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Estimation of psychoacoustic and noise indices from the sound pressure level of transportation noise sources: investigation of their potential benefit to the prediction of long-term noise annoyance

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Abstract

Few research works tackled the testing of noise annoyance models proposed in the literature by considering a new set of survey data. This lack contributes to limit the effect of endeavors in noise annoyance prediction. This lack is observed for both annoyance models built from field data and laboratory data. Different reasons might explain this. In the case of annoyance models based on psychoacoustic indices accounting for annoying auditory sensations, their relevance was highlighted in laboratory conditions as they might increase the part of explained variance of annoyance. But the use of these indices in field studies leads to issues. Actually, audio recordings are needed for their calculation, making too tedious their use in large-scale studies. This work proposed a methodology, and its testing, to estimate various psychoacoustic and noise indices from the A-weighted equivalent sound pressure level, L_{Aeq} , of different transportation noise sources. The transportation noise sources were urban and suburban road traffic noise, urban railway noise, and aircraft noise in cities close to French international airports. A database of index values has been built from various recordings of these transportation noise sources. From the database, relationships between the various indices and L_{Aeq} of the transportation noise sources were built, and satisfactorily tested by cross-validation. These relationships might be of interest for field studies dealing with transportation noise assessment. In the current study, the relationships were used to estimate variables of noise annoyance models based on different psychoacoustic and noise indices. The proposed relationships enabled the assessment of the prediction quality of these models also based on individual noise sensitivity. The comparison of their prediction quality with the one of noise annoyance models solely based on the day-evening-night level, L_{den} , and of a model based on both noise sensitivity and the day-night level, L_{dn} , highlighted an improvement of the correlation coefficients between the predicted and the field measured annoyance ratings

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with a ratio of 2 for the best enhancement. Such a ratio was observed as the correlation coefficient obtained for models solely based on L_{den} were weak. The results stated the interest of the proposed index relationships to be used in the investigation of improving noise annoyance models in future annoyance field studies.

Keywords: Psychoacoustic index, noise annoyance, road noise, railway noise, aircraft noise

1. Introduction

Environmental noise is an important health issue in industrial countries. Assessments in western Europe place the burden of disease due to traffic-related environmental noise as the second highest one after air pollution. Annoyance is one of the most important reactions among populations exposed to environmental noise (WHO Regional Office for Europe, 2011; World Health Organization, 2018).

The European Commission's Position paper on EU noise indicators (European Commission, 2000) recommended to consider the day-evening-night level, L_{den} index, as a common noise indicator for reporting data on environmental noise exposure outside dwellings, for managing annoyance, sleep disturbance and also other noise-related health effects of environmental noise. The European Directive 2002/49/EC (European Commission, 2002) makes it mandatory for European cities with more than 100,000 inhabitants to produce strategic noise maps for each type of transportation noise. These maps characterize noise exposure using L_{den} . These maps constitute a useful tool for managing environmental noise. They are also used to estimate the number of Disability-Adjusted Life Years (DALYs), *i.e.* healthy years of life lost from environmental noise in western European countries (World Health Organization, 2011). L_{den} index is used in exposure-effect relationships to estimate health effect, such as the percentage of people highly annoyed by a noise source (*e.g.* Miedema and Oudshoorn, 2001; World Health Organization, 2018). As pointed out in (World Health Organization, 2018), the best noise indicator from a scientific point of view is the one that best performs in predicting the effect of interest, but there are various criteria that may influence the choice of an indicator, such as being easy to be calculated (World Health Organization, 2018). Nevertheless, the choice of a mean energy-based index is often questioned to account for noise annoyance felt by the population (*e.g.* Lercher *et al.*, 2013), and the sole mean sound level is known to partly explain the variance of annoyance (*e.g.* Babisch *et al.*, 2009). Actually, such an index does not account alone for various acoustical features from the spectral or temporal content, which are well-known to be annoying in case of different environmental noises (*e.g.* Torija *et al.*, 2011; Lercher *et al.*, 2013; Schäffer *et al.*, 2018). It is also well-known that non-acoustical factors also influence noise annoyance, such as noise sensitivity (*e.g.* Guski, 1999; van Kamp *et al.*, 2004). Different works have built noise annoyance models considering multilevel regression to investigate the influence of various acoustical factors, such as psychoacoustic indices (*e.g.* Boucher *et al.*, 2019), and non-acoustical factors, such as noise sensitivity (*e.g.* Miedema and Vos, 2003), with the aim of

enhancing noise annoyance models. These contributions highlight relevant variables which might be considered with or instead of an energy-averaged index. Few works considered the testing of noise annoyance models proposed in the literature by using a new set of survey data (e.g. Lechner *et al.*, 2019a), and more rarely the testing of models considering other variables than the sole energy-averaged index. The lack of model testing necessarily contributes to limit the long-term goal of improving noise annoyance prediction. In the case of psychoacoustic indices used to account for annoying auditory sensations in noise annoyance models, their relevance is demonstrated under controlled conditions, but their use in field studies leads to issues, as for most of them audio recordings are needed for their calculation. This might be an important limitation to test noise annoyance models based on such indices. To overcome such a difficulty, Gille and Marquis-Favre (2019) proposed a methodology to estimate different psychoacoustic indices highlighted to be relevant for urban road and aircraft noise annoyance models. But the direct testing of such a methodology using a new set of index values was not proposed as a significant database of index values is needed to establish and test the methodology.

In the current work, a methodology is proposed to estimate various psychoacoustic and noise indices from the A-weighted equivalent sound pressure level, L_{Aeq} , of different transportation noise sources. This was carried out for urban and suburban road traffic noise, railway traffic noise in urban areas, and aircraft noise in cities in the vicinity of French international airports. To achieve this goal, a database of index values has been built from various recordings of the transportation noise sources. Using a new set of field index data, the current study assessed by cross-validation the prediction quality of the estimation of the psychoacoustic and noise indices from L_{Aeq} of the transportation noise sources. From the new set of field index data, the methodology proposed in Gille and Marquis-Favre (2019) to estimate psychoacoustic indices was also assessed. The obtained relationships between the various indices and L_{Aeq} of the transportation noise sources might be of interest for field studies assessing transportation noise sources in urban areas. In the current work, these relationships were used to test noise annoyance models, based on noise sensitivity and various psychoacoustic and noise indices, proposed in the literature (Gille and Marquis-Favre, 2019; Trollé *et al.*, 2014; Vallin *et al.*, 2018). Prediction quality assessment was carried out using survey data. This allowed to compare these annoyance models to other annoyance models from the literature solely based on L_{den} , or based on L_{dn} and noise sensitivity. The paper is organized as followed: section 2 presents the socio-acoustic survey; section 3 is dedicated to the construction and testing of the relationships between L_{Aeq} of the transportation noise sources and different psychoacoustic and noise indices; section 4 presents the testing of psychoacoustic index-based annoyance models proposed in the literature and their comparison with annoyance models solely based on L_{den} or on L_{dn} and noise sensitivity. Then results are discussed, and conclusions are given.

2. The socio-acoustic survey

The socio-acoustic survey was carried out during the autumn of 2012 by Ecotière *et al.* (2015) in 8 French cities to study different combined transportation noise sources. The transportation noise sources assessed were road traffic, railway traffic and aircraft noises. The sampling of the respondents was random in the survey areas. The respondents were interviewed face-to-face using a 30-minute questionnaire. In the current study, the main characteristics of the survey are briefly summarized hereafter from published articles (*e.g.* Gille *et al.*, 2017).

2.1 The questionnaire

The questionnaire was in French (*Cf.* Ecotière *et al.*, 2015) and organized with questions about (*Cf.* Gille *et al.*, 2017):

- Housing;
- Neighborhood;
- Global outdoor sound environment;
- Annoyance due to each transportation noise under study (depending on the city of residence);
- Annoyance due to the combined transportation noise sources (depending on the city of residence);
- Non-acoustical factors, such as the self-reported noise sensitivity.

The questions about noise annoyance complied with ISO/TS 15666:2003 (2003). Respondents were asked to give an annoyance rating due to the mentioned noise source(s) on a continuous scale ranging from “0” to “10”, with 11 evenly spaced numerical labels and two verbal labels at both ends (“not at all” and “extremely”). A similar continuous scale was used to assess the self-reported noise sensitivity in general (Ecotière *et al.*, 2015; Gille *et al.*, 2017).

2.2 Study population

A total of 823 people, between 18 and 80 years old, and living permanently in their dwelling for at least one year, were successfully interviewed (*Cf.* Gille *et al.*, 2017). Their socio-demographic characteristics are given in Table 1.

Table 1. Socio-demographic characteristics of the studied population (*Cf.* Gille *et al.*, 2017).

	N (%)	Mean \pm SD(Min-Max)
Gender		
Male	48.5%	
Female	51.5%	
Age		46 \pm 16.9 (18-80) years

Length of residence	13.4±14.1(1-77) years	
Occupation		
Working	55.9%	
Non-working	44.1%	
Retired	22.7%	
Student	4.9%	
Unemployed	7.4%	
Housewife	6.7%	
Disabled	1.2%	

Noise sensitivity ratings highlighted that 70.5% of respondents reported themselves to be sensitive or highly sensitive to noise in general (Cf. Marquis-Favre *et al.*, 2021), with a 50 % cut-off point. The value is equal to 27.6% for respondents reported to be highly sensitive to noise in general, with a 72% cut-off point. These values showed the importance of this individual predisposition regarding reaction to noise among the population.

2.3. Noise exposures

Noise exposures studied during the socio-acoustic survey were expressed in terms of L_{den} from the French strategic noise maps available in 2012 and based on the European Directive 2002/49/CE guidelines. Noise maps were available for each single transportation noise exposure for each city of the survey. Table 2 presents the different transportation noise exposures, the number of respondents and L_{den} range per noise exposure (Cf. Gille *et al.*, 2017).

Table 2. Noise exposure expressed in L_{den} (dB(A)) and the number of respondents in each of the 8 cities of the survey (Ecotière *et al.*, 2015; Gille *et al.*, 2017). Road: Road traffic; Rail: Railway; Air: Aircraft; ¹: city exposed to Orly airport noise; ²: city exposed to Roissy-Charles-de-Gaulle airport noise.

