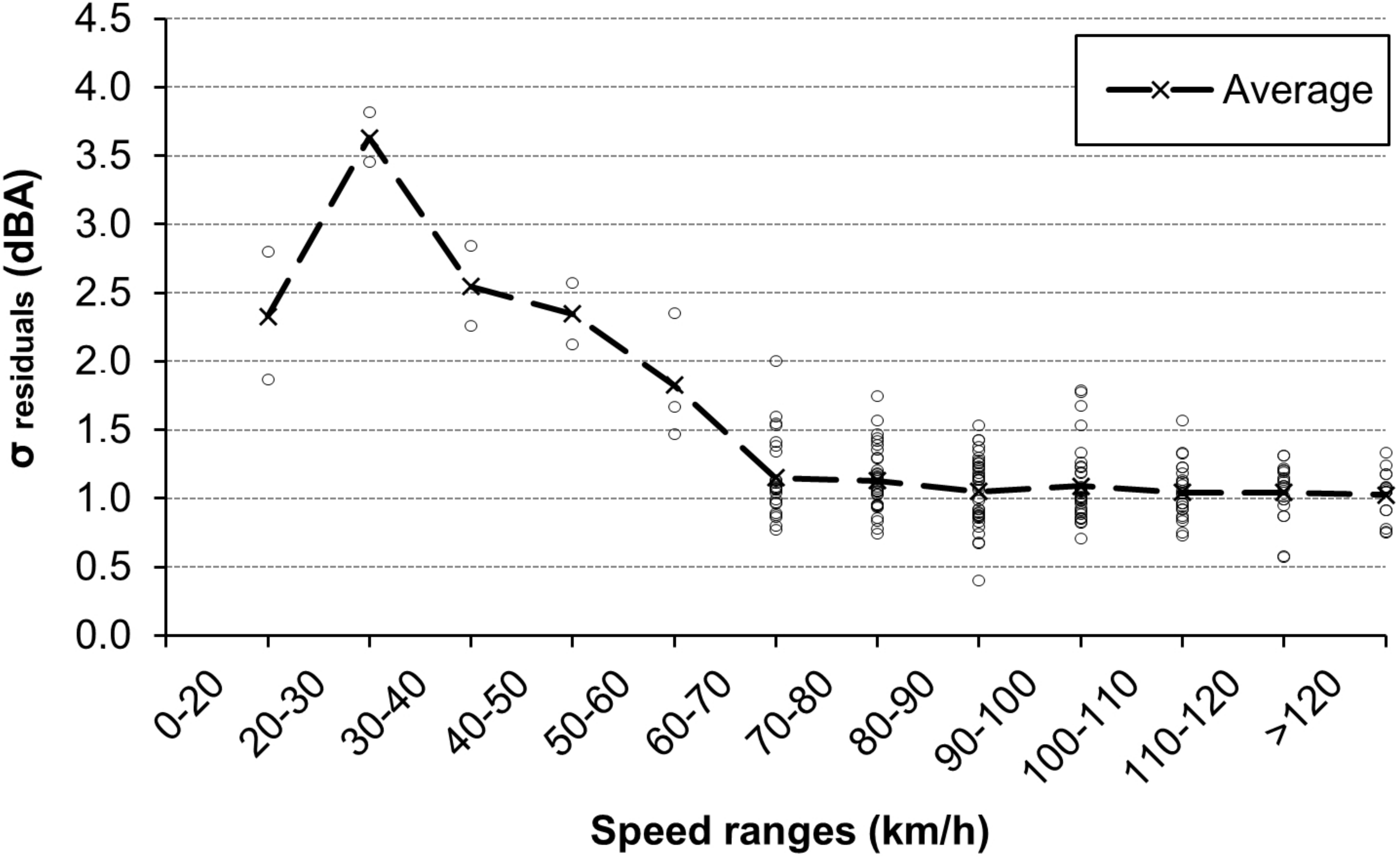
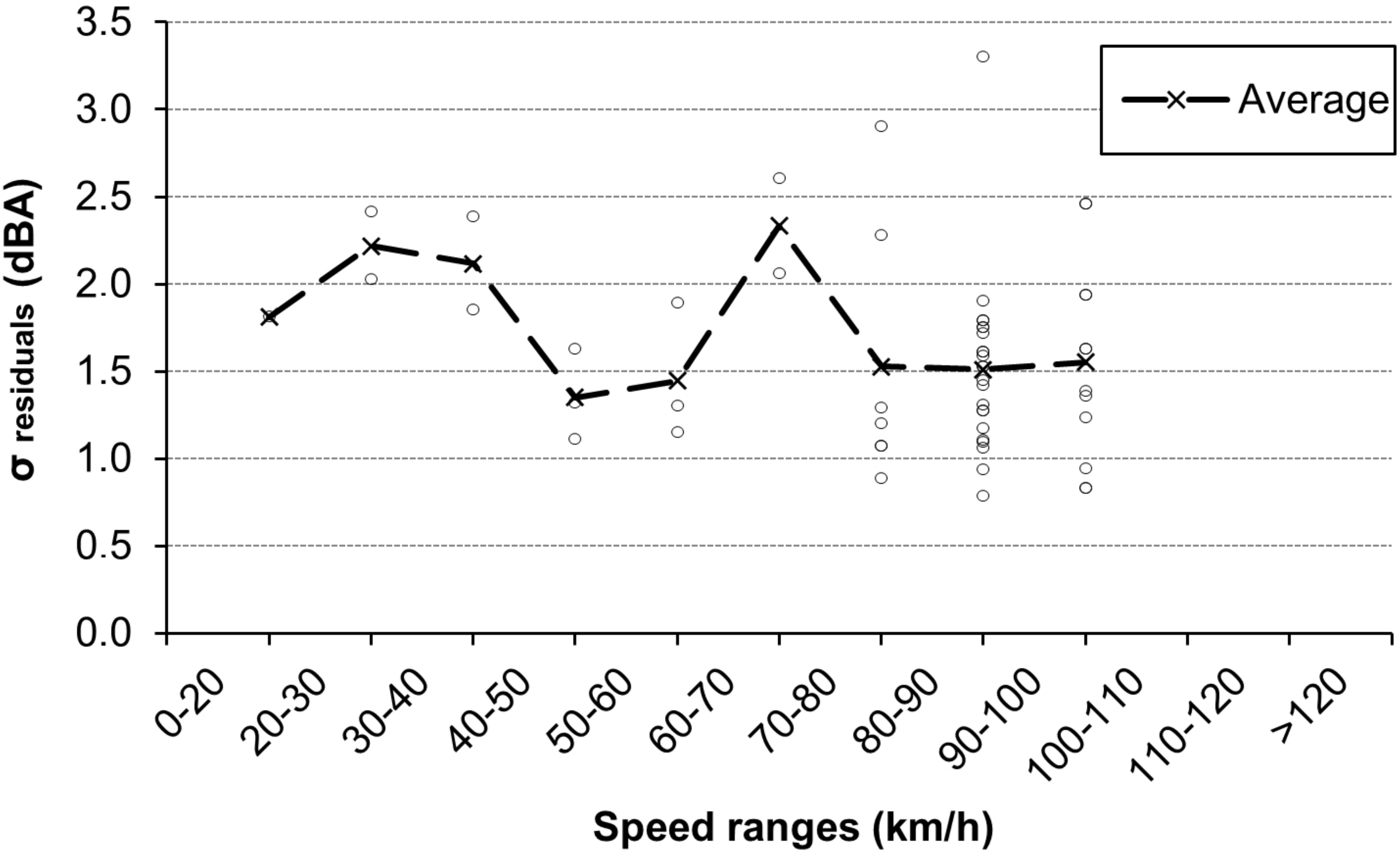
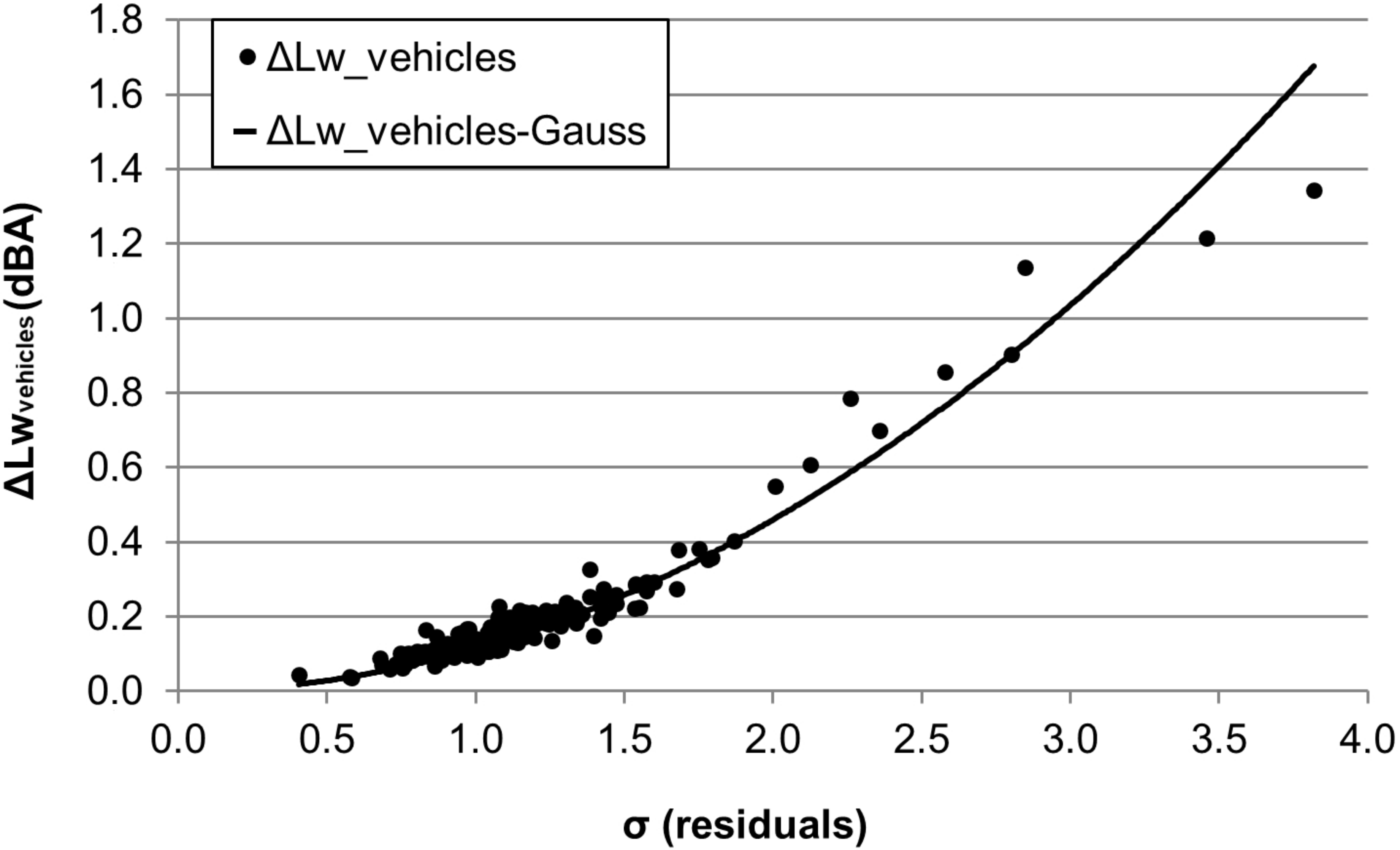
90
100
110
120
130
Speed (km/h)

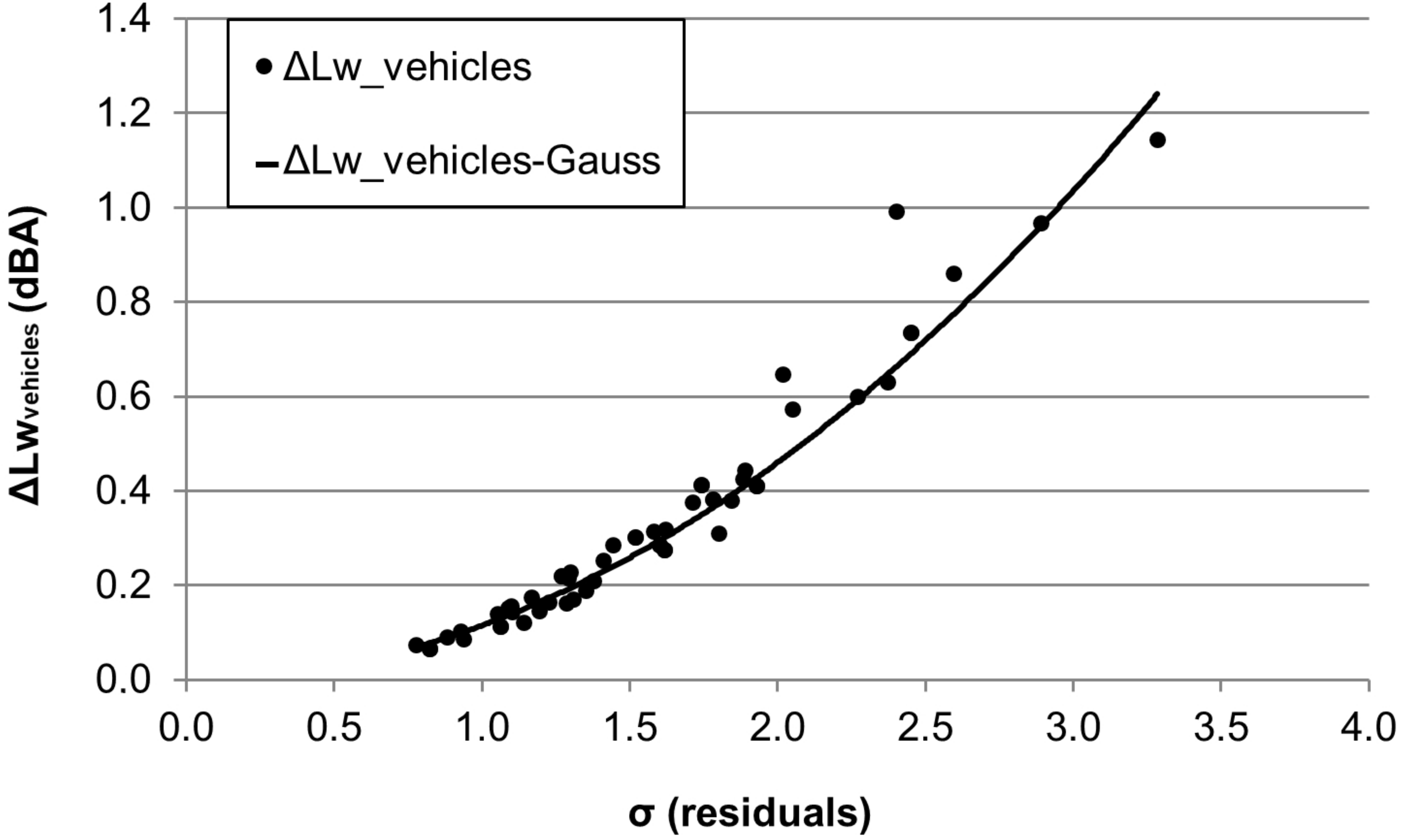


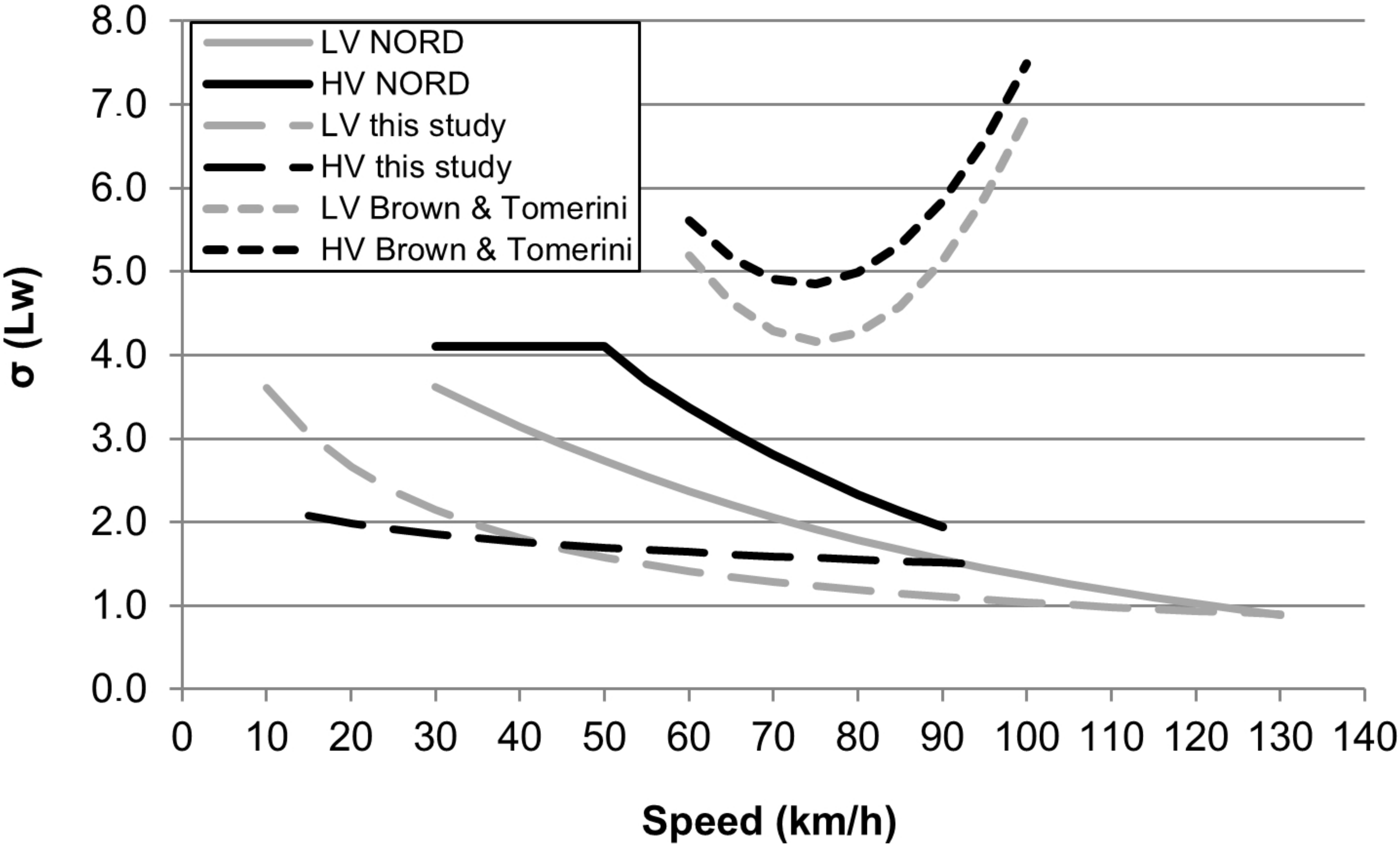
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
σ residuals (dBA)
Average
0-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100
100-110
110-120
>120
Speed ranges (km/h)



Average
σ residuals (dBA)
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100
100-110
110-120
>120
Speed ranges (km/h)


ΔLw_vehicles
ΔLw_vehicles-Gauss
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
ΔLw vehicles (dBA)
σ (residuals)


● ΔLw_vehicles
– ΔLw_vehicles-Gauss
ΔLwvehicles (dBA)
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
σ (residuals)



LV NORD
HV NORD
LV this study
HV this study
LV Brown & Tomerini
HV Brown & Tomerini
σ (Lw)
8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
Speed (km/h)

Author Statements:

Guillermo Rey Gozalo: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization, Supervision, Project administration, Funding acquisition. **Pierre Aumond**: Conceptualization, Methodology, Validation, Investigation, Resources, Writing - Original Draft, Supervision. **Arnaud Can**: Conceptualization, Validation, Investigation, Resources, Writing - Review & Editing, Supervision.