DOI: 10.61782/fa.2025.0233

FORUM ACUSTICUM EURONOISE 2025

COMPARISON OF STOCHASTIC AND MICROSCOPIC ROAD TRAFFIC NOISE MODELS USING VARIABLE LEVEL OF AGGREGATION OF TRAFFIC FLOWS

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ABSTRACT

The problem of assessing road traffic noise levels by means of predictive models is strictly related to the issue of using reliable and easy-to-obtain input data. This work focuses on evaluating the performance of a stochastic and microscopic traffic noise prediction model, using traffic flow inputs aggregated in two ways: by grouping multiple lanes together or analysing them separately.
The model incorporates stochastic distributions to account for the variability in single vehicle speeds, and consequently in noise emissions. It uses microscopic simulations to consider the motion of individual vehicles and to calculate the Sound Exposure Level (SEL) of each transit. To assess model effectiveness, predictions obtained using both aggregated and disaggregated traffic data are compared to field measurements collected in a long-term monitoring station site in France.
Results suggest that disaggregating traffic flow by lanes modifies the equivalent continuous sound levels distributions, by acting on the distances between each lane and the receiver point, particularly when the flows are asymmetric.
The study underlines the adaptability of the developed stochastic and microscopic model and provides valuable insights into optimizing the balance between accuracy and efficiency when dealing with traffic flow data collection at different levels of aggregation.

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Keywords: *road traffic noise, microscopic modelling, stochastic modelling, single lane linear source, experimental data validation.*

1. INTRODUCTION

The study of road traffic noise has become increasingly relevant due to its significant impact on urban health and environmental quality. As cities grow and traffic density rises, accurately modelling noise emissions is essential for both research and policy-making. This paper examines the effectiveness of stochastic and microscopic models in predicting road traffic noise, with a particular focus on how different levels of traffic flow aggregation influence noise estimates. The motivation for this study arises from a well-documented connection between prolonged noise exposure and adverse health effects, including cardiovascular diseases and metabolic disorders [1-3]. Moreover, traditional noise prediction models often struggle to capture the complex and dynamic nature of urban and non-urban traffic, highlighting the need for more refined methodologies [4-5]. In recent years, advancements in road traffic noise modelling have introduced a range of approaches, from empirical models to data-driven techniques such as machine learning. While empirical models, like many of those resumed in [6], remain widely used, they often fail to account for transient variations in traffic conditions [5, 7], or in correspondence of signal setting intersections [8]. On the other hand, machine learning methods, particularly artificial neural networks (ANNs), have demonstrated considerable promise in enhancing prediction accuracy by incorporating real-time traffic data [10-11]. Research indicates that ANNs, when

trained on detailed traffic characteristics, can outperform traditional statistical models in noise prediction [10]. Additionally, recent studies have explored the incorporation of stochastic elements into microscopic models, enabling a more detailed simulation of vehicle interactions and their cumulative impact on noise emissions [11-12].
The current direction in traffic noise modelling emphasizes context-sensitive and dynamic approaches. Various factors, such as vehicle type, speed, and road surface conditions, play a crucial role in noise propagation and should be incorporated into predictive models [5-6, 13]. For instance, Zuo et al. in [1] stress the importance of assessing individual noise exposure, which can vary significantly based on local urban design and traffic patterns. Moreover, recent efforts to integrate graph theory into noise modelling have opened new possibilities for analysing the relationships between traffic flow and noise emissions [14]. Such approaches allow for a more comprehensive understanding of how different traffic scenarios influence overall noise levels, offering valuable insights for urban planners and policymakers.
In conclusion, a comparative analysis of stochastic and microscopic road traffic noise models can provide a deeper understanding of noise dynamics in urban settings. By considering different levels of traffic flow aggregation, this study aims to contribute to the ongoing discourse on effective noise mitigation strategies and their implications for public health and sustainable urban planning.