City (population sample size)	L_{den}	L_{den}	L_{den}
	Road dB(A)	Railway dB(A)	Aircraft dB(A)
Bourg Les Valence (82)	58.0 to 80.8	58.1 to 77.4	no exposure
Caluire (79)	55.6 to 78.0	45.6 to 82.2	
Lyon 6 (140)	48.4 to 74.2	40.6 to 83.6	
Paray-Vieille-Poste ¹ (153)	49.9 to 77.9	no exposure	42.0
Saint Brice-sous-Forêt ² (59)	53.7 to 67.5		52.0 to 54.0

Goussainville ² (96)	Below 55,	52.0 to 72.0	52.0 to 72.0
Villeneuve-Le-Roi ¹ (25)	not studied	49.0 to 60.0	49.0 to 60.0
Villeneuve-Saint-Georges ¹ (189)	42.3 to 79.3	43.2 to 80.8	44.7 to 62.8
Respondent number per exposure	702	611	522

As there were no variations in aircraft noise L_{den} for respondents from the city of Paray-Vieille-Poste, aircraft noise exposure from this city was not considered in the following. Thus, the sample size of respondents exposed to aircraft noise exposure dropped to 369.

2.4. Correlation coefficients between annoyance and two factors collected during the survey

In order to use these survey data for testing literature noise annoyance models, a correlation analysis was carried out between L_{den} and noise annoyance ratings, and also between noise annoyance and noise sensitivity ratings gathered during the survey. Table 3 displays the correlation coefficients.

Table 3. For each type of transportation noise exposure, correlation coefficients r between annoyance ratings and the corresponding noise index L_{den} , and correlation coefficients r between annoyance and noise sensitivity ratings. Road: Road traffic; Rail: Railway; Air: Aircraft. $p < 0.001$. *: sample without the data from Paray-Vieille-Poste city.

Transportation	Sample size	r between annoyance ratings and L_{den}	r between annoyance and noise sensitivity ratings
Road	702	0.17	0.37
Rail	611	0.23	0.35
Air	369*	0.21	0.46

Correlation analysis highlighted significant but weak correlation coefficient values between annoyance and L_{den} , and emphasized better correlation coefficient values between annoyance and noise sensitivity ratings.

3. Construction of index relationships from L_{Aeq} of the noise sources and their testing

3.1 Index database from field audio recordings

After the socio-acoustic survey, Bruitparif involved in the consortium of the survey (Ecotièrre *et al.*, 2015) performed audio recordings in the 5 cities around Paris at receiver points located in the area of the survey using ICP® microphones. The locations of the receiver points were in the vicinity of dwellers or in their property (*e.g.* microphones attached with a pole to the façade of their dwellings facing a main road or railway tracks; Bruitparif's car with its microphone attached on the top of a vertical pole, and parked in streets of dwellers exposed to aircraft noise). The different recordings carried out during many days accounted for the exposure of dwellers in the area of the survey. From these recordings, audio excerpts with noise events from each studied transportation noise were selected by ENTPE with the criterion to be free from other noise sources. Road traffic in these cities was urban traffic (50 km/h speed limit) or suburban traffic (speed variation from traffic lights up to road portions limited at 90 km/h). The road traffic was composed of different types of vehicles (powered-two-wheelers, buses, heavy, and light vehicles) at different driving conditions (acceleration, deceleration, constant speed). Audio excerpts corresponded to road traffic noise and to isolated noise events due to vehicle pass-bys. Railway traffic in these urban areas corresponded to train pass-bys at low speeds. Audio excerpts depended on the type of trains (intercity train, high-speed train (TGV) at low speed, suburban train and freight train), and could correspond to one train pass-by or to railway traffic composed of different simultaneous train pass-bys. Audio excerpts for aircraft noise corresponded to takeoffs and landings of aircrafts as the studied cities were close to two international airports, Orly and Roissy-Charles-de-Gaulle airports. Psychoacoustic and noise indices were calculated for these different noise sources. The calculations were carried out at ENTPE using MATLAB® and dBSONIC software (ACOEM - *Cf.* 01dB-Metravib, 2005). All calculated indices are hereafter described in subsections dedicated to each noise exposure. This endeavor led to an index database per city and noise exposure as displayed in Table 4 with the A-weighted equivalent sound pressure level L_{Aeq} range of corresponding noise exposure. Each index database size is defined by the number of transportation noise excerpts. These different index databases provided data 1) to determine relationships between L_{Aeq} of each noise source and psychoacoustic and noise indices, and 2) to test by cross-validation the built relationships considering the index values from the field recordings.

Table 4. Index databases stemming from field audio recordings carried out in 5 cities of the survey around Paris. L_{Aeq} (dB(A)) of the audio excerpts and index database size defined by the number of identifiable noise event excerpts. Road: urban or suburban road traffic; Rail: urban railway; Air: Aircraft; ¹: city exposed to Orly airport noise; ²: city exposed to Roissy-Charles-de-Gaulle airport noise.

Cities concerned by the audio excerpts	Index databases from field audio recordings		
	Road traffic noise excerpts L_{Aeq} dB(A) {index database size}	Railway traffic noise excerpts L_{Aeq} dB(A) {index database size}	Aircraft noise excerpts L_{Aeq} dB(A) {index database size}
Paray-Vieille-Poste ¹ (PVP)	40 to 84.7 {120}	No exposure	No index calculation
Saint-Brice-sous-Forêt ² (SBF)	55.8 to 80.4 {125}	No exposure	55 to 85 {64}
Goussainville ² (GOUS)	No exposure	55.5 to 87.5 {80}	55 to 70 {51}
Villeneuve Le Roi ¹ (VLR)	No exposure	67.2 to 88.9 {82}	60 to 80 {50}
Villeneuve-Saint-Georges ¹ (VSG)	61.6 to 84.7 {286}	65.5 to 84.9 {15}	65 to 85 {19}

In the following subsections, methodology used to determine relationships between L_{Aeq} and psychoacoustic and noise indices, and then for testing the proposed relationships is detailed for road traffic noise exposure. Same methodology has been used for railway noise and aircraft noise index relationships. Psychoacoustic and noise indices under study are variables of noise annoyance models built in laboratory conditions and proposed in the literature. Validated relationships for these indices will enable, in this work, noise annoyance models to be tested by using the socio-acoustic survey data. Construction and testing of the relationships are presented per noise exposure in the following subsections.

3.2 Urban road traffic noise indices

Gille and Marquis-Favre (2019) showed that some psychoacoustic and noise indices may be of interest to be used in urban road traffic noise annoyance models. These indices are mean Zwicker's loudness denoted later by N , the derivative of loudness over time $\sigma'(N)$ and URA an indicator proposed by Klein *et al.* (2015) for urban road traffic noise annoyance. These indices appear to be useful to account for annoyance due to various vehicles of urban road traffic (*e.g.* powered-two-wheelers, buses, heavy vehicles and light vehicles). Hereafter, $\sigma'(N)$ and URA are shortly described.

- Derivative of loudness over time $\sigma'(N)$

$\sigma'(N)$ index proposed by Gille *et al.* (2016a) accounts for the irregular and regular fluctuation of loudness N over time. It is defined as follows:

$$\sigma'(N) = \sqrt{\frac{1}{T} \int_0^T \left(\frac{dN}{dt}\right)^2 dt} \quad (1)$$

- Urban Road vehicle pass-by noise Annoyance, denoted by *URA*

URA is a regression relationship using the indices N , $m_{sputt,10}$, $m_{nas,10}$ and *TETC* (Klein *et al.*, 2015). This aggregated index reports on the perceived acoustic intensity, and on sensations related to amplitude modulations and spectral content.

$$URA = 0.50 \cdot N + 2.85 \cdot m_{sputt,10} + 3.51 \cdot m_{nas,10} + 0.026 \cdot TETC_{16-24} - 0.79 \quad (2)$$

Total energy of the tonal components within critical bands from 16 to 24 Barks, denoted by $TETC_{16-24}$, is an index which accounts for tonal components at high frequencies. The general formula is as follows (Cf. Trollé *et al.*, 2014; Trollé *et al.*, 2015):

$$TETC_{z_1-z_2} = 10 \cdot \log_{10} \left(\int_{z_1-1}^{z_2} 10^{L(z)/10} dz \right) \quad (3)$$

With $L(z)$ the maximal level (across time) of the tonal components as a function of the critical-band rate z , integrated from z_1 to z_2 Barks. It has been originally proposed by Trollé and his colleagues (Trollé *et al.*, 2014; Trollé *et al.*, 2015) within the critical bands from 12 to 24 Barks. Klein and his colleagues (2015) have proposed for the urban road traffic noise to use this index within the critical bands from 16 to 24 Barks, and denoted by $TETC_{16-24}$.

Sputtering index m_{sputt} and nasal modulation index m_{nas} enable to characterize amplitude modulation due to urban road traffic noise (Klein *et al.*, 2015). Sputtering modulation index m_{sputt} accounts for modulation frequencies up to 100Hz:

$$m_{sputt_i} = \left[\frac{2 \cdot |P_{max}(2 - 100Hz)|}{P(0)} \right] \quad (4)$$

With $P(0)$ the dc component of the signal and P_{max} the highest modulation component in the frequency range from 2 to 100 Hz within a time frame i .

Nasal modulation index m_{nas} accounts for modulation at higher frequencies:

$$m_{nas_i} = \left[\frac{2 \cdot |P_{max}(100 - 200Hz)|}{P(0)} \right] \quad (5)$$

with $P(0)$ the dc component and P_{max} the strongest modulation frequency component in the range from 100 to 200 Hz, within a time frame i .

The indices $m_{sputt,10}$ and $m_{nas,10}$ correspond to the values of the indices which are exceeded in 10% of the time. They are respectively related to sensations of amplitude modulations at modulation frequency below 100 Hz (*i.e.* low-frequency modulation) and at modulation frequency between 100 and 200 Hz (Cf. the associated verbatim data “Scooter with a noise like a buzzing of a wasp” collected in the study of Klein *et al.*, 2015).

3.2.1 Construction of road traffic noise index relationships

The index database from Villeneuve-Saint-Georges city was considered to investigate the trend of N , URA and $\sigma'(N)$ index values displayed versus L_{Aeq} values for the 286 audio excerpts of the corresponding urban road traffic noise. For the 3 indices, their values displayed versus values of L_{Aeq} evolves exponentially (as illustrated in Figure 1 for loudness values).

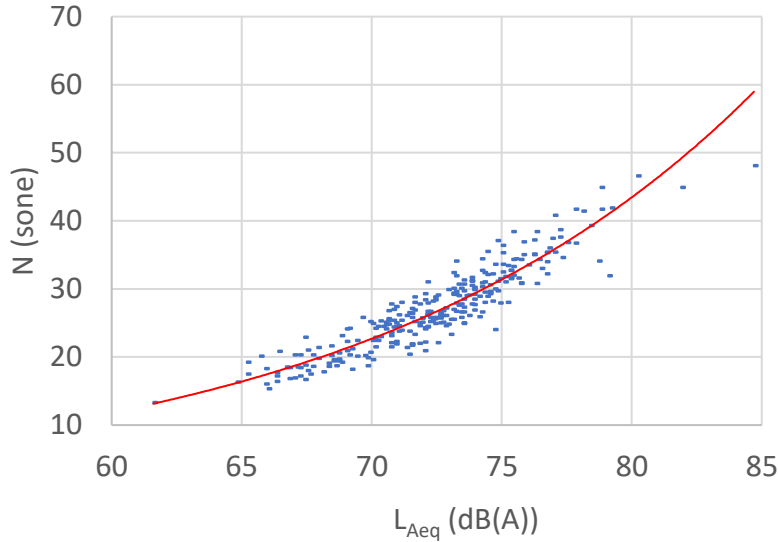


Figure 1. Loudness N values versus the values of L_{Aeq} for the 286 audio excerpts stemming from recordings carried out in Villeneuve-Saint-Georges city. The curve displays the exponential trend of the data.

