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Abstract

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Abstract

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Keywords: Traffic Noise; Time Series Models; Covid-19; Inductive Loops.

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1. Introduction and Research Objectives

The damages caused by the exposure to high noise levels on human health have been widely studied and, in particular, they range from temporary hearing problems and sleep disorders to serious complications such as anxiety and depression (Lan et al., 2020), hypertension (Ongel and Sezgin, 2016), increased blood pressure (Said and El-Gohary, 2016), and cardiovascular problems (Münzel and Mette, 2017). Moreover, as stated by the Noise Observation and Information Service for Europe, the road transportation sector represents the main contributor to environmental noise generation (Basu et al., 2020; Śliwińska-Kowalska and Zaborowski, 2017).

In order to tackle this problem, the European Union enacted the directive 2002/49/CE in which: i) established a framework to evaluate environmental noise, ii) imposed the creation of noise maps, and iii) obliged the European-countries members to reduce noise in critical areas (King and Murphy, 2016). Therefore, constant monitoring of noise levels in big metropolitan cities, where most of the population lives, is strongly required. However, this is not always possible due to the vastness of the monitoring areas and the high costs of the field campaigns. A conventional solution to these problems is the installation of noise sensors in strategic points of a given city.

The health emergency caused by the Covid-19 disease has been forcing governments to enact several and strict limitations to mobility that also involved the transportation sector. As consequence, a change in the environmental indicators (including the noise) was worldwide observed. For instance, Zambrano-Monserrate et al. (2020) highlighted how the restrictions imposed by the virus spreading had positive and negative effects on the environment. In fact, a reduction of noise levels and the decrease of Greenhouse Gases (GHG), nitrogen dioxide (NO_2), and Particulate Matter (PM) related concentrations were observed in China, France, Spain, and Italy; however, an increase in the production of domestic and medical waste occurred. Basu et al. (2020) analyzed the data of noise stations installed in Dublin, Ireland, observing a significant reduction of the noise levels during the lockdown period, which was attributed to traffic movement restrictions. Rumpler et al. (2020) conducted a study on acoustic-sensors data in Stockholm, Sweden, detecting a reduction in the noise-levels peaks despite the few restrictions imposed by the local government. Mostafa et al. (2021) underlined that although the restrictions imposed in Cairo and Alexandria cities, Egypt, led to positive impacts on the environment, with a reduction of 15% and 4% in NO_2 and GHG concentrations, respectively, and an abatement of 75% of the noise levels, these latter faced a deterioration, raising again in the post-crisis period. Finally, Gama et al. (2020) analyzed the data of 20 air quality monitoring stations in Portugal, observing a reduction of NO_2 and PM_{10} concentrations in March-May 2020 (41% and 18%, respectively) compared to the baseline related to March-May from 2015 to 2019. Although in some of the above-mentioned works, statistical methods were applied for the noise analysis (such as, for instance, linear regression and change point detection algorithm), there is no thorough use of Time Series Models (TSMs).

This research aims to evaluate the noise levels trends before, during, and after the first lockdown period in the city of Porto, Portugal, by analyzing data from installed sensors. Unrecorded noise levels were imputed through seasonal Auto Regressive Integrated Moving Average (ARIMA) models. Consequentially, the trends of the reconstructed series were extracted and contrasted with the different mobility limitations imposed by the government in the analyzed time periods. Finally, a Spearman correlation analysis was conducted between noise levels and traffic volumes. These latter were extracted from records of Inductive Loop (IL) detectors installed in proximity of the Noise Sensors (NSs).

Details about the sensors and the data employed, as well as the methodology followed in this paper are presented in Section 2. Results in terms of noise data imputation, noise series decomposition, and correlation between noise and traffic volumes series are shown in Section 3. Finally, Section 4 is devoted to the Conclusions.

