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# Temporal correlations in an urban noise monitoring network

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**Abstract.** DYNAMAP, a European Life project, provides a real-time image of the noise generated by vehicular traffic in urban and suburban areas, developing a dynamic acoustic map based on a limited number of low-cost permanent noise monitoring stations. Traffic noise data within a urban pilot area (Area 9 of Milan), collected by 24 monitoring sensors, are used to build-up a “real time” noise map. DYNAMAP is based on a statistical approach implying that information captured by each sensor must be representative of an extended area, and simultaneously uncorrelated from that of other stations. The study of the correlations among the sensors represents a further contribution in refining the sampling network design.

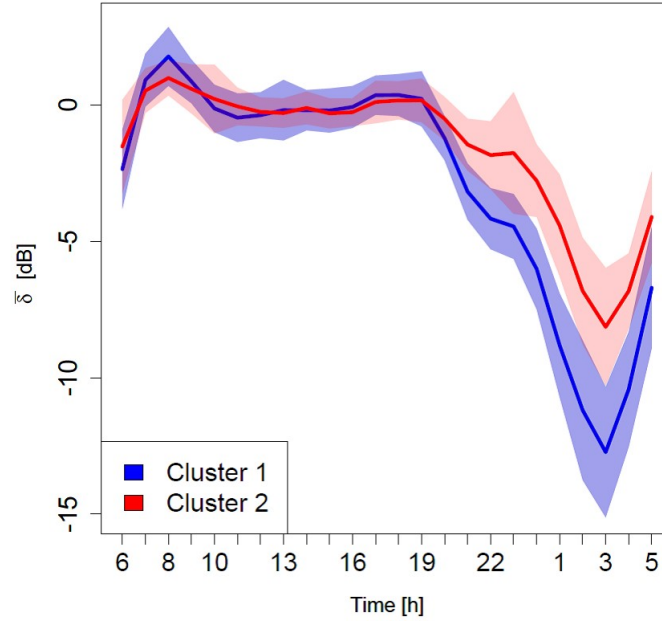
## 1. Introduction

Noise mapping are becoming a necessary tool for evaluating the noise exposure of citizens in large cities, as it has been recognized by the strict dose-harmful effect relationships reported both in the Directive 2002/49/EC [1] and the 2018 WHO Environmental noise guidelines [2]. Strategic Noise Maps have been implemented to enable effective diagnostics on the acoustic environment and provide useful information for local intervention measures and policy-making [3, 4]. They evaluate the overall exposure to noise in a given area due to different sources and, together with Action Plans, provide a framework to manage environmental noise and its effects. They represent the usual approach for noise prevention and control [5, 6]. Noise maps are recently evolving towards a multi-source predictive approach [7, 8, 9, 10]. However, the introduction of dynamic noise maps constituted a further evolution in the direction of better representing the “real” noise exposure. To this end, the European project DYNAMAP [11] has developed a dynamical acoustic map in two pilot areas: a large portion of the urban area of the city of Milan (Area 9) [12] and the motorway surrounding Rome [13]. In both cases, one can predict traffic noise in an extended area using a limited number of monitoring sensors and the knowledge of traffic flows. Traffic noise data, collected by the monitoring stations, each one representative of a number of roads within the zone sharing similar characteristics (e.g. daily traffic flow), are used to build-up a “real time” noise map [14, 15, 16]. In order to study how traffic noise in different parts of the city is correlated, we focused on the correlations among the 24 monitoring units belonging to DYNAMAP’s sensor network.



## 2. Network of sensors and dynamic noise mapping

A sample made of 93 (24-hour) noise profiles, distributed over the entire city of Milan, has been analyzed by standard clustering techniques. The result of the analysis is shown in Fig.1 illustrating the two mean normalized noise cluster profiles,  $\bar{\delta}$ .