2. MATERIALS AND METHODS

The starting point of this research can be retrieved in the development of microscopic Road Traffic Noise Models (RTNMs) developed and used by the authors in several case studies, for instance in [15-18]. In all these applications, the contribution at the receiver of the single vehicle is estimated in terms of the Sound Exposure Level (SEL) of the transit. This descriptor depends on the speed of the single vehicle, which, together with the category of the vehicle, mostly influences the noise emission and thus the pressure level at the receiver. In [19] a stochastic approach for assigning a speed to each transiting vehicle has been successfully calibrated and validated on a large dataset collected by a long-term monitoring station operating in France in the period 2002-2007 [20]. Anyway, in [19] the overall traffic flow over 15 minutes has been used as input of the stochastic model, considering an ideal linear source placed in the centre of the carriage, without separating traffic flows per lane. Despite the good results obtained, the detailed investigation of the errors and the outliers of the model reported in [19] suggested that further development can be pursued by considering the traffic flows in each lane and by modelling the highway with four different linear sources, placed at different distances from the receiver, i.e. the position of the sound level meter used for validation.

2.1 Resume of the stochastic and microscopic model

The model used in this paper, presented in [19], assumes that the vehicles' speeds are distributed according to a probability distribution whose shape depends on the traffic condition. For instance, steady-state flows are described by a normal distribution, while accelerating and decelerating conditions can be described by skewed distributions [21]. The idea of the model is to randomly assign a speed to each transiting vehicle and estimate the corresponding noise emission using the CNOSSOS-EU emission model [22-23], using its recent updates [24-25]. Then, the point-like source propagation formula is used to propagate the emitted noise at the receiver. This calculation is performed as a function of time and the resulting L_p is used to calculate the SEL, according to the standard formula, using the transit time as a temporal range. Then the SELs of all the vehicles are summed up and then the result is converted to the L_{eq} over 15 minutes.
This procedure exhibits some limitations that are listed below:

- Underestimation of noise at low traffic flows, due to the assumption that the equivalent level is made only of noise coming from vehicles. When a few vehicles pass, the background noise is not negligible anymore.
- Possible overestimation at high traffic flows, due to the overlapping of vehicles transits. The model assumes that each vehicle contributes at 100%, neglecting possible overlapping and screening effects.
- Single linear source placed in the centre of the road.

As for the first two limitations, they are related to the computational core of the model and need to be addressed by operating on the step that merges the single vehicle contributions.
The third limitation is addressed in this paper by performing a more detailed modelling of the source, i.e. by considering a linear source per each lane. Of course, each source has a different distance and will contribute differently to the overall equivalent level.

2.2 Case study description

The dataset adopted in this work comes from an extensive data collection performed by researchers affiliated with the former IFSTTAR institute ("*Institut français des sciences et technologies des transports, de l'aménagement et des* *réseaux*"), now merged into Université Gustave Eiffel in Nantes, France. This database is known as the Long-Term Monitoring Station (LTMS) database and it has been fully described in [20].

This data collection took place at an experimental station operating continuously, 24 hours a day, 365 days a year, over approximately six years (2002-2007). The monitoring site was situated in Saint-Berthevin, near the A81 motorway, in the link from Le Mans to La Gravelle. This highway consists of two carriageways, each with two lanes. Lane 1 and lane 2 are respectively the normal transit and overtaking lanes in the direction West-East (to Le Mans and Paris), while lanes 3 and 4 are respectively the transit and overtaking lanes in the other direction (to Rennes). This numbering will be used throughout the paper to identify each lane.

During the data collection period, acoustic, meteorological, and traffic data were systematically recorded in several points of the area. In this work, we will focus only on traffic counting in each lane and on equivalent continuous sound levels measured at the closer sound level meter (reference microphone), positioned 5 meters above ground and approximately 5 meters from the roadside, close to lane 1.

Data measured were validated at 10-second intervals, with cleaning of noise events unrelated to road traffic and then aggregated in 15-minute time slots.

