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A NEW APPROACH USING BIG DATA TO IMPROVE ROAD TRAFFIC NOISE MAPPING

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ABSTRACT

The present paper describes a new approach developed within the BEEP project (Big data for Environmental and occupational EPidemiology) aimed to improve road traffic noise mapping in epidemiological studies.
The BEEP project, funded by the National Institute for Insurance against Accidents at Work (INAIL), aims at using big data for the evaluation of negative health effects due to air and noise pollution on the Italian population and the risk of occupational injuries in sub-populations of workers.
Noise maps provide noise emissions that are usually calculated by traffic flows measured or derived by a model. The evaluation of traffic flows can determine significant uncertainty in noise estimate: accurate traffic data can significantly improve the meaningfulness of noise models.
In this paper, a new method based on Google API and Big Data treatment was developed to estimate traffic flow and to produce noise maps of Rome agglomeration.
Correlation between travel time and traffic flow considering road characteristics was found by street clustering. Noise maps when obtained will be compared to those produced by conventional means to investigate if the use of big data could improve traffic estimates, in particular during the night period, which is well known to be strongly related to health issues.

Keywords: noise mapping, big data, health effects

1. INTRODUCTION

The BEEP project, funded by the National Institute for Insurance against Accidents at Work (INAIL), aims at using big data for the evaluation of negative health effects due to air and noise pollution on the Italian population and the risk of occupational injuries in sub-populations of workers.

Noise maps provide noise exposure levels that are usually calculated by traffic flows measured or derived by a model.

The evaluation of traffic flows can determine significant uncertainty in noise estimate: accurate traffic data can significantly improve the meaningfulness of noise models.

The main objective of this paper was the development of a new approach within the BEEP project (Big data for Environmental and occupational EPidemiology) aimed to improve road traffic noise mapping in epidemiological studies.

In particular, a new method based on Google API and Big Data treatment was performed to acquire

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travel time information and to estimate traffic volumes using travel time functions and to produce noise maps of Rome agglomeration.

2. BIG DATA TREATMENT AND ACQUISITION OF COLLABORATIVE TRAFFIC DATA

2.1 Use of Big Data to improve noise mapping

As well known, correct traffic flow estimation contributes significantly to the final accuracy of a noise map (1,2).

Traffic models are often available only for rush hour and several approximations are made to provide the input parameters required for noise mapping, as average traffic flows, average speed and vehicles categories for reference periods.

In addition, in order to improve the noise level assessment in cities, another very important aspect is the street classification (3), required for the choice of in situ measurement points needed for the calibration of the used noise level model.

This point becomes critical in an agglomeration like Rome, the subject of this study, which presents tens of thousands of road links and in which several small roads were not considered in the traffic model.

To deal with these problems, the BEEP project wants to improve results of noise mapping with the help of reliable big data information on traffic flow as data from social media (4).

2.2 Acquisition of collaborative traffic data

In this study, road link travel times were acquired by means of a API developed by Google. During the experimental survey, described in a later section, the travel time acquisitions were made simultaneously with in situ noise measurements and traffic flow counts.

The travel times were later used to estimate traffic volumes through appropriate link delay functions.

Recently also other studies (5) have used collaborative traffic data for road noise mapping with a different final treatment.

3. TRAVEL TIME FUNCTIONS

3.1 Link congestion functions

In order to convert the extracted duration in traffic times in traffic volumes, the most commonly used volume-delay functions were considered.

In these models the travel time t (or the speed u) on a road link is expressed as a function of traffic volumes (6, 7, 8, 9, 10).

The main four models available in literature are summarised in Table 1.

The BPR (Bureau of Public Roads) function shows a simple mathematical form that has allowed its wide use and application. But, it is important to remark that this model is particularly suitable for links not subject to congestion conditions and does not take into account road characteristics as signalized links.

The Akcelik function is suitable for modelling traffic conditions characterized by delays due to intersections and signals.

Table 1 – Main volume delay functions

Model	Equation	References
BPR	$u = \frac{u_0}{(1+\alpha x^{\beta})}$; $t = t_0 * \left\{1 + \alpha * \left[\frac{q+\gamma(q')}{Q}\right]^{\beta}\right\}$	(6, 7, 8)
Davidson	$t = t_0 * \left[1 + \frac{J_D x}{1-x}\right]$	(9, 10)
Akcelik	$t = t_0 * \left\{1 + 0.25 r_f \left[(x-1) + \sqrt{(x-1)^2 + 8 J_D \frac{x}{r_f}}\right]\right\}$	(6,10)
Conical	$u = \frac{u_0}{\left[2 + \sqrt{\beta^2(1-x)^2 + \alpha^2} - \beta(1-x) - \alpha\right]}$	(6)

Legend

u_0 = speed at free flow; t_0 = travel time at free flow; q = flow rate; Q = capacity; q' = flow rate on the opposite direction of link; $x = q/Q$ = degree of saturation; α, β, γ, J_D = calibration parameters.