For each of the 3 indices N , URA and $\sigma'(N)$, exponential regressions were built between their respective values and L_{Aeq} values. The corresponding equations are given in Table 5.

Table 5. Index relationships between L_{Aeq} of urban road traffic noise sources and psychoacoustic and noise indices. These exponential regressions were built from the urban road traffic index database of Villeneuve-Saint-Georges (VSG). (p-values: $p < 0.001$. For 95 % confidence intervals, see Appendix A.1).

$N = 0.24 \cdot e^{0.065 \cdot L_{Aeq}}$
$URA = 0.184 \cdot e^{0.0607 \cdot L_{Aeq}}$
$\sigma'(N) = 1.55 \cdot e^{0.0599 \cdot L_{Aeq}}$

One may wonder whether the relationship obtained for loudness is relevant when compared to the well-known Stevens' equation (Stevens, 1955), and defined in the following as a function of sound pressure:

$$N = k \cdot p^{0.6} \quad (6)$$

The obtained relationship of loudness in the current study is in the form of the equation:

$$y = K \cdot e^{b \cdot L_{Aeq}} \quad (7)$$

The transformation of Eq. (7) into an equation written as Stevens' one led to the following expression:

$$y = \frac{K}{e^{20 \cdot b \cdot \log p_{ref}}} \cdot p_A^{\frac{20 \cdot b}{\ln(10)}} \quad (8)$$

with p_A the A-weighted sound pressure and p_{ref} the reference sound pressure equal to $2 \cdot 10^{-5}$ Pa.

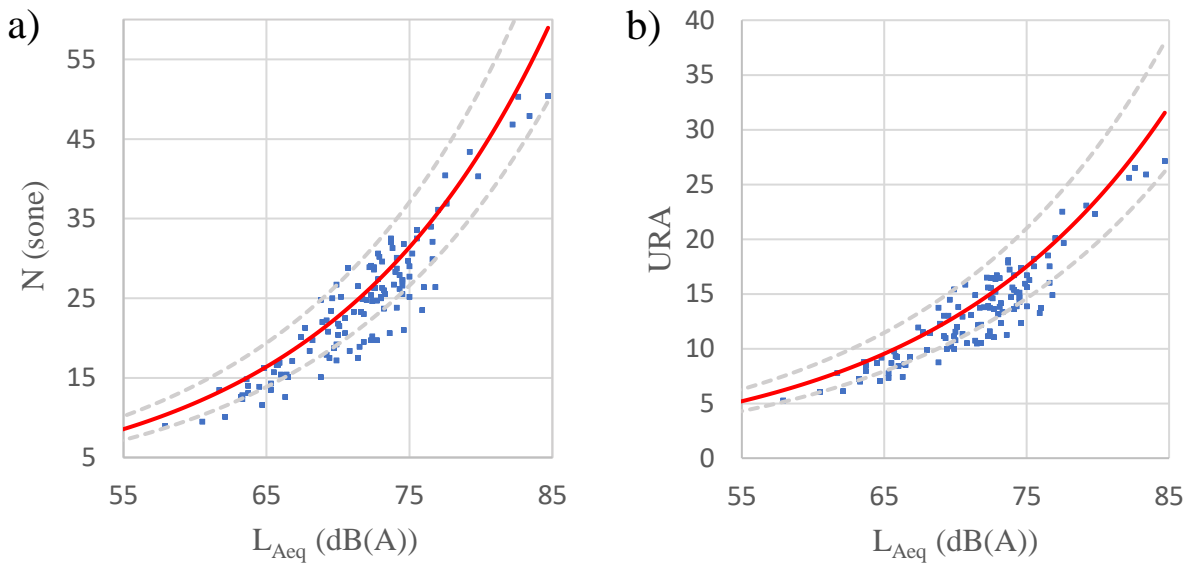
The value of $\frac{20 \cdot b}{\ln(10)}$ is equal in the current work to 0.564. The two equations are therefore very close. The slight difference in the exponent of pressure can be due to the facts: 1) complex sounds, with time-varying spectral content, were considered in this work, whereas the Stevens' equation was determined for pure tones, and 2) the A-weighted sound pressure was considered whereas the pressure was not weighted in Stevens' equation.

3.2.2 Testing of the built road traffic noise index relationships

Prediction intervals were used to assess prediction quality of the built exponential relationships. Details for prediction intervals are described in Annex A.1.

Testing of the relationships built for urban road traffic noise indices is presented hereafter by comparing the built relationships (Cf. their exponential expression given in Table 5) to index values from two new datasets: 1) another urban road traffic noise recorded in the city of Paray-Vieille-Poste (Cf. Figure 2), and 2) a suburban road traffic noise recorded in the city of Saint-Brice-sous-Forêt (Cf. Figure 3).

* Testing of the index relationships using the urban road traffic index database from Paray-Vieille-Poste (PVP) city



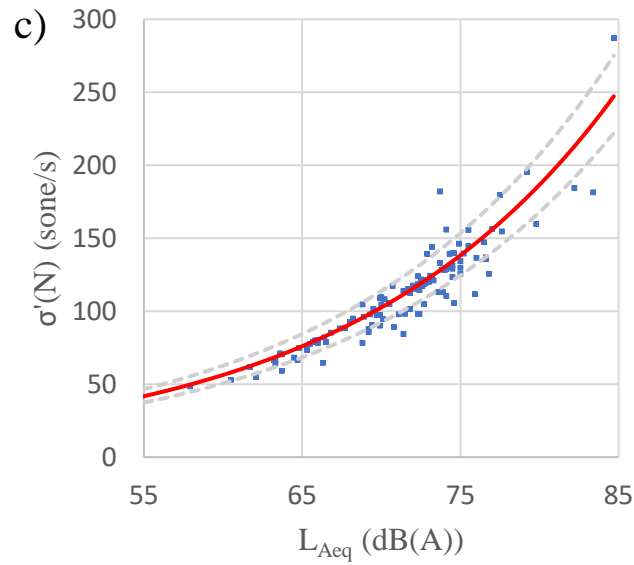
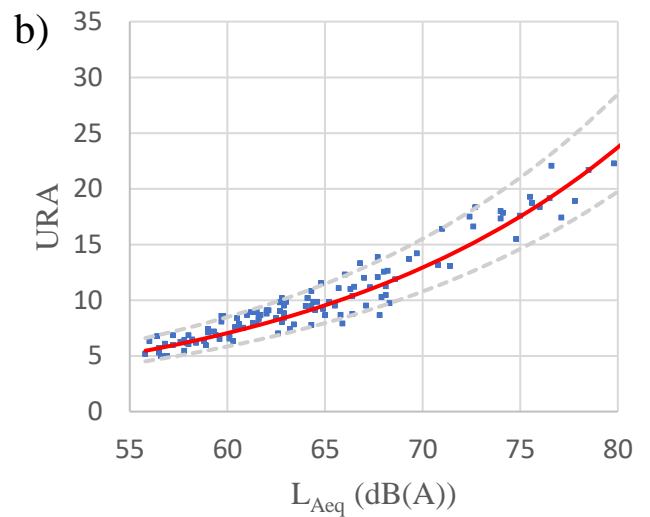
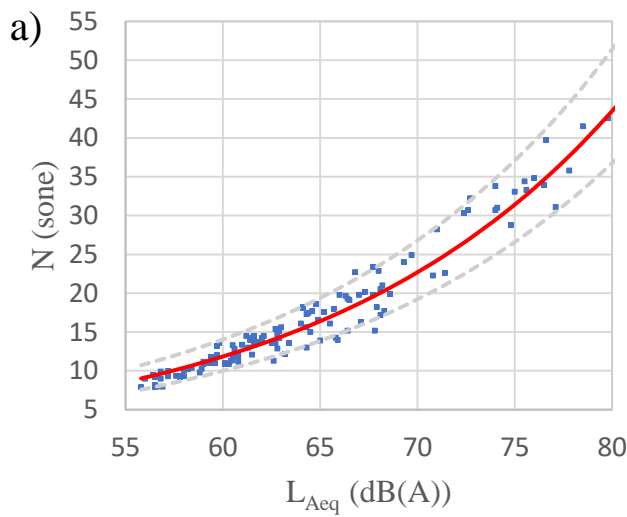


Figure 2. Testing of index relationships using the urban road traffic index database from PVP city. - : built index relationship (Cf. Table 5); - - - : 95% prediction intervals (Cf. Annex A.1); · : index values from PVP index database. a) N index; b) URA index; c) $\sigma'(N)$ index.

*** Testing of the index relationships using the suburban road traffic index database from Saint-Brice-sous-Forêt (SBF) city**



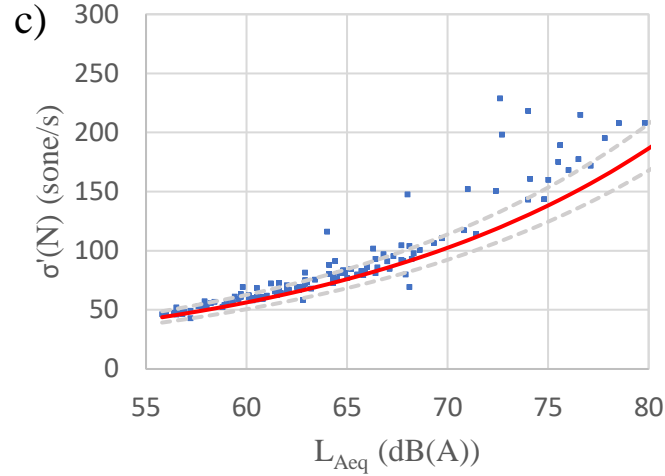


Figure 3. Testing of the index relationships using the suburban road traffic index database from SBF city. - : built index relationship (Cf. Table 5); - - - : 95% prediction intervals (Cf. Annex A.1); * : index values from SBF index database. a) N index; b) URA index; c) $\sigma'(N)$ index.