**Figure 1.** Mean normalized cluster profiles,  $\bar{\delta}$ , and the corresponding  $\pm$  standard deviation.

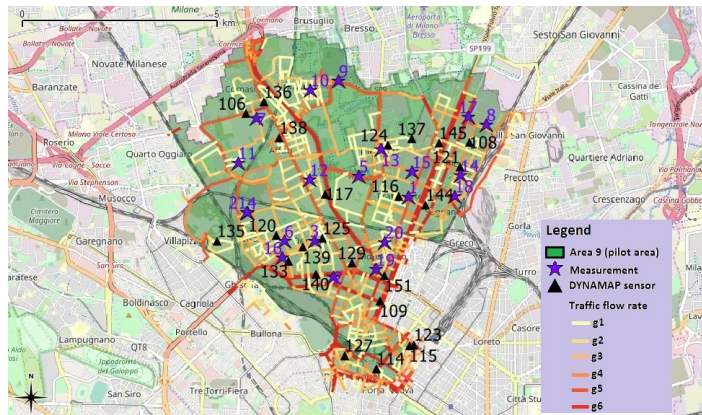
The two clusters present a similar trend during the daytime and behave differently during the evening/night-time and the morning rush-hour. This result suggested the idea to describe the noise profile of an arbitrary road as a combination of the two mean cluster profiles [17, 18, 19]. The generalization of the method to all non-monitored roads can be achieved thanks to the knowledge of a non-acoustic parameter  $x$  available for the entire road network, which we found to be the logarithm of the total traffic flow [20, 21, 22]. As we cannot describe the noise behaviour of each single road, because our approach is based on statistics, we decided to divide the entire range of non-acoustic parameter into six groups in such a way that each group contains approximately the same number of roads. For the effective implementation of DYNAMAP, we have 24 noise monitoring stations deployed within the pilot area, and the roads are sorted into six groups according to the value of  $x$  denoted as  $(g_1, g_2, \dots, g_6)$  [23, 24]. Each group of roads is represented by a single noise map. The latter is the result of two contributions: **(a)** a reference static contribution derived by the calculation of CadnaA at the time interval  $T_{ref} = (08:00-09:00)$ ,  $Leq_{ref}(T_{ref})$ , and **(b)** a dynamic contribution from each group  $g_i$  retrieved from 24 monitoring stations [25, 26]. The level  $Leq^a(t)$  at location  $a$  at time  $t$  can then be obtained by energetically adding the local contribution of each base map with its variation  $\delta(g_i)$ ,

$$Leq^a(t) = 10 \cdot \text{Log} \sum_{i=1}^6 10^{(Leq_{ref}(g_{i,a}) + \delta(g_i))/10}, \quad (1)$$

where  $\delta(g_i)$  is obtained by averaging the sensors'  $\delta(g_{i,j})$  in each group [12] [11]. Here,  $\delta(g_{i,j})$  for the generic monitoring sensor  $j$ , is obtained as,  $\delta(g_{i,j})(t) = Leq(g_{i,j})(t) - Leq_{ref}(g_{i,j})(T_{ref})$ .

### 3. Measurement campaign

The recorded noise time series from the 24 monitoring stations were analyzed using a specifically developed detection algorithm [27, 28] in order to detect possible anomalous noise events, which need to be erased in order to account just for traffic noise sources. Figure 2 contains the position of the 24 monitoring stations together with the indication of the six groups of roads represented by different colours.



**Figure 2.** Area 9 of the city of Milan. Colours correspond to the different groups of streets ( $g_1, g_2, \dots, g_6$ ). Black triangles represent the sites where the monitoring stations are installed.

### 4. Noise correlations

In this section, we study the “contemporaneity” of noise fluctuations as recorded by the monitoring stations. In order to describe the temporal correlation between two roads ( $x, y$ ) belonging to the same network, we will use the Pearson’s correlation coefficient,  $\rho$ , defined as the covariance,  $cov(x, y)$ , of the two variables divided by the product of their standard deviations,  $\sigma_{x,y}$ ,

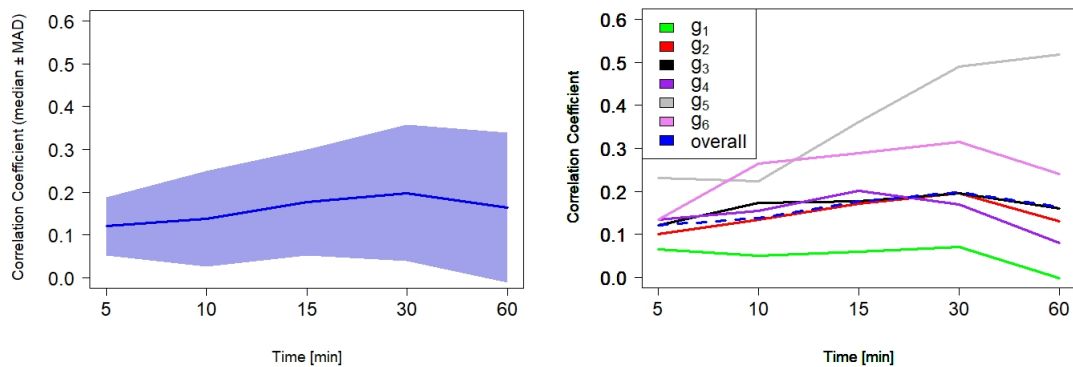
$$\rho(x,y) = \frac{cov(x, y)}{\sigma_x \sigma_y}, \quad (2)$$

