ForumAcusticum
2 0 0 5

Traffic noise and perceived soundscapes: a case study

G. Licitra, G. Memoli

ARPAT (Regional Agency for Environmental Protection of Tuscany), Via V. Veneto 22, 56127 Pisa (I), {**g.licitra, g.memoli**}**@arpat.toscana.it** ,

D. Botteldooren, B. De Coensel

Acoustics Group, Department of Information Technology, Ghent University, St. Pietersnieuwstraat 41, 9000 Gent (B), **d.botteldooren@ugent.be**

The present study will deal with a practical problem of noise mapping: the acoustical classification of roads in the medium size municipality of San Giuliano Terme, in Tuscany (I). At first, using a common approach in literature, the main road infrastructures have been classified in three clusters, applying threshold methods to traffic flow measurements. The time history of L_{Aeq} was then acquired in selected sites over a continuous period of 24 hours and the power spectrum $G(f)$ was then calculated from dB values of L_{Aeq} over 15 minute intervals. A power law was fitted to $G(f)$ in the range [0.02, 0.2] Hz, obtaining two parameters - $B(t)$ and $A(t)$ - over a complete day. Hierarchical clustering was finally performed and the clusters obtained resembled the ones based on traffic flow. The values of $B(t)$ and $A(t)$ have been compared with other indicators: comparison with Number of Noise Event (*NNE*) and L_{10}-L_{90} has been reported here. New fitting possibilities for $G(f)$ has also been explored and discussed in this work. Finally, statistical analysis has been used to get further information on the meaning of *B*.

1 Introduction

The search for new indicators to distinguish soundscapes is crucial for the noise control in existing quiet areas, as prescribed by the 2002/49/EC END, and for the drawing up of cost/effective action plans. In this direction, some studies classify external environments acquiring their "acoustical characteristic" and comparing it to people's perceptions both in "quiet" and "disturbed" areas. The final goal is to identify new indicators which could help to design new areas and improve existing ones, directing technical efforts to achieve the "ideal characteristic" of the site, as defined by the expected utilization.

In 1978, R. F. Voss & J. Clarke [1] studied long term variation of loudness, for different kind of man-produced music, in order to find a better way to generate stochastic computer music. They compared the loudness power spectrum of signals acquired during 12 hours in three different radio channels (classical, rock, news) with the ones due to a few classical masterpieces, finding that all these sources shared an *1/f* dynamical behaviour, where the "frequency" *f* is not related to the signal emitted every second, but to the occurrence of events in the time history (i.e.: if the explored range were [0.002, 0.2] Hz, target events would occur in the time interval between 500 ms and 5s). Their observations suggested that musical pieces where the frequency and duration of each note had been determined by *1/f* noise sources sounded "pleasing", while those generated by *1/f ²* (Brownian noise) sources sounded too correlated ("boring", in other words). The modern theory of stochastic chaos has linked *1/f* power spectrums to "self-organized criticality" [2]. As the latter description covers a great number of environmental situations, it

was thought to study the long-term noise dynamics in urban and rural scenarios, seeking in it a finite set of indicators to characterize the site [3]; [4].

A previous study [5] described different soundscapes with 13 parameters calculated from the long-term dynamics of three different signals: $L_{Aeq}(t)$, Zwicker loudness and instantaneous pitch. After acquiring a noise signal in a definite site (15 min. duration during daytime, in 1/3 octave bands), the power spectrum $G(f)$ of Zwicker's loudness and pitch in the range [0.002, 5] Hz was fitted in [5] with:

$$G(f) = A \cdot f^{B} \qquad (1)$$

Hierarchical clustering (H-C, in the following text) based on "within-group linkage" was then performed on the data, using Pearson's correlation coefficient *r* as a distance, obtaining two large clusters that could be characterized as "pleasing" and "predictable".

In more recent works [6] [7], the correlation between the clustering and the soundscape perception was investigated, with particular interest in sites infected by traffic noise. In particular, in [7] it was shown that a fair correlation exists between the perceived soundscape (assessed by simple questionnaires) and clustering results, obtained using the values of *B* at fixed moments during the 24 hours. They also showed that, for each site, the fitted values of *B* did not depend directly on the corresponding L_{Aeq}, but that they gave complementary information, to be interpreted through a deeper study. It was also seen that, when the traffic was low or in night hours, the $G(f)$ dependence in eq. (1) failed to describe the acquired power spectrums over the frequency range.