Regarding vehicle flow data, the available dataset includes only the total number of light and heavy-duty vehicles recorded within each 15-minute interval. However, thanks to the availability of raw data provided by one of the coauthors, it was possible to work on single lane counts and speeds per 10-second intervals, making it possible to perform the analysis presented in the following sections.

As already shown in [19], the case study under analysis exhibits free-flow traffic conditions and allows to use of Gaussian distributions for the speed. The mean speeds per category per 15-minute intervals are available in the public database. As for the dispersion of the distribution, starting from the 10-second raw data, it is possible to calculate the standard deviation of speeds in each 15-minute interval. Anyway, to compare with previous studies (e.g., in [19]), the choice was to set the standard deviation at 10% of the mean speed. Under free-flow conditions, constant speed values were assigned for vehicle transits, meaning acceleration effects were not factored into the model at this stage.

2.3 Dataset presentation and analysis

The case study presented above has been used in [19] for the validation of the model. Due to occasional missing data, only complete 15-minute intervals containing all necessary variables (traffic flow, mean speeds, and $L_{A,eq,15min}$) were included in the analysis. As a result, the dataset was refined to 30437 usable 15-minute intervals. Anyway, in this application, since the aim is to highlight the variations of model performance when using more detailed input data, i.e. when using information for a single lane or the two directions of the highway, a subset of the entire dataset has been selected. After running the model on different periods, for the sake of brevity, only results obtained in the period from March 5 to April 1, 2007, will be presented.

In Figure 1, the light (top plot) and heavy (bottom plot) vehicles' flows are represented versus the ID of the quarter-hour, over the 28 days under analysis, i.e. 2688 15-minute intervals.

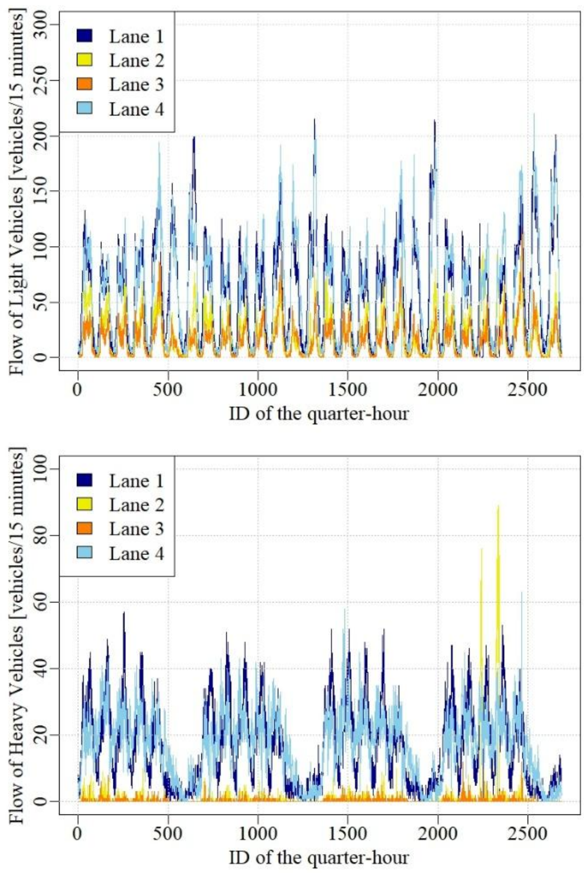

Figure 1. Light (top) and heavy (bottom) vehicles flows plotted versus the ID of the quarter-hour, over the 28 days under analysis.