4. ROAD-LINK CLUSTERING AND EXPERIMENTAL PLAN

4.1 Study area description and initial road-link clustering

An experimental survey was designed within a study area located in the city of Rome and covering an area of 144 Km^2. Figure 1 shows the road links inside the study area.

Figure 1 - Road links inside the study area

The road links were appropriately divided into homogeneous groups defined on the basis of the daily traffic trend. In particular, a link clustering process was carried out considering the percentage trends with respect to the total daily traffic flow provided by traffic model for 7 periods as summarized in Table 2.

This analysis led to the definition of three clusters, named C1, C2 and C3 containing respectively 3665, 1194 and 6581 links. Figure 2 shows the result of the clustering process.

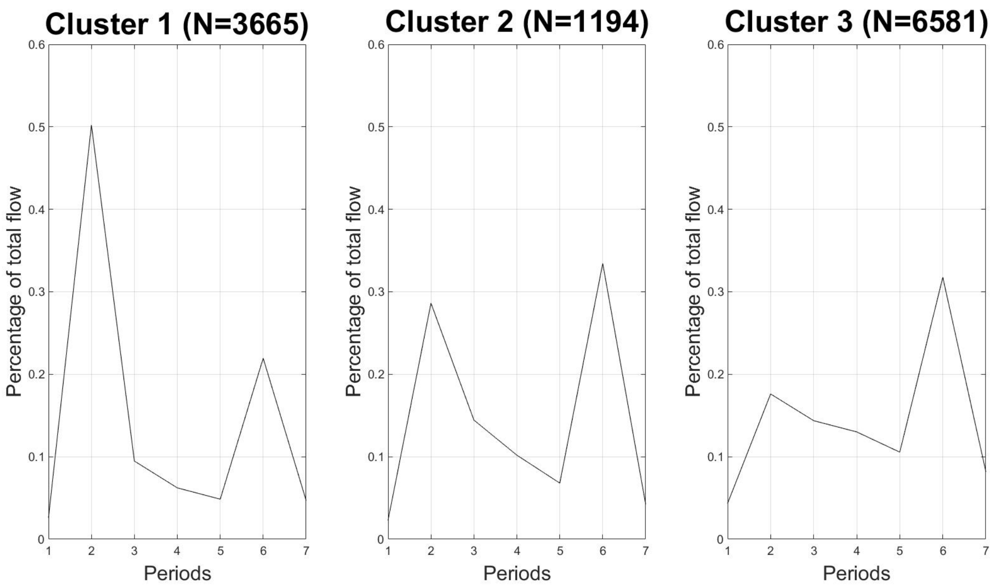

Figure 2 - Result of the clustering process

Table 2 – Periods

Periods	Time range
1	12-7 a.m.
2	7-9 a.m.
3	9 a.m.-12 p.m.
4	12-2 p.m.
5	2-4 p.m.
6	4-8 p.m.
7	8 p.m.-12 a.m.

4.2 Experimental Plan

An experimental plan was designed to simultaneously collect in situ noise and traffic data and travel times by Google API.

The experimental survey combined noise and traffic volumes (light, heavy and motorcycles) measurements in 42 road links during day, evening and night periods. The 42 measure points were selected on the basis of the clustering process.

In particular, road links of the three identified clusters and with different geometric characteristics (one-lane, two-lanes and three-lane roads in each traffic direction) were chosen.

At each measure point, four 30-min measurements were performed during two periods: 6-8 a.m. and 20-23 p.m.

5. First analysis of results

This section contains the first interesting analysis of the results in terms of the comparison of the data extracted by Google API with the traffic data collected in situ.

5.1 Critical issues

Before proceeding with the estimate of the traffic volumes by the travel times of Google API, it is necessary to highlight a series of possible critical issues occurred from the preliminary analysis and reported in the following points:

- for 18 roads out of 42, the travel times taken are characterized by constant or too little variable values in the examined periods;
- in some cases the travel time values appear to be too high in relation to the reduced number of counted vehicles;
- in one case the extracted travel time is lower than that corresponding to the free flow condition.

The road links mainly affected by these problems were those with one-lane and characterized by low flow rate. For the roads affected by these issues, it was not possible in this first phase of analysis to obtain estimates of traffic volumes.

5.2 Comparison between estimated and counted traffic flows

The best results have been obtained in the case of two-lane roads in each direction characterized by flows exceeding 200 PCE (Passenger Car Equivalent) per hour. The following figure 3 seems to show a good correlation between travel time per unit distance extracted by Google API and in situ counted traffic volumes (expressed as PCE per hour).