After dealing with a practical case, using H-C and calculated values of *B* to classify the main roads in a

municipality, the present work will try to cast a deeper glance into the physics of the problem. Values of *B* will be compared with other indicators and *G(f)* will be fitted with other functions, in order to get its full behaviour (i.e.: over the complete frequency range). The last part of this work uses heavy-tail distributions to describe the output of the statistical analysis of $L_{Aeq}(t)$. A possible influence on *B* of the parameters obtained with this approach will be shown.

Figure 1: The municipality of San Giuliano Terme. Spots indicate measurements sites, colors describe the road class (green: 1; yellow: 2; red: 3)

2   Basic classification

Figure 1 presents the main roads that interest the territory of San Giuliano Terme, a 30000 inhabitants municipality near Pisa, in Tuscany (I). A classification of the main roads is needed to harmonize the limits for other activities (due to land planning and decided by the municipality) with those specific for transport infrastructures (which depend mainly on road geometry and have been fixed on a national scale). In order to do that, the usual approach is to assess the noise actually present near the roads of interest to classify them [8].

The streets of San Giuliano were classified using traffic flow data, speed limits (as determined by traffic signs) and road geometry as input data to the CETUR model [9], [10]. Velocity measurements were performed in a few critical situations, in order to check the input information, showing that speed limits were overcome by not more than 10 km/h. Traffic flows were taken between 7:00 AM to 7:00 PM (15 minute interval) and during springtime in two different campaigns: one in 1997 (promoted by San Giuliano municipality) and one in 2002 (Pisa Provincial authority). When two measurements were taken at the same site in the two campaigns, the most recent one has been used here.

Sites were discriminated using a threshold method: less than 350 vehicles/hour (class 1), between 350 and

800 v/h (class 2), over 800 v/h (class 3). The number of classes was decided according to Tuscany's regional guidelines (as a comparison, 4 classes were used in [8]). Calculation at 10 m gave a maximum emission value of 63.5 dB(A) for class 1 and minimum value of 66.5 dB(A) for roads in class 3.

The final classification is graphically represented in Figure 1. Roads where the traffic data changed along the path were divided in homogeneous stretches, as calculated noise emission was different.

The validity of this classification was checked by performing a comparison between the two campaigns over the sites in common. A mean 30% increase of the traffic over the considered period was found (correlation coefficient *R*=0.84): even if 1997 data were updated to 2002, then, the calculated emission would be increased by nearly 1 dB and the proposed classification would not change. A final check was performed for the period 2002-2004 acquiring 1-hour measurements close to rush hour, over a selection of sites. Even using the latter data, no change was observed in the class assignment.

3   Hierarchical clustering

Comparison between the basic road classification, described in section 2, and the land planning issued by the municipality allowed to select the sites where to take sound pressure measurements, in order to check the limits and quantify the actions to be taken. Noise time histories were acquired over a 24-hour period (1 second step) using unassisted sound level meters on the spot (4.0 ± 0.1 m height). The map in Figure 1 highlights the measurement sites, while Table 1 reports the corresponding traffic data.

After acquisition, every signal was partitioned in intervals of 900 seconds and the power spectrum *G(f)* was calculated for each of them, so that:

$$G(f) = \hat{L}_{Aeq}(f) \cdot \hat{L}^*_{Aeq}(f) \qquad (2)$$

where $\hat{L}_{Aeq}(f)$ is the Fourier transform of $L_{Aeq}(t)$ and $\hat{L}^*_{Aeq}(f)$ is its complex conjugate. Fourier transforms were calculated using `Matlab` and digitalized using 800 output values for each interval spectrum. This choice of parameters, optimized after a few tests, gives for every interval a function *G(f)* with 400 points in the range [0.00125, 0.5] Hz.