2. Methodology

Data from four NSs and five IL detectors, installed in different locations in the city center of Porto, Portugal, were employed. The GPS coordinates and the positions of all the sensors are shown in Fig. 1. The NSs are installed in proximity of important urban roads of the city and, particularly, the first (NS1) and the second (NS2) along *Praça da Liberdade* and *Sá de Bandeira* street, respectively, both in the city center, close to *São Bento* train station and other commercial activities; the third sensor (NS3) is placed on *Carmelitas* street, in a commercial zone with the presence of restaurants and shops; finally, the last one (NS4) is set between *Carvalho* and *Restauração* streets, next to *St. António* General Hospital. The first four IL detectors are close to NS1, NS2, and NS3 and placed along *Avenida dos*

Aliados, *Sá de Bandeira* street, *Avenida Dom Afonso Henriques*, and *São Felipe de Nery* streets, respectively. The fifth IL detector is installed in *Restauração* street, which has less traffic comparing with other streets in this study.
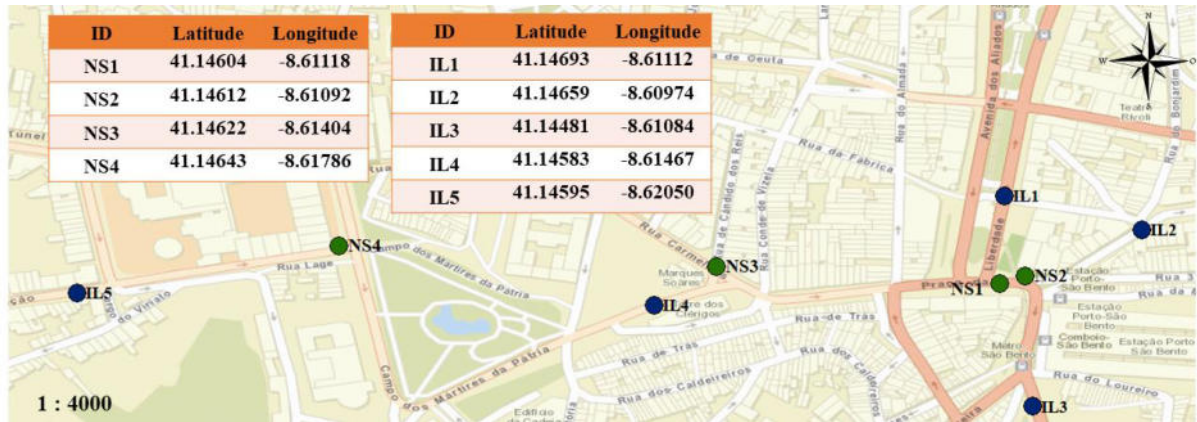

Fig. 1. Coordinates and positions of noise sensors and inductive loops detectors.

The NSs and the IL detectors record the equivalent continuous A-weighted sound pressure level (L_{Aeq}) and the traffic volumes, respectively, on a five-minute time basis; however, to have more stable and handleable data, L_{Aeq} values were aggregated on an hourly time basis, using the following equation:

$$L_{Aeq}^{1h} = 10\log_{10}\left[\frac{1}{12}\left(\sum_{i=1}^{12}10^{0.1(L_{Aeq,i}^{5min})}\right)\right]. \tag{1}$$

The traffic volumes were aggregated to one hour time basis as well. Noise levels recorded from January 1, 2020, to September 13, 2020, were adopted for the analyses, while traffic volumes data are available from January 1, 2020, to June 30, 2020. Due to sensor-related issues, data from IL5 were recorded only from February 11, 2020.

2.1. Missing Noise Data Imputation

Due to sensor or server-related issues, there exist missing data in the NSs' datasets. They constitute approximately 4.6% of the dataset for each sensor (i.e., 281 of the 6168 hourly observations), and were imputed through ARIMA(p,d,q)(P,D,Q)$_m$ models, where p, d, and q are the orders of the autoregressive model, the differentiation, and the moving average model, respectively; P, D, and Q represent the autoregressive, differencing, and moving average orders of the seasonal part, respectively; and m is the seasonal lag. These types of models are basically based on the seasonal ARMA(p,q)(P,Q)$_m$ models which are defined through the Auto-Regressive (AR) and Moving Average (MA) characteristic polynomials (Guarnaccia et al., 2016), expressed in eq. 2 and 3, respectively:

$$\begin{cases}\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p \\ \Phi(B^m) = 1 - \Phi_1 B^m - \Phi_2 B^{2m} - \ldots - \Phi_p B^{Pm}\end{cases}; \tag{2}$$

$$\begin{cases}\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \\ \Theta(B^m) = 1 - \Theta_1 B^m - \Theta_2 B^{2m} - \ldots - \Theta_Q B^{Qm}\end{cases}; \tag{3}$$

where B is the backshift operator. ARMA models turn in ARIMA when a dth or D^{th} differentiation is applied to the data. The choice of the seasonal lag depends on the presence of seasonal patterns in the data, revealed by the

Autocorrelation and the Partial Autocorrelation Functions (ACF and PACF, respectively), while, the criterion adopted for the tuning of the hyperparameters (i.e., *p*, *d*, *q*, *P*, *D*, and *Q*) is based on the minimization of the Akaike and Bayesian Information Criteria (*AIC* and *BIC*, respectively) (Kuha, 2004):

$$AIC = 2k - 2\,ln(\,L\,); \tag{4}$$

$$BIC = k\,ln(\,n\,) - 2\,ln(\,L\,); \tag{5}$$

where *k* is the number of model parameters; *L* is the maximized value of the likelihood function; and *n* is the number of observations used for the model calibration. Therefore, the choice of a model with the lower *AIC* and *BIC* values contemporary allows to respect the parsimony principle (and use as few parameters as possible) and fit well the data. The models were calibrated on portions of the dataset immediately before the missing points and, consequentially, used to forecast (and thus impute) the unrecorded noise levels. The models were not re-calibrated if slots of missing points were interspersed by short portions (maximum-associated length equal to 70 observations) of correctly recorded data. Hence, these latter were contrasted with the corresponding values provided by the models, allowing to evaluate their forecasting goodness.

2.2. Time Series Decomposition and Correlation Analysis

The Seasonal and Trend decomposition by Loess (STL) (Cleveland et al., 1990) was applied to the reconstructed noise time series using the open-source software *R*. In this paper, a multiplicative model was chosen. Originally, the STL algorithm extracts three components from the series following an additive model:

$$X_t = T_t + S_t + R_t; \tag{6}$$

where X_t is the observation of the series at time *t*; T_t is the trend component at time *t*; S_t is the seasonal component at time *t*; and R_t is the random component at time *t*. First, a logarithmic transformation was applied to the noise series and then, the STL algorithm was applied (eq.7). Finally, the anti-logarithmic transformation was performed which led to obtain a multiplicative model (eq. 8):

$$ln\left(X_t\right) = ln\left(T_t\right) + ln\left(S_t\right) + ln\left(R_t\right) = ln\left(T_t\,S_t\,R_t\right); \tag{7}$$

$$e^{ln(X_t)} = e^{ln(T_t\,S_t\,R_t)} \rightarrow X_t = T_t\,S_t\,R_t; \tag{8}$$

Note that the STL algorithm requires as input the number of consecutive observations to use in the Loess window for the trend extraction, according to (Cleveland et al., 1990). This value was set to 720 observations (15 days) to avoid excessive oscillations in the trend. The fitting-goodness of the decompositions was evaluated by contrasting the recorded values (X_t) with the fitted ones (F_t), which are defined in each temporal step as the product between the trend and the seasonal components.

Finally, a Spearman correlation analysis between the noise and the traffic volumes series was conducted. Data from NS1, NS2, and NS3 were correlated with those recorded by IL1, IL2, IL3, and IL4, from January 1, 2020, to June 30, 2020. In the same way, the noise levels recorded by NS4 were correlated with the traffic volumes registered by IL5, from February 11, 2020, to June 30, 2020.

3. Results

3.1. Reconstructed Time Series

Figure 2 shows the ACF and PACF related to the hourly noise levels recorded by NS1; the functions revealed a local maximum after 24 lags. The other NSs are characterized by similar results. This clearly suggests the presence of a daily seasonal pattern in the data and drove in turn the choice of the parameter *m*.