Lane 1 (blue curve) and lane 4 (light-blue curve) are normal transit lanes, with lane 1 closer to the sound level meter position, while lane 2 (yellow curve) and lane 3 (orange curve) are the overtaking lanes. In each lane flow, there is a seasonal pattern with regular peaks, related to the day-night oscillation. A seasonality related to the working days and weekends of the 28-day period is also observed, showing that during Saturday and Sunday, there is an increase in light vehicles' flows and a decrease in heavy vehicles. The normal march lanes (1 and 4) show higher traffic volumes than the passing lanes (2 and 3), as expected.
As for the heavy vehicles' flows in 15 minutes (Figure 1b), the curves follow the same colour scheme. The flow of heavy vehicles is generally lower than that of light vehicles, and it is almost entirely running on the normal march lanes (1 and 4). Overtaking lane 2 flows curve (yellow line in the plot) shows peaks of heavy traffic during the fourth week of the observation period. Going more in depth with the analysis, it was found that during those two periods, lane 1 was closed, in fact, the flows in that lane were zero for both light and heavy vehicles categories.
Figure 2 shows the boxplots of vehicle flows on the four lanes, distinguishing between light (L) and heavy (H) vehicles, using the 10-second raw data. The comparison of the flows' distributions makes it possible to analyse the different uses of the lanes and to make some considerations about the overall behaviour of light and heavy traffic.
The flows of light vehicles in normal transit lanes (L1 and L4) are the highest. This confirms that lanes 1 and 4, which are configured as normal march traffic lanes, are largely used in comparison to lanes 2 and 3 which are occasionally used for overtaking.
The flow of heavy vehicles in lanes 2 and 3 (H2 and H3) is basically negligible, confirming that heavy vehicles rarely use the overtaking lane, probably for regulation reasons.
All the above comments are confirmed by looking at the boxplots of the mean speeds in Figure 3, calculated by averaging the speeds of the vehicles in each 15-minute slot, starting from the 10-second raw data. It is evident that the overtaking lanes (L2 and L3) exhibit higher speeds with respect to the normal transit lanes (L1 and L4), and that the heavy vehicles' mean speeds are always lower than 100 km/h, i.e. the speed limit in the highway segment under study for such category.
It must be noticed that, while lanes 1 and 4 are basically balanced in all the parameters, lane 2 shows slightly higher light vehicles' flows and mean speed than lane 3. This small asymmetry will be commented in the equivalent continuous sound levels results since it will produce an increase of the simulated levels when moving from 1 source to 4 sources.

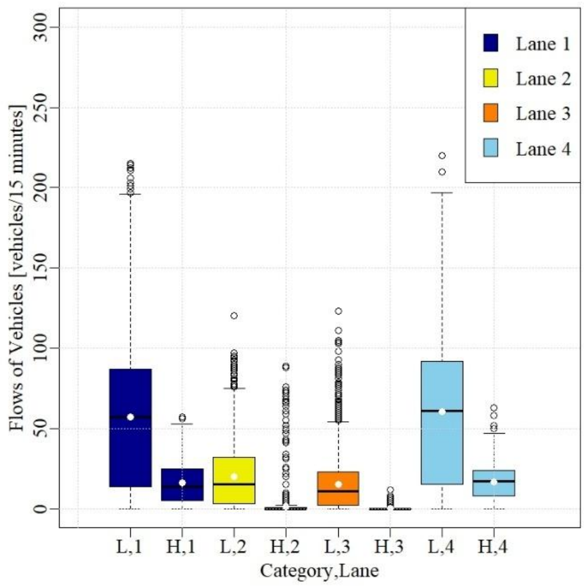

Figure 2. Boxplots of light and heavy vehicles flows, divided by lane, over the 28 days under analysis.