A typical power function for a class 1 road can be found in Figure 2. It must be stressed again that the obtained "frequency" is not related to the signal emitted every second, but to the time history of L_{Aeq} over an interval of 900 seconds: a peak in the spectrum evidences a repetitive event during this acquisition time. As an example, a peak in the range 0.1 –0.2 Hz was observed sometimes, especially in "class 1"

locations (Figure 2a): a close look at the time history showed that the time lag among peaks in the background was between 5 and 10 seconds (perhaps due to other traffic sources nearby). In the region $f < 0.02$ Hz almost all power spectrums $G(f)$ were flat. This phenomenon was probably due to numerical fluctuations in the calculation of $\hat{L}_{Aeq}(f)$, because of the finiteness of the interval (very few points can be found below 0.01 Hz).

A power function of the frequency as in eq. (1) was finally fitted to $G(f)$ in the range 0.02 - 0.2 Hz, using a least-squares method. The chosen frequency range was slightly reduced respect to the one used in [6], in order to exclude the peaks in $G(f)$, when present, and the region where the power spectrum is flat.

Table 1: Some traffic data used in this work.

Site	Vehicles/hour			Theor. L_{Aeq}	Class
	Mean	Max.	Heavy %		
Asciano	740	1139	7	69.0	3
Orzignano	1044	1321	11	68.3	3
Pontasserchio	920	1234	12	67.4	3
Aurelia	1184	1384	22	71.6	3
Mezzana	936	1174	6	69.0	3
Gello_NEW	262	320	7	63.5	1
Puccini	605	833	10	67.3	3
Molina	323	496	9	63.8	2
San Giuliano	677	928	13	66.4	2
San Jacopo	691	939	4	67.6	3
Palanche	469	588	9	64.4	2
Sites with less than 2500 v/day: Agnano, Ghezzano, Metato					

Two time dependences for the fitting parameters were obtained in this way: the exponent $B(t)$ and the multiplying factor $A(t)$. As an example, choosing 900 s intervals gave 96 points in a day with a calculated value of A and B for each. The error on the values of the fitting parameters was estimated as 10%.

Figure 3 presents the calculated values of B for two different sites. It can be seen that this parameter can change very much along a day and from site to site, especially during the night. A detailed discussion on B can be found in [7], where it was demonstrated that $A(t)$ does not add information to the trend of $L_{Aeq}(t)$.

Hierarchical clustering, based on "within-group linkage", was performed using the statistical toolbox of `Matlab` and a distance defined as:

$$d_1(x_1, x_2) = 1 - r(x_1, x_2) \qquad (3)$$

where $r(x_i, y_i)$ is the Pearson's coefficient as in [6]. Figure 4 reports the clustering result, using the 96 values of B calculated over a day; this technique divided the selected sites into two main groups ("noisy" and "quiet" ones).
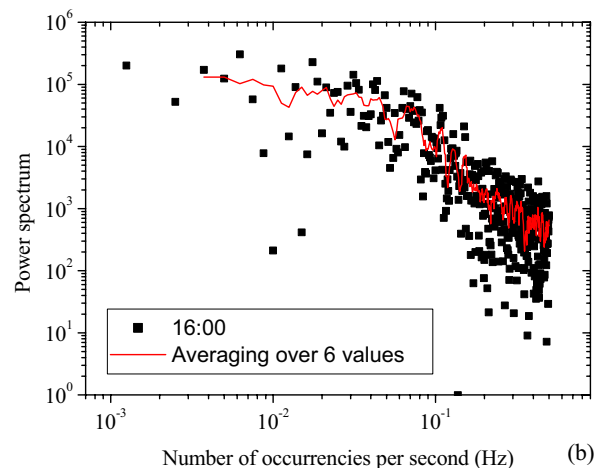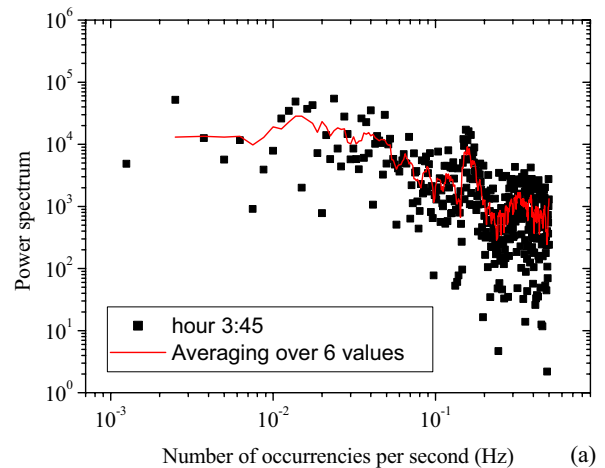

Figure 2: Calculated $G(f)$ at a class 1 location during two 15 minutes intervals (starting at 3:45 AM and at 4:00 PM). Averaged curves underline the trend.