Index relationships built for N and URA from the urban road traffic noise source L_{Aeq} at VSG city globally allow a good prediction of N and URA for another urban road traffic noise (PVP city – Cf. Figure 2), and also for a suburban road traffic noise (SBF city – Cf. Figure 3). Index relationships built for $\sigma'(N)$, derivative of loudness over time, allow in general a good prediction of this index for another urban road traffic noise (PVP – Cf. Figure 2), but the prediction quality may fail for a suburban road traffic noise (SBF – Cf. Figure 3) at high values of L_{Aeq} . It seems that the relationship of the index accounting for fluctuation and built from audio excerpts of urban road traffic (*i.e.* with 50 km/h speed limit) fails to account for strong amplitude fluctuations present in the suburban road traffic noise in which vehicle speed variation might be higher from traffic lights to a maximum speed equal to 90 km/h.

Thus, the relationship for this index has also been built in this study from suburban road traffic noise of SBF index database, its equation is given as follows ($p < 0.001$; Appendix A.1 gives 95 % confidence interval information):

$$\sigma'(N) = 0.90 \cdot e^{0.070 \cdot L_{Aeq}} \quad (9)$$

This equation built from noise of suburban road traffic (with 90km/h speed limit) of SBF index database has been tested using noise of urban road traffic (*i.e.* with 50km/h speed limit) of VSG index database. Due to index databases available, it was not possible to test this equation for another suburban road traffic noise. Figure 4 displays the results of the testing. Most of the index values from VSG index database are within the prediction intervals. This relationship tested for VSG urban road traffic noise seems to lead to a good prediction quality. The location of the points from VSG index database close to the lower 95% prediction interval curve might be explained by the difference of the speed limits of the respective road traffics used for the relationship determination and testing.

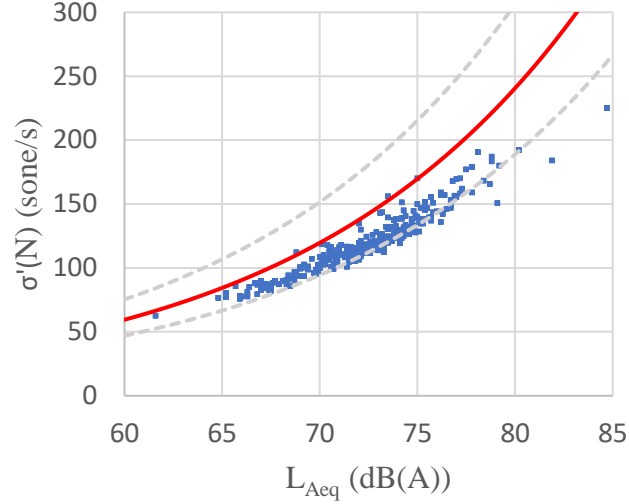


Figure 4. The $\sigma'(N)$ index relationship built from the suburban road traffic noise of SBF index database and tested using urban road traffic of VSG index database. - : built index relationship (Cf. Eq.(9)); - - - : 95% prediction intervals (Cf. Annex A.1); · : index values from VSG index database.

The different index relationships proposed for urban and suburban road traffic noise are summed up in Table 6.

Table 6. Index relationships between L_{Aeq} of urban and suburban road traffic noise sources and psychoacoustic and noise indices. (p-values: $p < 0.001$. Appendix A.1 displayed information for 95 % confidence and prediction intervals).

$$N = 0.24 \cdot e^{0.065 \cdot L_{Aeq}}$$

$$URA = 0.184 \cdot e^{0.0607 \cdot L_{Aeq}}$$

$$\sigma'(N) = 1.55 \cdot e^{0.0599 \cdot L_{Aeq}} \text{ for urban road traffic}$$

$$\sigma'(N) = 0.90 \cdot e^{0.070 \cdot L_{Aeq}} \text{ for suburban road traffic}$$

These index relationships can be used to account for psychoacoustic and noise index estimation from noise source L_{Aeq} in field studies dealing with urban and suburban road traffic noise assessment (*e.g.* soundscape, annoyance). In section 4, the relationships will be used to define variables of road traffic noise annoyance models proposed by Gille and Marquis-Favre (2019).

3.2.3 Testing of index relationships proposed in the literature

In this section, the proposed relationships are compared with those built in Gille and Marquis-Favre (2019) for urban road traffic noise following a different methodology. These relationships were built from 120 pass-by noises at PVP city. Each index relationship resulted

from the average of 120 relationships. Each of the 120 relationships had been built by varying the mean sound pressure level of a pass-by noise among the 120 excerpts. The averaged index relationships are given in Table 7.

Table 7. Index relationships between psychoacoustic indices and urban road traffic noise source L_{Aeq} built from the methodology proposed in Gille and Marquis-Favre (2019) for urban road traffic noise from PVP city.

$$\begin{aligned}
 N &= 23.99 \cdot e^{(0.0747 \cdot (L_{Aeq} - 71.1))} \\
 URA &= 13.29 \cdot e^{(0.0528 \cdot (L_{Aeq} - 71.1))} \\
 \sigma'(N) &= 113.87 \cdot e^{(0.0568 \cdot (L_{Aeq} - 71.1))}
 \end{aligned}$$

The relationships were tested using VSG and SBF index databases. As the variance and covariance matrices for the relationships were not known, the testing of these relationships was classically carried out by calculating the correlation coefficient r , the slope and intercept of the simple regression line drawn between predicted index values and index values stemming from the index databases. For a perfect prediction, r , slope and intercept have to be respectively equal to 1, 1 and 0. Correlation coefficient, slope and intercept, are given in Table 8, for the three relationships tested using two sets of data.

Table 8: Results for Gille and Marquis-Favre (2019) relationships built from PVP index database, and tested using VSG and SBF index databases. $p < 0.001$.

Databases used for the testing	Index relationships	Correlation coefficient	Slope	Intercept
Urban road traffic noise (VSG)	N	0.92	1.01	-0.29
	URA	0.91	0.69	3.86
	$\sigma'(N)$	0.96	0.91	15.26
Suburban road traffic noise (SBF)	N	0.98	1.00	-1.10
	URA	0.97	0.79	1.72
	$\sigma'(N)$	0.92	0.58	30.67

For a comparison with the relationships proposed in the current study, the testing carried out in section 3.2.2 is expressed in Table 9 in terms of correlation coefficients between predicted index values and index values from the index databases.

Table 9: The current index relationships built from VSG index database (Cf. Table 5) and tested using PVP and SBF index databases. $p < 0.001$.

Databases used for the testing	Index relationships	Correlation coefficient	Slope	intercept
Urban road traffic noise (PVP)	N	0.93	0.93	3.42
	URA	0.93	0.93	2.19
	$\sigma'(N)$	0.93	0.90	14.11

Suburban road traffic noise (SBF)	N	0.98	0.90	1.56
	URA	0.97	0.94	0.33
	$\sigma'(N)$	0.92	0.58	25.92

These results depict a same order of magnitude and a similar precision between relationships from Gille and Marquis-Favre (2019) and those constructed following the methodology proposed in the current work. Testing of Gille and Marquis-Favre's relationships (2019), carried out in the current work, highlights the validity of the method proposed in Gille and Marquis-Favre (2019) in order to build relationships between L_{Aeq} of urban road traffic noise sources and psychoacoustic and noise indices. The testing of these relationships and of the relationships proposed in the current work (Cf. sections 3.2.2) shows a good prediction quality, and indicates their use for field studies dealing with urban and suburban road traffic noise assessment (e.g. soundscape, annoyance).

3.3 Railway traffic noise indices

Methodology detailed in the previous section for road traffic noise indices has been applied to construct and to test the relationships between noise indices and railway noise L_{Aeq} . Thus, results of the main steps are given in this section after the presentation of the railway noise indices under consideration. The indices were highlighted in Trollé *et al.* (2014; 2015) dealing with tramway noise, and Vallin *et al.* (2018) dealing with different types of trains in urban areas. These works carried out in laboratory conditions considered different indices in multilevel noise annoyance models and showed an enhancement of the explained variance in comparison with the one from noise annoyance models solely based on mean sound pressure level. The noise indices, denoted by $TETC$, L_{fluc} and $\sigma'(L, T)$, are presented hereafter.

- Total energy of the tonal components in critical bands: $TETC_{12-24}$ and $TETC_{16-24}$
 $TETC_{12-24}$ was proposed by Trollé *et al.* (2014; 2015) to be used in a tramway noise annoyance model to account for annoying sensations at high frequencies such as squeal noise. The index stems from Eq. (3) with an integration from 12 to 24 Barks. This index was also used to account for annoying sensations evoked by railway noise by Sharp *et al.* (2014). The index $TETC_{16-24}$, with an integration from 16 to 24 Barks, was used by Vallin *et al.* (2018) to account for annoying high frequency content due to different types of trains (intercity trains, suburban trains, freight trains, etc.) in urban areas.

- Fluctuation index L_{fluc}
 L_{fluc} is an index accounting for irregular temporal amplitude fluctuations. Vallin *et al.* (2018) defined this index as the arc length of the instantaneous A-weighted level $L_A(t)$, sampled every 2 ms and with a normalized duration between 0 and 1:

$$L_{fluc} = \int_0^1 \left\| \frac{dL_A}{dt} \right\| dt = \int_0^1 \sqrt{1 + \left(\frac{dL_A}{dt} \right)^2} dt \quad (10)$$

This index may account for sensations evoked by irregular variations in amplitude.

- Fluctuation duration-related $\sigma'(L_A, T)$

This index accounts for amplitude fluctuations due to train pass-bys, and considers the pass-by noise duration T (Vallin *et al.*, 2018):

$$\sigma'(L_A, T) = \sqrt{\int_0^T \left(\frac{dL_A}{dt}\right)^2 dt} \quad (11)$$

This index may account for sensations due to regular and irregular variations in amplitude.

3.3.1 Construction of railway traffic noise index relationships

Methodology proposed and tested in section 3.2 for road traffic noise was applied in this section on railway index databases to build and test index relationships. Index databases presented in Table 4 for railway noise exposure were divided into two index databases, one for the relationship construction, and one for the relationship testing. Due to the small sample size of the railway index databases (*Cf.* Table 4), the index database stemming from the cities Villeneuve-Le-Roi and Goussainville, denoted later by VLR+GOUS, was used for the construction of the relationships between the noise indices and the railway noise source L_{Aeq} . Index database from Villeneuve-Saint-Georges (VSG) city was considered to test the built index relationships.

VLR+GOUS index database enabled to investigate the trend of the index values versus L_{Aeq} values. Variation of the indices L_{fluc} and $\sigma'(L, T)$ versus L_{Aeq} evolved exponentially, whereas $TETC$ indices displayed a linear variation versus the mean sound pressure level. Relationships were thus an exponential function of L_{Aeq} , for L_{fluc} and $\sigma'(L, T)$, and a linear function of L_{Aeq} for $TETC$ indices. The equations are presented in Table 10.