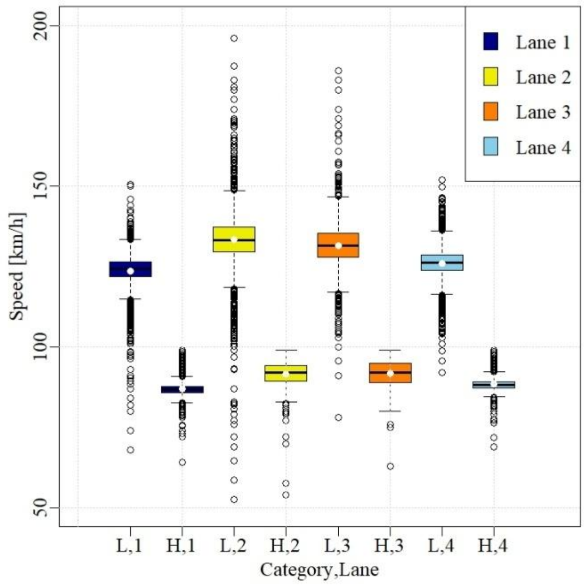

Figure 3. Boxplots of light and heavy vehicles mean speeds, divided by lane, over the 28 days under analysis.

2.4 Cleaning procedure of the dataset

After the careful analysis of the input data performed and reported in subsection 2.3, cleaning of the dataset has been performed. To validate the model results compared with measured equivalent levels on 15 minutes, all the entries of the database in which the measured levels were missing have been discarded. This process reduced the number of 15-minute slots from 2688 (96 slots for 28 days) to 443, spread over the entire 4-week original period.

A comparison between mean values and standard deviations for each parameter, per single lane, calculated on the raw database and the filtered dataset is reported in Table 1. It can be noticed that the filtering of the dataset didn't change drastically the central tendency and the dispersion of the parameters' distributions, since mean values and standard deviations are very similar before and after the data cleaning.

3. RESULTS

The detailed exploratory data analysis performed on the input data of the noise model, resumed in section 2, allowed to gain useful insights into the traffic phenomenon in the case study area, in the 28 days selected for testing. The asymmetries found suggest that a modelling of the source that considers the different flows in the directions and the lanes, could improve the performance of the microscopic and stochastic model presented in [19].

The model has then been run in three different configurations:

- Single source, placed in the middle of the carriageway (1-source model)
- Two sources, placed in the middle of each direction (2-sources model)
- Four sources, placed in the middle of each lane of the carriageway (4-sources model)

Of course, the source-receiver distances were fixed according to the source simulation scheme, considering that lane 1 is the closest to the receiver (i.e., the sound level meter position) and lane 4 is the farthest.

The results of the simulations with the above-listed source modelling schemes are reported in Figure 4, in which the measured levels boxplot is compared with the simulated ones. It can be noticed that the boxplot that best approaches the simulated distribution is the one produced with the 4-sources model. Anyway, all the simulated distributions present a larger spread of the data, being the interquartile ranges greater than that of the measured distribution.

The main descriptive statistics are reported in Table 2. It can be noticed that the central tendency metrics, mean and median, of the simulated distributions are always lower than the measured ones, but, moving from 1 source to 4 sources, the discrepancy is lower. The standard deviations of the simulated distributions do not change significantly, meaning that the different modelling schemes do not affect the dispersion of the simulations.

Table 1. Mean values and standard deviations of the distributions of parameters for each lane, for both reference databases. Raw databases (before any filtering) include 2688 entries (28 days) while filtered databases (filtering on quarters-hour that include the measured L_{eq}) have 443 entries.

	Parameter calculated over 15 min	Database	Mean value	St. dev.
Lane 1	Flow light [veh/15min]	Raw	57,02	45,24
		Filtered	63,09	46,11
	Flow heavy [veh/15min]	Raw	16,18	12,34
		Filtered	14,97	11,64
	Speed light [km/h]	Raw	123,58	5,73
		Filtered	125,14	4,51
	Speed heavy [km/h]	Raw	86,93	2,50
		Filtered	87,36	2,76
Lane 2	Flow light [veh/15min]	Raw	19,93	19,31
		Filtered	21,00	18,88
	Flow heavy [veh/15min]	Raw	1,20	6,65
		Filtered	1,87	9,44
	Speed light [km/h]	Raw	133,59	10,45
		Filtered	133,84	11,47
	Speed heavy [km/h]	Raw	91,67	4,31
		Filtered	91,54	4,58
Lane 3	Flow light [veh/15min]	Raw	15,02	16,02
		Filtered	14,63	14,10
	Flow heavy [veh/15min]	Raw	0,31	0,82
		Filtered	0,32	0,92
	Speed light [km/h]	Raw	131,64	8,05
		Filtered	133,07	7,33
	Speed heavy [km/h]	Raw	91,73	4,87
		Filtered	90,73	7,38
Lane 4	Flow light [veh/15min]	Raw	60,40	45,73
		Filtered	62,38	41,17
	Flow heavy [veh/15min]	Raw	16,54	9,96
		Filtered	15,37	10,80
	Speed light [km/h]	Raw	126,04	5,33
		Filtered	127,56	4,19
	Speed heavy [km/h]	Raw	88,51	2,31
		Filtered	88,85	2,73