It can also be seen that the obtained clusters resemble the grouping based on traffic flow data, even if no direct correlation was found between the calculated value of B and the corresponding number of passing vehicles for a 900 s intervals.

Clustering by H-C also allocated class 2 roads in one of the two groups. If the link between H-C and perception proposed in [7] were confirmed by a larger study, the clustering in Figure 4 would be more powerful than the one obtained by thresholds. In fact, it would contain both the information given by traffic flow data (not explicitly needed in this section), and an indication on the way people perceive the local soundscape.
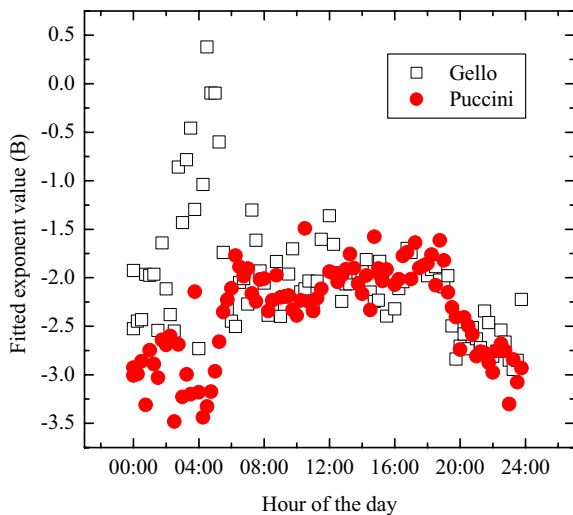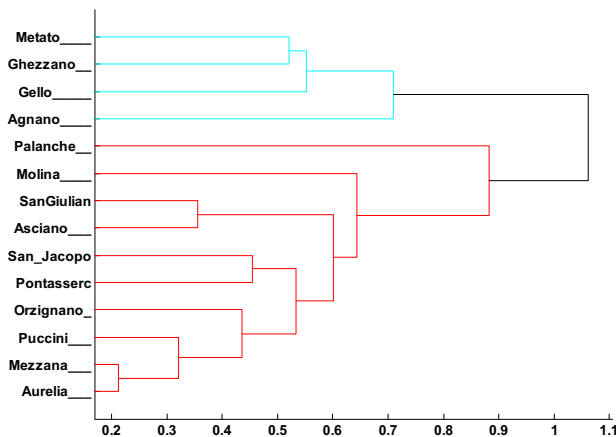
Figure 3: Dependence of *B(t)* for two different sites.

Figure 4: Results of hierarchical clustering using all the 96 values of *B* over a day.

4   Other indicators

If *B(t)* is well related to perception, it seems natural to correlate its value with the number of noise events exceeding the "disturbance threshold" by a certain amount. A good parameter to be compared with *B(t)* is then the Number of Noise Events (*NNE*), defined in the literature as "the number of noise events exceeding an agreed constant limit by a certain amount".

In this study, *NNE* will be defined as the number of events that, in a 15 minutes interval, overcome L_{90} by at least 10 dB(A). This quantity resembles the "number of emergences" indicator, as proposed in [10]; the latter being "the number of times the L_{Aeq} (30s) exceeds the L_{50} (10min) by more than 15 dB(A)" (L_{99} is used as the reference level for school and hospitals, instead). The different choice of reference levels (L_{90} and 10 dB overcome) has been optimized to maximize the trend in

Figure 5, where results have been reported. The behavior of "noisy" (squares) and "quiet" (circles) sites could not be distinguished during daytime, when a slight decrease of *B* corresponded to an increase in *NNE*, so Figure 5 just reports the effect during night hours, when it was possible to characterize two different types of time histories:

- few events over a low background (circles);