Table 10. Index relationships between noise indices and railway traffic noise source L_{Aeq} . The relationships were built from the VLR+GOUS railway traffic index database. (p-values: $p < 0.05$. For 95 % confidence intervals, see Appendix A.2).

$TETC_{12-24} = -10.61 + 1.35 \cdot L_{Aeq}$
$TETC_{16-24} = 28.3 + 0.70 \cdot L_{Aeq}$
$L_{fluc} = 22.69 \cdot e^{0.031 \cdot L_{Aeq}}$
$\sigma'(L, T) = 96.45 \cdot e^{0.003 \cdot L_{Aeq}}$

3.3.2 Testing of the built railway traffic noise index relationships

Testing of the built index relationships (expression given in Table 10) was carried out considering their respective 95% prediction intervals (*Cf.* Appendix A.2) using railway noise index database obtained from the audio excerpts from VSG city (*Cf.* Figure 5).

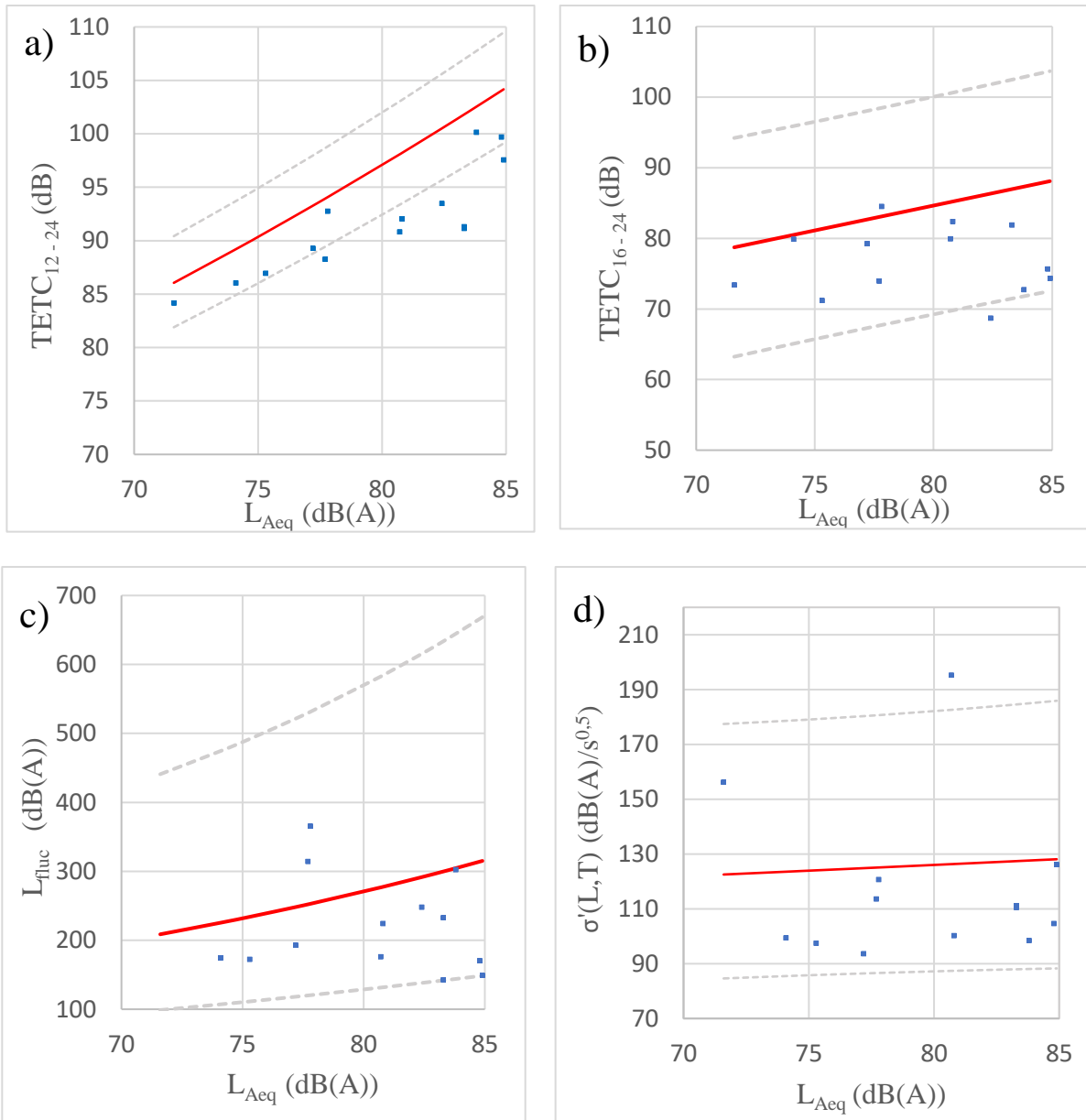


Figure 5. Testing of index relationships using VSG railway traffic noise index database.

- : built index relationship (Cf. Table 10); - - - : 95% prediction intervals (Cf. Annex A.2);
- : index values from VSG index database. a) $TETC_{12-24}$ index; b) $TETC_{16-24}$ index; c) L_{fluc} index; d) $\sigma'(L,T)$ index.

Despite the small size of railway index databases compared to the ones available for road traffic noise (Cf. Table 4), construction and testing of railway index relationships lead to a satisfactory prediction quality, with most of the index values from VSG index database within the 95% prediction intervals (Cf. Figure 5).

3.4 Aircraft noise indices

Methodology presented in section 3.2 for road traffic noise is considered in this section for aircraft noise index databases in order to build and test index relationships. For aircraft noise, some psychoacoustic indices have been shown to be interesting for noise annoyance modeling (Cf. Gille and Marquis-Favre, 2019). The indices are:

- mean loudness denoted by N ,
- total loudness exceeded 10% of the time N_{10} ,
- derivative of loudness over time $\sigma'(N)$ (Cf. Eq. 1),
- N_{1-12} mean specific loudness integrated between Barks 1 and 12, to account for low and medium frequency content of aircraft noise,
- total energy of the tonal components (Cf. Eq. 3), $TETC_{13-18}$ within the critical bands from 13 to 18 Barks, to account for annoying tonal components in aircraft noise at high frequencies.

3.4.1 Construction of aircraft noise index relationships

From Table 4, two index databases were respectively considered for the construction and the testing of the index relationships. Due to the small size of aircraft index databases, index database stemming from the cities Villeneuve-Le-Roi, Goussainville and Saint-Brice-sous-Forêt (later denoted by VLR+GOUS+SBF) was used for the construction of the relationships. Index database from Villeneuve-Saint-Georges (VSG) city was considered for testing the built index relationships.

As in sections 3.2 and 3.3, relationships based on loudness were well approximated by an exponential function of L_{Aeq} , whereas $TETC$ index was a linear function of the mean sound pressure level. The obtained relationships are displayed in Table 11.

Table 11. Index relationships between indices and aircraft noise source L_{Aeq} . The relationships were built from the aircraft noise index database (VLR+ GOUS+SBF). (p-values: $p < 0.05$. For 95 % confidence intervals, see Appendix A.3).

$$N = 0.10 \cdot e^{0.075 \cdot L_{Aeq}}$$

$$N_{10} = 0.59 \cdot e^{0.056 \cdot L_{Aeq}}$$

$$\sigma'(N) = 0.59 \cdot e^{0.072 \cdot L_{Aeq}}$$

$$N_{1-12} = 0.17 \cdot e^{0.065 \cdot L_{Aeq}}$$

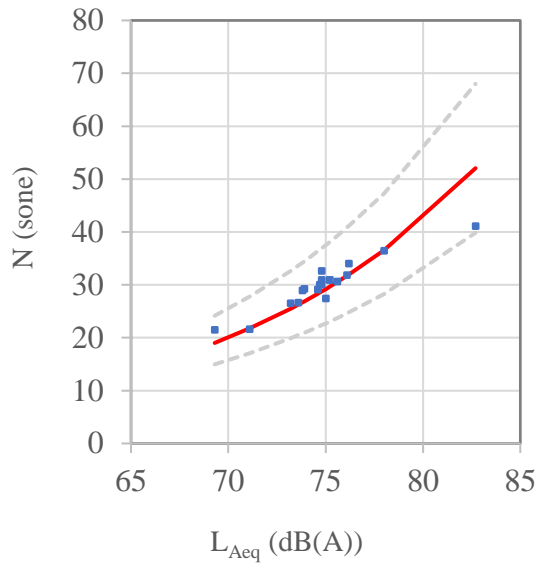
$$TETC_{13-18} = -36.17 + 1.78 \cdot L_{Aeq}$$

Comparison of the loudness relationship to the equation from Stevens (1955) obtained between loudness and the pressure of pure tones following the rationale described in section 3.2.1 led to a coefficient equal to 0.65 for aircraft noise loudness which is close to 0.6, the one in Stevens' equation.

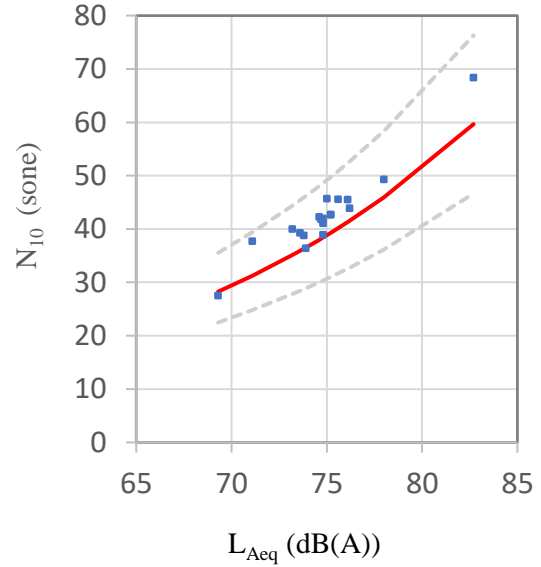
3.4.2 Testing of the built aircraft noise index relationships

VSG aircraft noise index database was used for testing the proposed aircraft noise index relationships.