being the covariance a measure of the joint variability of the two variables  $x$  and  $y$  and defined as the mean value of the product of the deviations from their mean values [29].

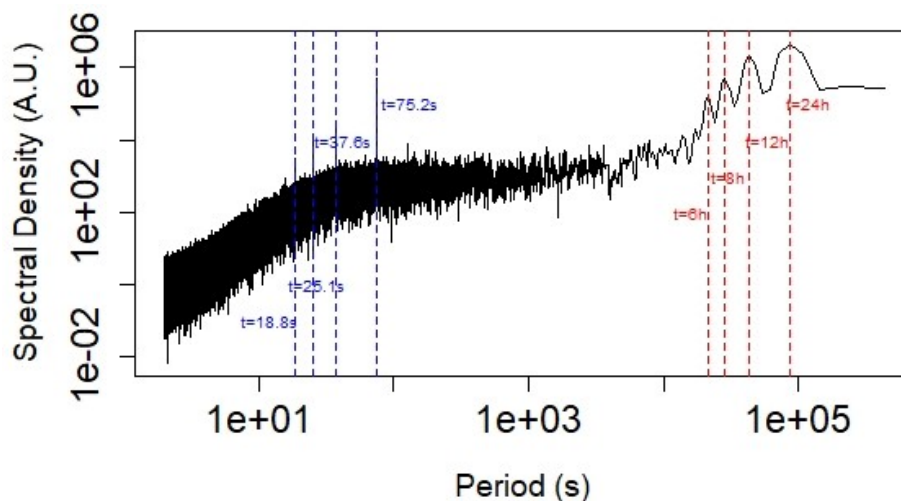
#### 4.1. Noise correlations among network monitoring stations

To study the noise correlations among the 24 sensors, we use the equivalent levels recorded over a period of five consecutive days, and employ two normalization procedures: (P1) From each time series, we remove the hourly median value. In this way, we obtain what we called a de-trended time series. (P2) From each time series, we remove the mean  $Leq$  level calculated between (06:00)-(22:00). We calculate the correlation coefficient  $\rho$ , Eq.(2), and took the median value. The left panel in Fig.3 reports the median of the correlation coefficient among all the de-trended monitoring stations (P1). The reported band corresponds to the median absolute deviation,  $MAD = |x_i - \tilde{X}|$ , where  $\tilde{X} = \text{median}(X)$  and  $X = (x_1, \dots, x_n)$ . The correlation coefficient is rather low, around 0.1, for all the integration times considered (5 min, 10 min, 15 min, 30 min, 60 min). The results within each group  $g$  are reported in the right panel of Fig.3.

Procedure P1 removes all long period fluctuations, thus only high frequency fluctuations remain. To analyse this feature, we calculated the power spectrum of a five-day time series recorded at the monitoring station  $hb129$ . In this case, the normalization refers to a “standard” normalization, i.e. according to procedure P2. The resulting periodogram is shown in Fig.4. We can clearly identify two regions: a long period regime (low frequencies) and a short period regime (high frequencies). The former is associated with daily, morning and night long time