- a lot of events with the same energy, but almost undistinguishable among them (squares).
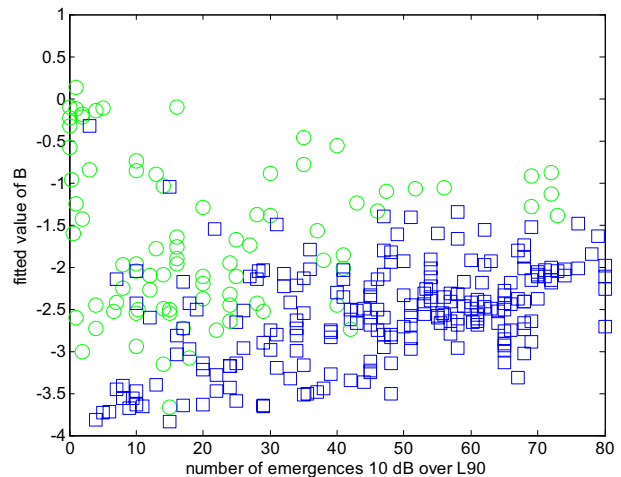

Figure 5: Comparison of *B* and *NNE* for locations in Table 1 in the period 00:00-5:45 AM. The sites have a different L_{Aeq}(period).

The scattering in Figure 5 could be due to the fact that not all the variables were monitored there: "quiet" and "noisy" sites may have a very different distribution for the measured short L_{Aeq}.

Trends very similar to the ones in Figure 5 were in fact obtained using L_{10}-L_{90} (15 min) as independent variable (instead of *NNE*): the latter parameter might mask the actual dependence between *B* and the observed emergences. For this reason Matlab was used to generate artificial signals (24h duration), adding two different sources:

- a signal with well defined peaks (40 s duration) at random positions over the 24 hours (S_1);

- a random signal S_2 given by

$$S_2 = background + gaussian(0,\sigma) \text{ dB(A)} \quad (4)$$

where *gaussian(0,σ)* is a gaussian-distributed value with 0 mean and σ standard deviation. The total signal for each second is then given by a weighted sum:

$$S_F = 10Log\left(C_1 10^{0.1S_1} + C_2 10^{0.1S_2}\right) \text{ dB(A)} \quad (5)$$

where C_1 and C_2 were adjusted before further processing, in order to preserve the total energy (i.e.: the L_{Aeq} over S_F duration) and the difference L_{10}-L_{90}.

These two parameters actually describe the distribution of values for the short L_{Aeq}, so that then dependence of B on it can be controlled. Figure 6 reports the dependence of B on NNE for different values of L_{10}-L_{90}, as calculated by the model: each series of data was obtained varying σ in the range 0-4 dB(A). There is an evident decrease of B with NNE when L_{10}-$L_{90} \leq 14$ dB(A), even if the uncertainty in the value of B at a fixed NNE is very large. The trend stays almost flat, with B comprised between –2 and –3, when higher peaks are present i.e.: for L_{10}-$L_{90} \geq 20$ dB(A),
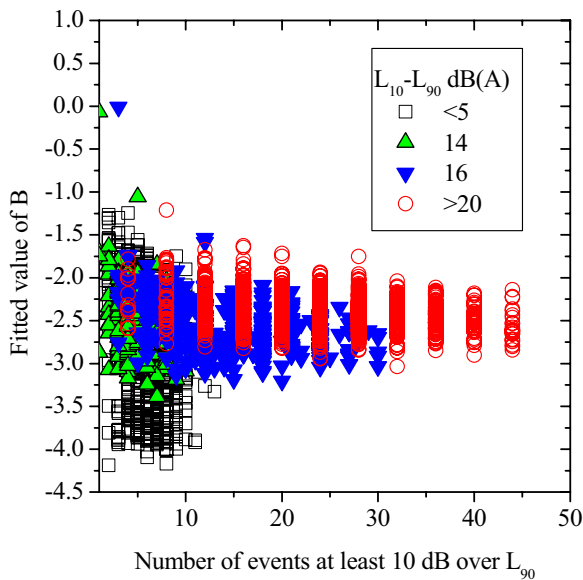

Figure 6: Values of B and NNE calculated with the model for different values of L_{10}-L_{90}.

These observations lead to the conclusion that B is related to the number of "noisy" events mainly in the range $14 \leq L_{10}$-$L_{90} \leq 20$ dB(A), when peaks are well defined over background noise, but not numerous. When $NNE > 10$ the variation of B is in fact very weak, whatever the value of L_{10}-L_{90} (i.e.: how much the peaks overcome the background noise). What has been said also partially explains the trends shown in Figure 3: the two types of locations are similar during the day, when the number of emergences is high, while they differ at night. H-C probably detects this difference.