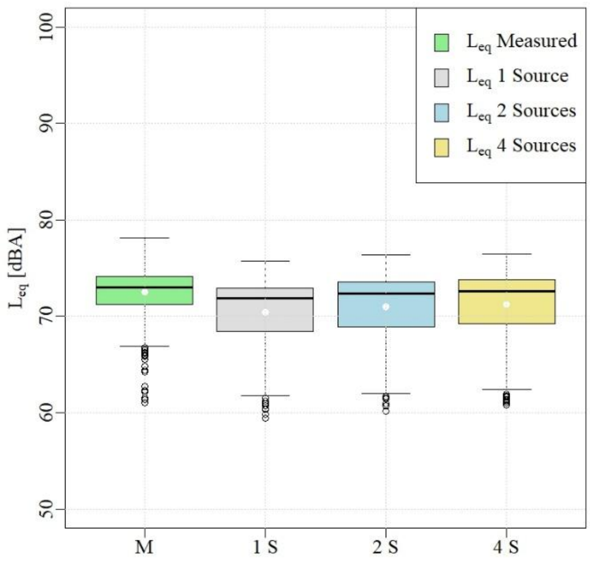

Figure 4. Boxplots of measured and simulated equivalent levels calculated in the 15-minutes time slots. The results obtained with the three modelling schemes are plotted.

Table 2. Main descriptive statistics of measured and simulated equivalent levels with the three modelling schemes.

	Mean [dBA]	Median [dBA]	Std. dev. [dBA]	Skew	Kurt
Measured $L_{eq.15min}$	72.50	73.01	2.78	-1.19	2.52
Simulated $L_{eq.15min}$ 1-source	70.46	71.86	3.39	-1.09	0.49
Simulated $L_{eq.15min}$ 2-sources	70.99	72.37	3.43	-1.04	0.29
Simulated $L_{eq.15min}$ 4-sources	71.25	72.57	3.38	-1.04	0.33

3.1 Error analysis

To provide a quantitative assessment of the modelling scheme performances, an error analysis has been pursued, calculating the error as the difference between measured and simulated equivalent levels. Such a definition leads to assessing an overestimation when the error is negative and, vice versa, an underestimation is associated with a positive error. The error distributions statistics are reported in Table 3. The mean and median of the errors are reduced when using a more detailed modelling of the source. Standard deviation is less sensitive, due to the same reasons explained above.

Table 3. Main descriptive statistics of error distributions, obtained with the three modelling schemes.

	Mean [dBA]	Median [dBA]	Std. dev. [dBA]	Skew	Kurt
Error (1-source)	2.04	1.00	3.01	1.56	2.82
Error (2-sources)	1.51	0.46	2.96	1.48	2.37
Error (4-sources)	1.25	0.14	2.91	1.54	2.52

A further analysis is provided in Figure 5, in which a pairs panel plot is given. In this plot, the variables are plotted one versus the other below the diagonal in bivariate scatter plots, while numbers above the diagonal are the Pearson correlation coefficients. The histograms of the variables are reported in the diagonal.