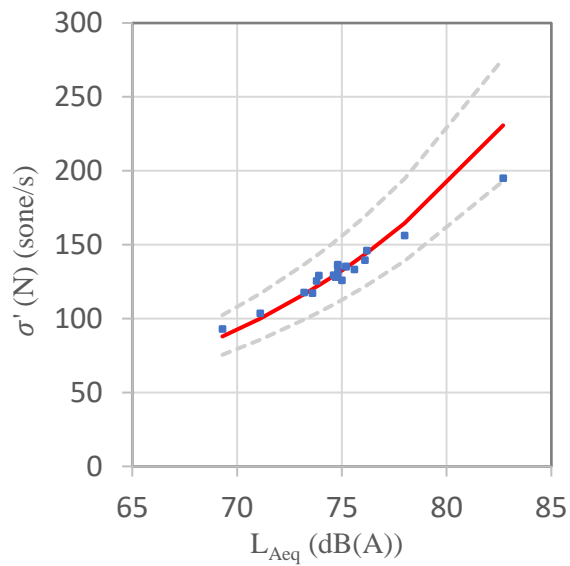
a)



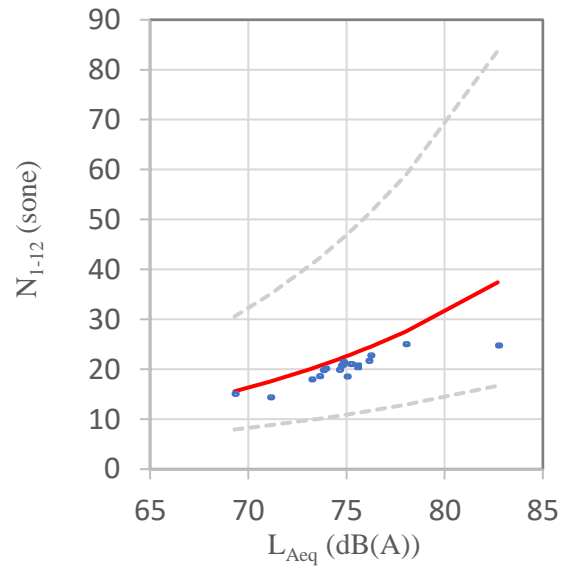
b)



c)



d)



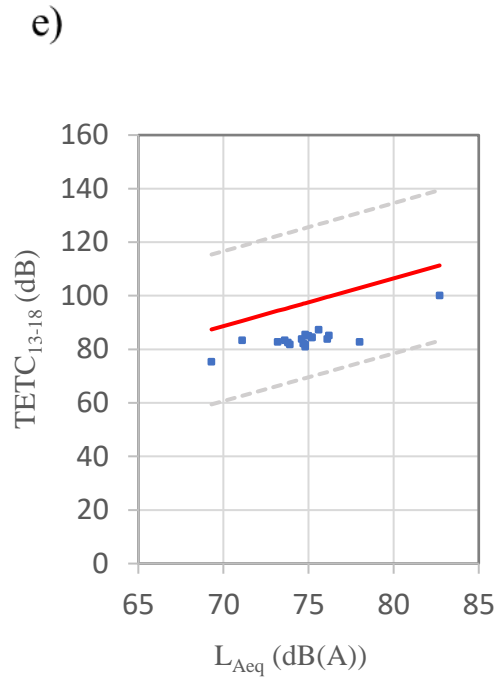


Figure 6. Testing of index relationships using VSG aircraft noise index database.

-: Built index relationship (Cf. Table 11); --- : 95% prediction intervals (Cf. Annex A.3); ·: index values from VSG index database. a) N index; b) N_{10} index; c) $\sigma'(N)$ index; d) N_{1-12} index; e) $TETC_{13-18}$ index.

As in the case of railway noise (section 3.3), construction and testing of the aircraft noise index relationships lead to a satisfactory prediction quality despite the small size of the available index databases (Cf. Table 4).

3.4.3 Testing of other index relationships proposed in the literature

As in section 3.2.3 for road traffic index relationships, aircraft index relationships might be compared with those proposed in the literature. Actually, Gille and Marquis-Favre (2019) proposed relationships to estimate psychoacoustic indices from L_{Aeq} of aircraft noise following a methodology based on the determination of a relationship per source (Cf. section 3.2.3 detailing the methodology), *i.e.* per flyover, and the final proposed relationship obtained by averaging the coefficients of the different relationships determined for flyovers recorded in the survey area close to airport Orly during takeoffs and landings (see Gille and Marquis-Favre, 2019). The proposed averaged index relationships are reminded in Table 12.

Table 12. Index relationships proposed in Gille and Marquis-Favre (2019) for aircraft traffic noise.

$$\begin{aligned}
 N &= 14.83 \cdot e^{(0.0676 \cdot (L_{Aeq} - 68.1))} \\
 N_{10} &= 25.78 \cdot e^{(0.0647 \cdot (L_{Aeq} - 68.1))} \\
 \sigma'(N) &= 75.52 \cdot e^{(0.0591 \cdot (L_{Aeq} - 68.1))} \\
 N_{1-12} &= 11.58 \cdot e^{(0.0656 \cdot (L_{Aeq} - 68.1))} \\
 TETC_{13-18} &= 53.7 + 0.5980 \cdot (L_{Aeq} - 68.1)
 \end{aligned}$$

These relationships were tested in the current work using VSG index database, by calculating the correlation coefficient r , the slope and intercept of the simple regression line drawn between predicted index values and index values stemming from VSG index database (Cf. Table 13). For a perfect prediction, r , slope and intercept have to be respectively equal to 1, 1 and 0.

Table 13: Results for Gille and Marquis-Favre's relationships tested using VSG index database. $p < 0.001$.

Database used for the testing	Index relationships	Correlation coefficient	Slope	intercept
aircraft noise (VSG)	N	0.92	0.96	-5.08
	N_{10}	0.97	0.96	-0.28
	$\sigma'(N)$	0.98	0.92	-3.64
	N_{1-12}	0.83	1.08	15.26
	$TETC_{13-18}$	0.84	0.29	33.29

For a comparison of these results with the relationships proposed in the current study, the testing carried out in section 3.4.2 is expressed in Table 14 in terms of correlation coefficients between the predicted index values and the index values from the index database.

Table 14: The current index relationships tested using VSG index database. $p < 0.001$.

Database used for the testing	Index relationships	Correlation coefficient	Slope	intercept
aircraft noise (VSG)	N	0.92	1.34	-10.64
	N_{10}	0.97	0.78	5.71
	$\sigma'(N)$	0.98	1.35	-44.44
	N_{1-12}	0.83	1.34	-4.41
	$TETC_{13-18}$	0.84	0.87	24.43

The comparison between Gille and Marquis-Favre's relationships (2019) and the current proposed relationships, showed a similar prediction quality when they were both tested using a new index database. As in the case of road traffic noise index relationships from Gille and Marquis-Favre (2019), the current study has enabled the validity of the methodology proposed in Gille and Marquis-Favre (2019) to determine relationships between psychoacoustic indices

and L_{Aeq} of noise sources to be pointed out. The good prediction quality of these relationships and the relationships proposed in the current work indicates their potential relevance to be used in field studies dealing with noise environment assessment such as soundscape or annoyance field studies.

4. Testing of annoyance models from the literature

4.1 Noise annoyance models from the literature under consideration

The different noise annoyance models considered in this work stemmed from the literature. They were built using multilevel regression analysis, either from survey data, or from laboratory data. They are summarized with their respective references in the following subsections per type of transportation noise sources.

4.1.1 Road traffic noise annoyance models from the literature

A road traffic noise annoyance model based on L_{den} was tested in the current study, this model stemmed from (Miedema and Oudshoorn, 2001). The other road traffic noise annoyance models considered in this work were based on the different indices presented in section 3.2. They were built from annoyance and noise sensitivity data collected in laboratory conditions considering different simulated urban road traffic noise exposures (Gille and Marquis-Favre, 2019). The annoyance models are presented in Table 15 hereafter.

Table 15: L_{den} -based model from (Miedema and Oudshoorn, 2001), and different urban road traffic noise annoyance models based on noise sensitivity and indices from (Gille and Marquis-Favre, 2019). A_j : noise annoyance response of the individual j ; $sens_j$: noise sensitivity of the individual j .

Name of Models	Index(ices)	Annoyance model equation
L_{den} -based model	L_{den}	$A_j = 2.22 \cdot L_{den} - 106.97$
L_{Aeq} rand	L_{Aeq}	$A_j = 1.31 + 0.54 \cdot sens_j + 0.34 \cdot (L_{Aeq} - 56.3)$
N mod	N	$A_j = 2.25 + 0.47 \cdot sens_j + (0.35 + 0.05 \cdot sens_j) \cdot (N - 5.67)$
URA mod	URA	$A_j = 2.32 + 0.50 \cdot sens_j + (0.67 + 0.09 \cdot sens_j) \cdot (URA - 4.74)$
LD rand	$N, \sigma'(N)$	$A_j = 3.04 + 0.34 \cdot sens_j + 0.39 \cdot (N - 5.67) + 0.05 \cdot (\sigma'(N) - 33.49)$
$URAD$ fix	$URA, \sigma'(N)$	$A_j = 2.11 + 0.45 \cdot sens_j + 0.37 \cdot (URA - 4.74) + 0.08 \cdot (\sigma'(N) - 33.49)$

4.1.2 Railway noise annoyance models from the literature

A railway noise annoyance model based on L_{den} was considered in the current study, this model was proposed by Miedema and Oudshoorn (2001). Other railway noise annoyance

models considered in this work were based on the different indices presented in section 3.3. These annoyance models were built from annoyance and noise sensitivity data collected in laboratory conditions, simulating tramway noise exposure (Trollé *et al.*, 2014; Trollé *et al.*, 2015) or different railway noise exposures in urban areas (*e.g.* freight train, intercity train, suburban train, high-speed train (TGV) passing-by at low speed - Vallin *et al.*, 2018). The model equations are presented in Table 16.

Table 16: L_{den} -based model from (Miedema and Oudshoorn, 2001), and urban railway noise annoyance models based on noise sensitivity and different indices and proposed by Trollé *et al.* (2014; 2015) and Vallin *et al.* (2018). A_j : noise annoyance response of the individual j ; $sens_j$: noise sensitivity of the individual j .

Name of Models	Index(ices)	Annoyance model equation
L_{den} -based model	L_{den}	$A_j = 2.10 \cdot L_{den} - 110.09$
<i>HF-Fluc. Duration</i> Vallin <i>et al.</i> (2018)	L_{Aeq} , $TETC_{16-24}$, $\sigma'(L, T)$	$A_j = 1.893 + 0.458 \cdot sens_j + (0.032 + 0.014 \cdot sens_j) \cdot (L_{Aeq} - 57.5) + 0.08 \cdot (TETC_{16-24} - 50) + 0.014 \cdot (\sigma'(L, T) - 348.5)$
<i>HF-Fluc.</i> Vallin <i>et al.</i> (2018)	L_{Aeq} , $TETC_{16-24}$, L_{fluc}	$A_j = 1.893 + 0.458 \cdot sens_j + (0.035 + 0.014 \cdot sens_j) \cdot (L_{Aeq} - 57.5) + 0.084 \cdot (TETC_{16-24} - 50) + 0.003 \cdot (L_{fluc} - 146.9)$
<i>MTW</i> Trollé <i>et al.</i> (2014;2015)	L_{Aeq} , $TETC_{12-24}$	$A_j = 1.98 + 0.431 \cdot sens_j + 0.158 \cdot (L_{Aeq} - 57.5) + 0.148 \cdot (TETC_{12-24} - 46.1)$

4.1.3 Aircraft noise annoyance models from the literature

For aircraft noise, the models under consideration in the current work were a model based on L_{den} proposed by (Miedema and Oudshoorn (2001), a model based on noise sensitivity and the day-night level, L_{dn} from (Miedema and Vos, 2003), and different annoyance models based on the different indices introduced in section 3.4. The latter were determined from annoyance and noise sensitivity data collected under laboratory conditions (Gille and Marquis-Favre, 2019) simulating noise exposures in cities close to international airports in France. Equations of all these models from the literature are given in Table 17.