5 Different models for $G(f)$

As previously stated, eq. (1) describes $G(f)$ just in a limited range of frequencies: it cannot predict the flat behavior at low frequencies or the decrease in slope for $f > 0.2$ Hz. For these reasons, new dependences are needed.

It is well known, by the Wiener-Khinchin (W-K) theorem, that the power spectrum is related to the

autocorrelation function via a Fourier transform. Investigating the frequency dependence of $G(f)$ is then a way to get information about the degree of correlation between the events in the time history. As an example, Lorentzian functions are usually used to describe in the frequency domain a system whose correlation function $C(\tau)$ decreases exponentially:

$$G(f) = \frac{1}{1 + 4\pi^2 a^2 f^2} \leftrightarrow C(\tau) = \frac{1}{a\sqrt{8\pi}} \exp\left(-\left|\frac{\tau}{a\pi}\right|\right) (6)$$

where τ is the lag time used in calculating the autocorrelation and $1/\pi a$ is the half-height width of the $G(f)$. This is the typical behaviour for systems characterized by independent, identically distributed random events, as in theoretical random traffic. In this model, it can be shown that the number of events at a given time has a Poisson Probability Density Function.

A Lorenz peak similar to the one in eq. (6) was tried as fitting function for $G(f)$ in order to get the behavior for $f > 0.02$ Hz. The position of the peak center was left free to optimization. As an example, the best fit for the data in Figure 2b (B=-0.9) gives: center at 0.03 Hz and half-height width equal to 0.048 Hz, but R^2=0.052. As similar low values of R^2 were obtained when $B = -2$, which should be the closer behaviour to a Lorentz shaped $G(f)$, the "zero-memory" Lorentzian model was rejected.

Next step was to consider long-tailed distributions. These models come into play where rare events still happen relatively commonly (e.g.: when isolated peaks are present), from the variation of stock prices to the internet traffic. As the measured short L_{Aeq} signals seem to fall into the description above, long tailed distributions should be used to get a further insight into the physics behind the parameter B. The step from the probabilistic model to the correlation function and to $G(f)$ is generally non trivial when long-tailed distributions come into play; for this reason a different approach will be proposed in next section.

6 Statistical analysis

The problem of investigating the meaning of B will be approached here from another point of view. The first step was to treat the measured short L_{Aeq} in each interval as a random variable, with a definite probability distribution function (PDF). This function can be seen producing a "smoothed" histogram, depicting relative frequencies of the measured data. Cumulative density function – CDF(x), giving the probability to have a L_{Aeq} value lesser than x – is then obtained from each experimental PDF. Figure 7 show a few examples, corresponding to fixed values of B.

When the value of B gets closer to zero, the initial and final part of the corresponding "experimental" CDF

grow in importance: they are related to the tails of PDF, which get less steep as peaks become more numerous. In this sense, the shape of PDF (or CDF, as the effect is enhanced in it) might be related to the number of peaks and the way they stand over the background, like *NNE*. The final step was to fit the obtained trend known probability distributions, in order to find the best one to describe the phenomenon.
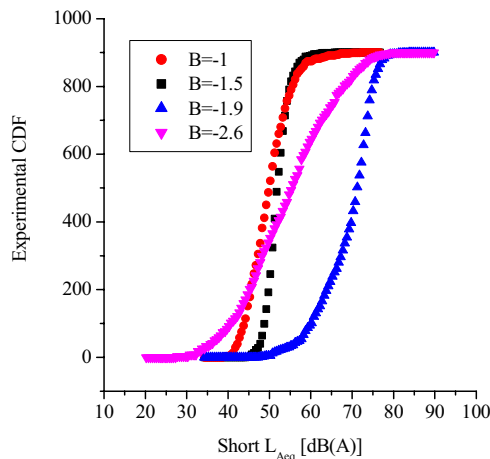

Figure 7: Experimental CDFs relative to different values of B, as determined by the measured data.