The pairs-panel plot was first performed using all the variables, to check the correlations between errors and input data. Since the errors did not correlate significantly with the speeds (correlation coefficients ranging from -0.07 to -0.09 for light vehicles' speed and from 0.14 to 0.16 for heavy vehicles' speed), Figure 5 reports only the pairs between errors and total light and heavy vehicles' flows.

Looking at the scatter plots between the errors (for all the modelling schemes) and total flow light and heavy, it is evident that, when the flows increase, the errors tend to converge to low values with low dispersion. This is an interesting finding since it confirms that greater errors are obtained when the flow is small. The plots of errors versus L_{eq} measured (rows 4, 5 and 6, column 3) show that for equivalent levels higher than 75 dBA the errors are always greater than 5 dBA. Those measurements can be found also in row 3, column 1, in the low flow range. This means that those high errors are probably due to external reasons, such as other sources. In addition, since all the source modelling schemes present the same behaviours versus the plotted variables, the presented approach is sensitive to the parameters' ranges in the same way, regardless of the source modelling. This result shows that the improvement obtained when moving from 1-source to 4-sources scheme is dependent on the lanes where the vehicles transit rather than on the absolute traffic flow values.

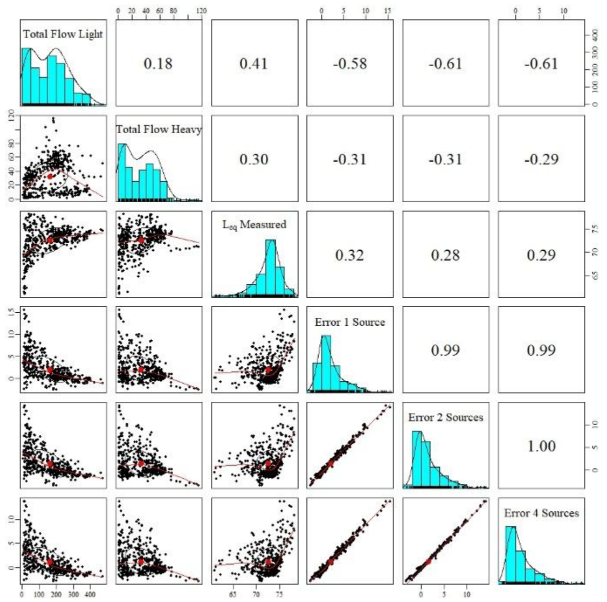

Figure 5. Pairs panel of the errors, obtained with the three modelling schemes, versus the total flow of light and heavy vehicles.

4. CONCLUSIONS

In this paper, a microscopic and stochastic model for road traffic noise prediction has been tested with variable levels of aggregation of input parameters. In particular, traffic flows and mean speeds for light and heavy vehicles, estimated on 15 minutes, have been considered per single lane, per direction (grouped by two lanes) and aggregated, to simulate three different schemes for the noise source.

After presenting a detailed exploratory data analysis, useful to understand the scenarios occurring in the case study area and to infer information for noise model performances understandings, the authors implemented the modelling schemes, using a single source in the middle of the carriageway (1-source model), two sources in the centre of each direction (2-sources model) and four sources in the middle of each lane (4-sources model).

The results show an improvement of the prediction, in terms of mean and median errors. The standard deviation of the error does not improve significantly, suggesting that the dispersion of simulations need to be furtherly investigated, for instance with a parameter sensitivity analysis. An outlier analysis can be also performed, to better understand the non-standard conditions that occur in the case study location.

In conclusions, standing the parsimony principle, that, with similar performances, suggests using the model with lower parameters, the 4-sources model is a good candidate for replacing the 1-source approach. The presented results confirm that in cases in which the traffic flows are asymmetric, the single line source placed in the middle of the carriageway is not anymore a suitable choice and that a more detailed modelling of the source is able to better predict the equivalent continuous sound levels.

5. ACKNOWLEDGMENTS

This study was carried out within the MOST – Sustainable Mobility National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1033 17/06/2022, CN00000023). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

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