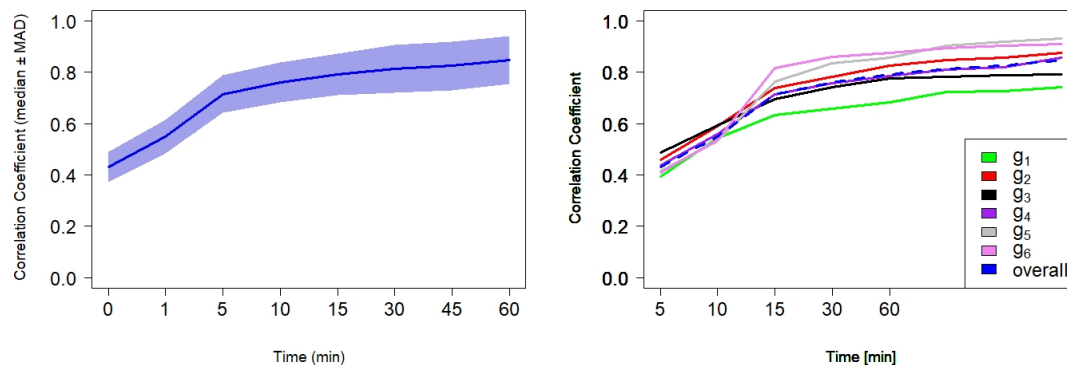
**Figure 3.** **Left panel:** Median of the correlation coefficient among all the de-trended monitoring stations normalized according to P1. The reported band corresponds to the median absolute deviation, MAD. **Right panel:** Median of the correlation coefficient among the de-trended monitoring stations within each group  $g_i$  (P1). The dashed line is the median correlation among all stations, and is included for comparison.



**Figure 4.** Power spectrum of a five-days time series recorded by the monitoring station *hb129*. Blue vertical lines refer to high frequency fluctuations. Red vertical lines refer to low frequency fluctuations.

fluctuations (the maximum period is at 86400s corresponding to 1 day (the dashed red lines are harmonics), and the second one regards time periods of the order 1 min ( $\sim 75$ s, the dashed blue lines in Fig.4 are harmonics). The features at high frequencies are the result of short time scale fluctuations as those produced by the presence of traffic lights. Thus, the low correlation coefficients at “high frequencies” are much likely due to the low strength of the spectral density observed. For P2, the correlation coefficient increases considerably even at very low integration times. At 1s integration time, the correlation coefficient is 0.4 going up to about 0.8 at 1h, as displayed in the left panel of Fig.5 for all the monitoring stations. The coefficients within each group are reported in the right panel of Fig.5. In both right panels of Figs. 3 and 5, group  $g_1$

presents the lowest correlation. This is due to the group classification process based on the road membership according to its non-acoustic parameter  $x$ . In fact, group  $g_1$  contains roads with  $x$  values within the interval  $(0 - 3)$ , corresponding to a total daily flow of  $(1 - 1000)$  vehicles and therefore with a large dynamic variability. This variability impacts considerably on the intra-group correlation over long time scales.



**Figure 5. Left panel:** Median of the correlation coefficient among all the monitoring stations normalized according to procedure P2. The reported band corresponds to the median absolute deviation, MAD. **Right panel:** Median of the correlation coefficient among all the monitoring stations normalized according to procedure P2. The dashed line is the median correlation among all stations, and is included for comparison.

## 5. Discussion and Conclusions

Designing a dynamic noise mapping is a complex task owing to the large number of parameters that need to be considered in order to describe with sufficient accuracy the traffic noise in urban areas [12]. Here we stress that, in designing a DYNAMAP network, one needs to calculate correlations among sensors at different times scales to optimize their locations. As traffic flow is highly fluctuating on short time scales, we expect the correlations among monitoring sensors to be very low. This is illustrated for the Milan network in Fig.3, using procedure P1 aimed at detecting short time correlations. Indeed, only for group  $g_5$  we observe an increase of correlations over times 30-60 min, which could be a sign that some sensor locations within the group have not been chosen appropriately. This behavior remains to be understood. On the other hand, DYNAMAP requires a high correlation over long time scales to be accurate. In this sense, Fig.5 (using procedure P2 suitable for long time correlations) suggests that correlations are high at long times, as required, but one loose correlations within a group over times shorter than 5 min. This would imply that roads belonging to a group could undergo a group change.

To conclude, in this paper we studied the correlations among monitoring sensors that make up the dynamic noise mapping of DYNAMAP. In general, in statistically-based noise mapping over large areas, each monitoring sensor must provide as much independent information as possible, as it represents also the noise of a broader area (group). For this reason, as a general rule, each sensor should be uncorrelated with respect to the other sensors, both inside its own group and within the whole network, over short time scales, and become highly correlated over long time scales within each group to achieve optimal predictive results.

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