Table 17: L_{den} -based model from (Miedema and Oudshoorn, 2001), noise sensitivity and L_{dn} -based model from (Miedema and Vos, 2003), and annoyance models based on noise sensitivity and indices (Gille and Marquis-Favre, 2019). A_j : noise annoyance response of the individual j ; $sens_j$: noise sensitivity of the individual j .

Name of Models	Index(ices)	Annoyance model equation
L_{den} -based model	L_{den}	$A_j = 2.17 \cdot L_{den} - 91.42$
Noise sensitivity and L_{dn} -based model	L_{dn}	$A_j = 2.41 \cdot L_{dn} + 0.0084 \cdot L_{dn} \cdot sens_j - 98.3$
L_{Aeq} rand	L_{Aeq}	$A_j = 2.03 + 0.30 \cdot sens_j + 0.21 \cdot (L_{Aeq} - 49.3)$
N rand	N	$A_j = 2.89 + 0.24 \cdot sens_j + 0.39 \cdot (N - 7.05)$
N_{10} rand	N_{10}	$A_j = 3.56 + 0.28 \cdot sens_j + 1.14 \cdot (N_{10} - 5.18)$
$\sigma'(N)$ mod	$\sigma'(N)$	$A_j = 1.53 + 0.39 \cdot sens_j + (0.08 + 0.01 \cdot sens_j) \cdot (\sigma'(N) - 22.64)$
$LMLHT$ fix	$N_{1-12}, TETC_{13-18}$	$A_j = 1.43 + 0.40 \cdot sens_j + 0.87 (N_{1-12} - 2.67) + 0.06 (TETC_{13-18} - 44.5)$

4.2 Testing of noise annoyance models using the French survey data

Annoyance models from the literature and summarized in section 4.1. have been tested considering their respective equation displayed in Tables 15 to 17 and using the French survey data presented in section 2, without the constant aircraft noise exposure for PVP city (cf. section 2.3). For the model testing carried out in this work, the variable $sens_j$ in the literature models (Cf. Tables 15 to 17) was replaced by noise sensitivity measured during the survey. For the testing of Miedema and Vos's model (2003), the relation $L_{den} = L_{dn} + 1.2$ was used as the one considered in the literature (e.g. Miedema and Oudshoorn, 2001). The variables given by the different psychoacoustic and noise indices (Cf. Tables 15 to 17) were estimated using the relationships proposed in section 3 and L_{den} from noise maps considered during the survey (Cf. section 2.3). For use of the relationships, an approximation as the one made in the literature (e.g. Nguyen *et al.*, 2012) was done by replacing L_{Aeq} by values of L_{den} . This strong approximation concerns all short-term L_{Aeq} used in this study.

Prediction quality of these noise annoyance models was assessed by calculating the correlation coefficient r , the slope and intercept of the simple regression line drawn between the predicted and the long-term noise annoyance measured during the survey. For a perfect prediction, r , slope and intercept have to be respectively equal to 1, 1 and 0. The results are presented in Table 18.

Table 18: Testing of noise annoyance models from the literature, using measured noise sensitivity and L_{den} from the survey data. r: correlation coefficient between predicted and measured annoyance ratings. Slope and intercept from the line drawn between predicted and measured annoyance ratings. $p < 0.001$.

Models from the literature (Cf. Equations in Tables 15 to 17) and numbers of respondents per noise exposure from the survey	r between predicted and field measured annoyance	Slope	Intercept
Road (702 respondents)			
L_{den} -based model	0.17	0.05	1.6
$L_{Aeq\ rand}$	0.32	0.4	3.5
$N\ mod$	0.34	0.9	7.7
$URA\ mod$	0.33	0.8	6.9
$LD\ rand$	0.26	0.6	8.6
$URAD\ fix$	0.28	0.6	7.2
Railway (611 respondents)			
L_{den} -based model	0.23	0.09	-0.8
HF -Fluctuation Duration	0.42	0.3	4.9
HF -Fluctuation	0.41	0.3	4.8
MTW	0.35	0.4	8.8
Aircraft (369 respondents)			
L_{den} -based model	0.21	0.9	23.6
Noise sensitivity and L_{dn} - based model	0.26	1.3	33.4
$L_{Aeq\ rand}$	0.45	0.2	3.6
$N\ rand$	0.41	0.2	3.0
$N_{10}\ rand$	0.28	0.5	11.5
$\sigma'(N)\ mod$	0.43	0.4	2.8
$LMLHT\ fix$	0.38	0.4	5.7

For information, testing of the urban road traffic noise annoyance model, *LD rand*, based on noise sensitivity and $\sigma'(N)$, led to the same prediction quality whatever the urban or the suburban road traffic noise relationship considered to estimate $\sigma'(N)$ (Cf. the two proposed relationships for $\sigma'(N)$ in Table 6). This was certainly due to the fact that the road traffic noise in the survey under consideration was mainly composed of urban road traffic noise, and thus less adapted to assess a potential benefit of $\sigma'(N)$ relationship proposed for suburban road traffic noise.

Comparison of the testing of the different literature models has overall highlighted that the models originally built in laboratory conditions, and involving noise sensitivity, psychoacoustic, noise indices such as short-term L_{Aeq} , display a better prediction quality compared to models solely based on the long-term mean-energy index L_{den} , and also to the model based on both noise sensitivity and L_{dn} for aircraft noise. The estimation of the different indices from L_{den} of the survey data seems then to be interesting for such an application of environmental noise impact assessment. The prediction quality of models solely based on L_{den} was expected thanks to the correlation coefficients obtained in section 2.4 between the survey variables. The prediction quality of the model based on both the energy-based index L_{dn} and noise sensitivity was expected to be higher due to the good correlation obtained in section 2.4 between noise sensitivity and aircraft annoyance from the survey. In contrarily, the prediction quality of this model is close to the one of the model solely based on L_{den} . The same stands for the aircraft annoyance model based on the psychoacoustic index N_{10} and noise sensitivity: the perceived sound intensity (*i.e.* loudness) exceeded 10 % of the time does not bring a great improvement compared to L_{dn} used in a model also based on noise sensitivity.

Comparison of the prediction quality among the different models based on noise sensitivity and psychoacoustic and noise indices has enabled to highlight differences between the different models proposed in the literature. For railway noise annoyance models, the model originally proposed for tramway noise (*i.e.* light train - Cf. Trollé *et al.*, 2014; Trollé *et al.*, 2015) has a weaker prediction quality than models proposed for various types of trains passing-by in urban areas (suburban train, intercity train, TGV at low speed, freight train). For urban road traffic noise, models based on L_{Aeq} or mean loudness of the pass-bys, or on URA, seem to be interesting for further use in field studies. For aircraft noise annoyance, models based on L_{Aeq} , mean loudness, or the temporal derivative of loudness $\sigma'(N)$ of the flyovers, seem to be also interesting for further use in field studies. Concerning the comparison of aircraft and road traffic noise annoyance models based on noise sensitivity, it seems that their initial construction in laboratory conditions places the model based on both noise sensitivity and short-term L_{Aeq} of the noise sources (*e.g.* road vehicle traffic, aircraft flyovers) in the best ranking of the different models tested, even with L_{Aeq} index roughly approximated by L_{den} for the testing.

5. Discussion

This work proposed relationships between various indices and the A-weighted sound pressure level of different transportation noise sources. The various indices were

psychoacoustic and noise indices highlighted in previous studies to be relevant to account for short-term annoyance assessed in laboratory conditions. Using an index database obtained from field audio recordings, construction and testing of the index relationships proposed in the current work were successful. Thus, the relationships might be useful in large-scale studies dealing with environmental noise assessment. In the current study, it was proposed to use these relationships to investigate the potential benefit of considering various psychoacoustic and noise indices in the long-term goal of enhancing the prediction of annoyance due to transportation noise. To achieve this goal, annoyance models from the literature based on noise sensitivity and these indices were under consideration. French survey data were used to assess the prediction quality of the annoyance models.

The brief analysis of the survey data highlighted that 27.6% of the respondents declared themselves to be highly sensitive to noise, and 70% of them to be sensitive or highly sensitive to noise. These results were in line with findings from the literature (*e.g.* van Kamp *et al.*, 2004; Lechner *et al.*, 2019b). Correlation coefficients between annoyance and L_{den} of the French survey were weak in comparison with some findings from the literature (*e.g.* Brink, 2014), but they were in agreement with some results observed in the literature, even for wide ranges of L_{den} (*e.g.* results from the project HYENA dealing with road traffic noise annoyance in Athens and cited by Guski *et al.*, 2017). From correlation analysis between annoyance and noise exposures of the French survey, it appeared that the ranking of the different transportation noise sources in terms of correlation coefficients was in agreement with the ranking of transportation noise sources in terms of explained variance calculated between annoyance and noise exposure from 41 surveys (Brink, 2014). Correlation coefficients between annoyance and noise sensitivity were in line with findings from the literature (*e.g.* Ryu and Jeon, 2011). These correlation coefficients were also in line with the structural equation analysis carried out on the data of this French survey, highlighting the great contribution of noise sensitivity to annoyance models (*Cf.* Gille *et al.*, 2017).

From the index database built from field audio recordings, the index relationships proposed in the current study were tested by cross-validation. Their testing highlights a good prediction quality. The index database has also enabled to test and validate the relationships proposed by Gille and Marquis-Favre (2019) to estimate psychoacoustic and noise indices from L_{Aeq} of road and aircraft noise sources by following a different approach for the relationship construction. Comparison of their approach and the one proposed in the current work was carried out by testing the respective relationships by cross-validation. The comparison highlights a similar good prediction quality of the respective relationships. These two approaches validated for different environmental noises might be of interest to be considered for other environmental noises (*e.g.* industrial noises, unmanned aerial vehicles, *etc.*) in order to estimate, from L_{Aeq} of the noise sources under study, various psychoacoustic and noise indices which might highlight relevant acoustic features of the noises.