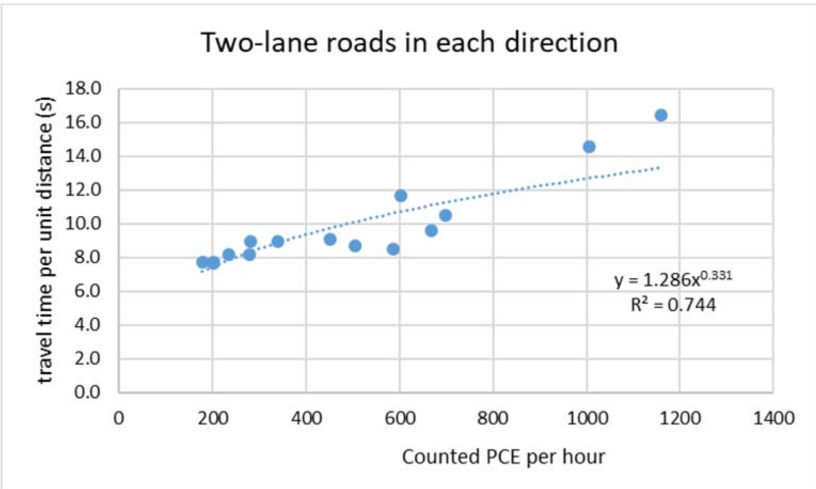

Figure 3 – Acquired travel times vs PCE per hour

In the analysis carried out, since the investigated road links did not present traffic light systems and were not affected by congestion conditions, we used the model BPR to estimate the traffic volumes. The figure 4 shows the comparison between counted traffic flows and estimated traffic flows using the acquired travel time by Google API for two lanes roads in each direction.

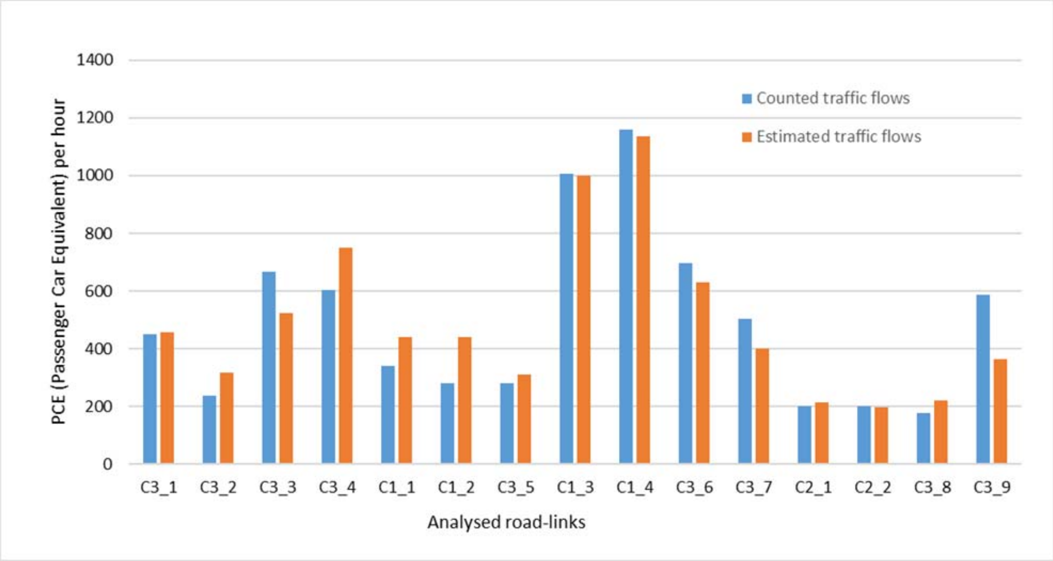

Figure 4 - Comparison between estimated and counted traffic flows

In the case of two lanes roads in each direction, for flow rates greater than 200 PCE per hour but less than capacity, the results seem to be very interesting.

6. CONCLUSIONS

In this study, a new method based on Google API and Big Data treatment was performed to acquire travel time information and to estimate traffic volumes using travel time functions and to produce noise maps of Rome agglomeration.

For this purpose, an experimental plan was designed to simultaneously collect in situ noise and traffic data and travel times of Google API.

The first analysis showed a series of possible critical issues mainly for the road links with one-lane and characterized by low flow rate.

Otherwise, encouraging results have been obtained in the case of two-lane roads in each direction characterized by flows exceeding 200 PCE (Passenger Car Equivalent) per hour but not affected by congestion conditions. Under these conditions, it was possible to estimate traffic volumes using the extracted travel times.

In the next analysis, noise maps when obtained will be compared to those produced by conventional means to investigate if the use of big data could improve traffic estimates, in particular during the night period, which is well known to be strongly related to health issues.

Big Data can be a great help to improve the accuracy of the noise maps, but future research is needed to define well conditions and their field of application.

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