Pareto and Logistic distributions (the latter being used in place of the Gaussian distribution when longer tails are needed) were taken as fitting functions, as both present a sigmoid CDF. The fitting session showed that the Logistic model:

$$CDF(x, m, b) = \Gamma\left(1 + \exp\left(\frac{m - x}{k}\right)\right)^{-1} \qquad (7)$$

was much better. Eq. (9) could in fact fit most of the experimental CDFs with $0.98 < R^2 < 0.99$, while $R^2 < 0.9$ using Pareto, which has an hyperbolic power behavior. The comparison between *B* and the Logistic parameter (related to the slope) has been reported in Figure 8, for five different "noisy" sites: even with some dispersion, a definite trend is shown. Figure 8 is then another way to say that, at least for "disturbed" sites, the value of *B* is related to how much peaks modify the L_{Aeq}. The differences with "quiet" sites will be investigated in future studies.

7   Conclusions

Hierarchical clustering has been used to classify the streets in the municipality of San Giuliano Terme using the different values of the parameter *B*, obtained from a power fit on the noise dynamical spectrum over 24 hours. The parameter *B* was then compared with *NNE*, showing that the two indicators do not give the same information. Other fitting functions were then tested on

G(f), trying to relate *B* with "no-memory" and "highly correlated" distributions, in order to understand its meaning. A statistical approach to the dynamic was finally proposed, showing that a Logistic exponential model fits measured CDFs better than a Pareto hyperbolic power dependence. Logistic's main parameter was well correlated to *B*, at least in "noisy" sites.
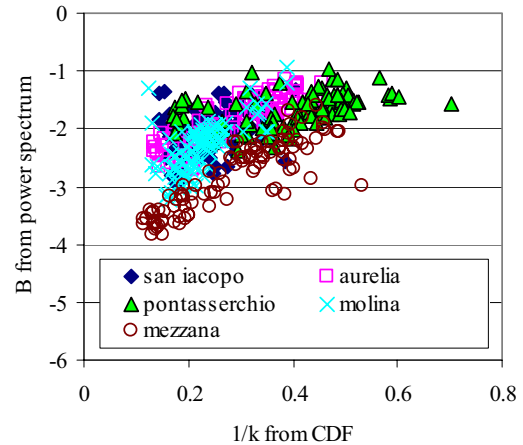

Figure 8: Logistic slope of CDF from eq. (9) vs. power exponent obtained from eq. (1), for 5 fixed locations.

References

[1] Voss R. F. & Clarke J., 1/f noise in music: music from 1/f noise, *J. Acoust. Soc. Am.* **63**, 258-263 (1978)

[2] Davidsen J. & Schuster H., 1/f noise from self organized critical models with uniform driving, *Phys. Rev. E* **62**, 6111-6115 (2000)

[3] Berglund B., P. Hassmen, A. Preis, Annoyance and spectral contrast are cues for similarity and preference of sounds, *Journal of Sound and Vibration* **250**, 53-64 (2002)

[4] Botteldooren D., Verkeyn A., Lercher P., A fuzzy rule based framework for noise annoyance modeling, *J. Acoust. Soc. Am.* **114**, 1487-1498 (2003)

[5] De Coensel B., Botteldooren D., De Muer T., 1/f noise in rural and urban soundscapes, *Acta Acustica* **89**, 287-295 (2003)

[6] De Coensel B., De Muer T., Yperman I., Botteldooren D., The influence of traffic flow dynamics on urban soundscapes, *Appl. Acous.* **66,** 175-194 (2005)

[7] Licitra G., Memoli G., Noise indicators and hierarchical clustering in soundscapes, *Proceedings of INTERNOISE 2005* (in press)

[8] Gabrieli T., Adami C., Characterization of road traffic noise using an analytic model based on SEL, *Proceedings of the 31st Congress of the Italian Acoustical Association* (in Italian), Venezia 5th-7th May 2004

[9] WG-AEN, *Good Practice Guide for StrategicNoise Mapping and the Production of Associated Data on Noise Exposure*, Position Paper 5/12/2003

[10] Beaumont J., Petitjean E., *Driving Force, Pressure and State Indicators*, Technical meeting on noise indicators, Brussels - April 2003

Forum**Acusticum**
BUDAPEST

29 Aug – 2 Sep, 2005
Budapest, Hungary

PROCEEDINGS

www.fa2005.org

EAA