Testing of noise annoyance models using field data has highlighted that, for all transportation noise exposures, the models solely based on L_{den} from Miedema and Oudshoorn (2001) present smaller prediction quality than models based on noise sensitivity and various psychoacoustic and noise indices estimated from noise map L_{den} (*Cf.* Table 18).

For urban road traffic noise annoyance, results obtained by Gille and Marquis-Favre (2019) highlighted that models based on psychoacoustic indices seemed to fit better to the laboratory data than a model based on L_{Aeq} and noise sensitivity. Actually, the model *LD rand* displayed a very good adjustment quality (see Gille and Marquis-Favre, 2019), but in the current work this model was not among the models with the best prediction quality when tested using field data. A possible reason of this weaker performance might be the fact that this model might suffer from a double effect of index approximation as it was based on two psychoacoustic indices and noise sensitivity compared to other models based on noise sensitivity and one estimated index only (Cf. Table 15). The weaker prediction quality for this tested model was in line with its prediction quality when tested using a smaller set of survey data in (Gille and Marquis-Favre, 2019). The same remark stands for the model *URAD fix*, also based on two psychoacoustic indices, in comparison with models based on noise sensitivity and one estimated index (e.g. mean loudness N or L_{Aeq}). In the results of the current testing, the model based on noise sensitivity and short-term L_{Aeq} of the noise sources, which seemed to have a relatively weak adjustment quality in laboratory conditions (Cf. Gille and Marquis-Favre, 2019) presents a good prediction quality and thus, might be interesting for future consideration in field studies. Such a result is in line with the findings from Gille and Marquis-Favre (2019) when the testing of this model using survey data was compared to the other proposed models. Loudness or *URA* indicator used with noise sensitivity within annoyance models also seems to be relevant to be considered in future field studies dealing with urban road traffic noise annoyance.

For railway noise annoyance, the two models built in laboratory conditions for different types of trains passing-by in urban areas (intercity train, suburban train, etc. – Cf. Vallin *et al.* 2018) seem to perform better than a model proposed for tramway pass-bys (Cf. Trollé *et al.* 2014; Trollé *et al.* 2015), when they were tested using survey data including various types of trains in urban areas such as suburban train. One reason may be due to the fact that the light train noise due to tramway was not present in the survey area and the corresponding index database (Cf. section 3.1). It has to be highlighted that the different models based on noise sensitivity and various estimated psychoacoustic and noise indices accounting for annoying sensations perform better than a model solely based on L_{den} .

For aircraft noise annoyance, the different noise annoyance models based on noise sensitivity and various psychoacoustic and noise indices lead to a better prediction quality than the model solely based on L_{den} (Miedema and Oudshoorn, 2001) and a model based on noise sensitivity and the day-night level L_{dn} (Miedema and Vos, 2003). It has to be highlighted that for aircraft noise, road traffic noise and railway noise, models based on noise sensitivity and L_{den} , and built by Gille *et al.* (2016b) from the current survey data, did not show a better adjustment quality than models solely based on L_{den} (Cf. Gille *et al.*, 2016b). Surprisingly, the aircraft annoyance model, based on noise sensitivity and the percentile loudness N_{10} , does not display an interesting prediction quality. The aircraft annoyance model *LMLHT fix*, based on two psychoacoustic indices with the weakest adjustment quality in (Gille and Marquis-Favre, 2019), appears to be interesting in terms of prediction quality when tested using survey data. Other models based on noise sensitivity and one index (short-term L_{Aeq} , mean loudness N , or its temporal derivative $\sigma'(N)$) also show a good prediction quality.

From this current attempt in the long-term goal of enhancing noise annoyance models by proposing relationships between psychoacoustic indices and L_{Aeq} of transportation noise sources, it seems relevant to consider noise sensitivity, the various indices and their related index relationships for future investigations in field studies dealing with annoyance model enhancement.

A limitation of the work is, as mentioned earlier, due to the rough approximation of replacing short-term L_{Aeq} of noise events or of traffic by the long-term mean-energy index L_{den} . Such an extrapolation might be enhanced for some specific applications in soundscape or in field studies dealing with annoyance by defining expressions between short-term L_{Aeq} and noise map L_{den} for the areas studied. Another limitation of the current work might be the proposed index relationships with a validity limited to some study areas. Actually, the relationships have been built from audio recordings carried out in different cities close to Paris. Thus, their use for very different study areas (*e.g.* with different traffics, different topographies) would be an extrapolation. But the extrapolation can be estimated by considering new audio recordings and new testing of the index relationships. In case of no validity of the proposed relationships, new index relationships might be built from the new audio recordings following the methodology proposed and validated in the current work. Another limitation of the current study is to consider annoyance models built from laboratory data. But this limitation has allowed to highlight the good prediction quality of models built from short-term L_{Aeq} in comparison with models built from long-term index such as L_{den} or L_{dn} .

Perspectives to this work would be to consider index relationships in order to build multilevel annoyance models based on noise sensitivity, psychoacoustic indices and short-term L_{Aeq} from survey data with an important sample size, and then to test these new annoyance models using new sets of survey data in order to assess their prediction quality in comparison to the one of models solely based on L_{den} . This would allow to assess whether it would be a benefit to consider the various studied variables to enhance field annoyance prediction.

6. Conclusion

This study proposed a methodology to estimate different psychoacoustic and noise indices from the knowledge of the A-weighted equivalent sound pressure level of different transportation noise sources. For this estimation, a database of index values has been built from audio recordings of road traffic noise, railway noise, and aircraft noise in different French cities. From the index database, index relationships between L_{Aeq} of the transportation noise sources and various psychoacoustic and noise indices were determined, and tested by cross-validation. A good prediction quality of the index relationships, and the validity of the proposed methodology were highlighted. This might be of interest for field studies dealing with environmental noise assessment. In the current study, the index relationships were used to test noise annoyance models from the literature and based on noise sensitivity, various psychoacoustic and noise indices. The model testing considered survey data, with annoyance

and noise sensitivity measured during a survey, and L_{den} from noise maps. The relationships proposed in this work enabled to estimate values of the different indices from L_{den} . The prediction quality of the annoyance models, based on noise sensitivity and the various indices, was satisfactorily compared with the prediction quality of noise annoyance models solely based on L_{den} , and of a model based on both noise sensitivity and aircraft day-night level, L_{dn} .

This work points out the potential interest of the proposed methodology and index relationships in the investigation of enhancing noise annoyance models in future field studies, with the possibility to specifically establish index databases and index relationships for other study areas to account for different acoustic characteristics or different noise sources in these areas.

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Appendix A: 95% confidence and prediction intervals

A.1 Road traffic noise index relationships

For the built exponential relationships (*Cf.* Table 5 and Eq. (9)), variance and covariance matrix coefficients are needed to define both their confidence and prediction intervals. These matrix coefficients were obtained from the linear equations $\ln(index)=a+b \cdot L_{Aeq}$ corresponding to each exponential equation. Coefficients of the covariance and variance matrix S of the linear equations were obtained using Statistica. The coefficients are given in Table A.1 for the exponential relationships obtained for the built index relationships for urban road traffic noise indices (*Cf.* their respective expression in Table 5), and for $\sigma'(N)$ relationship given in Eq. (9) for the suburban road traffic noise.

Table A.1. Coefficients of the variance (Var) and covariance (Covar) matrix S for the corresponding linear regression $\ln(index)=a+b \cdot L_{Aeq}$ of the index relationships obtained for urban road traffic noise (*Cf.* Table 5), and for $\sigma'(N)$ relationship for the suburban road traffic noise (*Cf.* Eq. (9)).

	Regression coefficients (p<0.001)		Coefficients of the symmetric matrix S		
	a	b	Var (a)	Var(b)	Covar(a,b)
$\ln(N)$	-1.43	0.065	0.013	0.0000024	-0.0001747

$\ln(URA)$	-1.69	0.061	0.015	0.0000029	-0.0002091
$\ln(\sigma'(N))$	0.44	0.060	0.005	0.0000010	-0.0000691
$\ln(\sigma'(N))$ Cf. Eq.(9)	-0,105	0.070	0,014	0,000003	-0,000212

Prediction intervals for the linear equations classically correspond to confidence intervals with the additional term, the mean square error (MSE) value, an unbiased variance estimator. Both intervals take into account the variance and covariance matrix S . Thanks to the condition of constant standard deviation of $\ln(index)$, the 95% prediction intervals for the exponential equations are defined as follows:

$$Y_{nl} = \exp(\text{mean}(a) + \text{mean}(b) \cdot L_{Aeq}) \cdot \exp\left(\pm 1.96 \cdot \sqrt{\mathbf{X}^T \cdot \mathbf{S} \cdot \mathbf{X} + \text{MSE}}\right) \quad (\text{A.1})$$

A.2 Railway noise index relationships

For both the 95% confidence and prediction intervals of the built railway noise index relationships and based on the rationale described in annex A.1, the coefficients of the variance and covariance matrix of linear equation $Y=a+b \cdot L_{Aeq}$ are given in Table A.2.

Table A.2. Coefficients of the variance (Var) and covariance (Covar) matrix S for linear equation $Y=a+b \cdot L_{Aeq}$ for the different built index relationships.

	Regression coefficients (p<0.05)		Coefficients of the matrix S		
	a	b	Var (a)	Var(b)	Covar(a,b)
$TETC_{12\ 24}$	-10.61	1.35	15.54	0.002594	-0.20045
$TETC_{16\ 24}$	28.3	0.70	167.47	0.028	-2.160
$\ln(L_{fluc})$	3.12	0.031	0.390558	0.000065	-0.005038
$\ln(\sigma'(L,T))$	4.57	0.003	0.095738	0.000016	-0.001235

A.3 Aircraft noise index relationships

For both the 95% confidence and prediction intervals of the built aircraft noise index relationships and based on the rationale described in annex A.1, the coefficients of the variance and covariance matrix of linear equation $Y=a+b \cdot L_{Aeq}$ are given in Table A.3.

Table A.3. Coefficients of the variance (Var) and covariance (Covar) matrix S for linear equations $Y=a+b \cdot L_{Aeq}$ for the different built index relationships.

	Regression coefficients (p<0.05)		Coefficients of the matrix S		
	a	b	Var (a)	Var(b)	Covar(a,b)
$\ln(N)$	-2.30	0.075	0.000116	0.000002	-0.000015
$\ln(N_{10})$	-0.53	0.056	0.003242	0.000002	-0.000075
$\ln(\sigma'(N))$	-0.53	0.072	0.00299	0.000002	-0.000068
$\ln(N_{1-12})$	-1.77	0.065	0.004659	0.000003	-0.000376

<i>TETC</i> ₁₃₋₁₈	-36.17	1.78	0.012098	58.6	-0.83907
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