Then, the models were calibrated using portions of the series immediately before the missing values in the datasets, and the hyperparameters were chosen with the purpose of minimizing *AIC* and *BIC*. The forecasting goodness of the models was evaluated by following the procedure described in Section 2.1. The measured noise levels were plotted against the forecasted ones, and, additionally, the first quarter bisector was shifted up and down by 3 dBA, forming a region (Fig.3). It must be underlined that these values correspond to the doubling/halving of the sound pressure. Thus, the percentage of points belonging to the aforesaid range was computed.
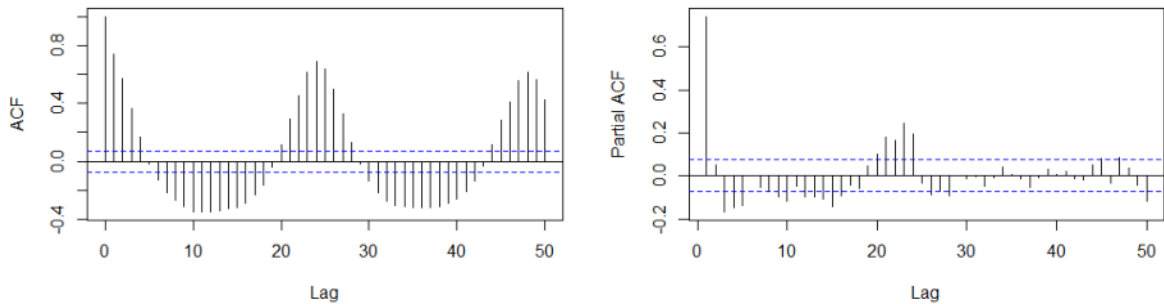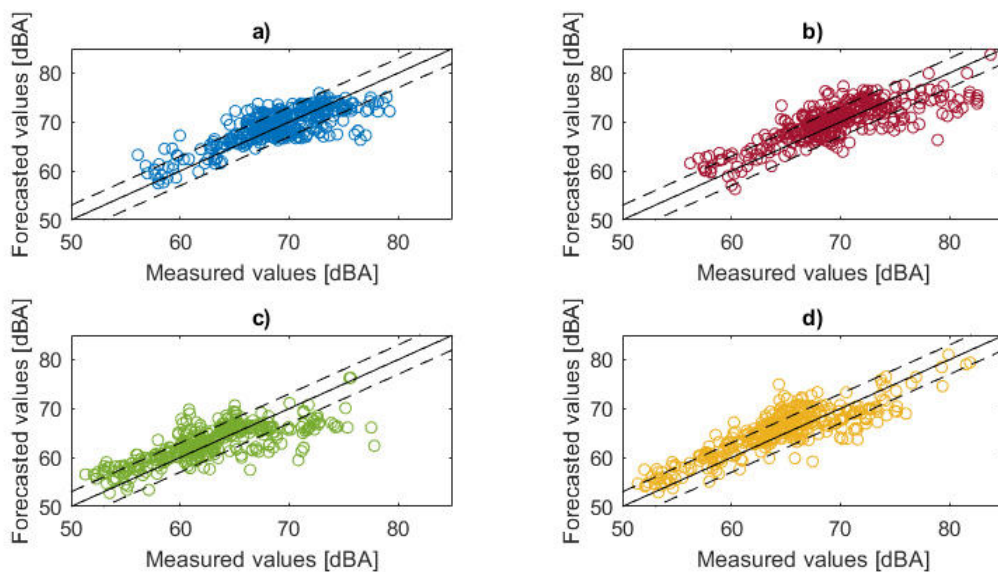

Fig. 2. Data ACF and PACF.

Fig. 3. Models forecasting goodness evaluation for: a) NS1; b) NS2; c) NS3; d) NS4.

In particular, 77%, 70%, 71%, and 71% of the points are in this range for NS1, NS2, NS3, and NS4, respectively. The models tend to both overestimate and underestimate some noise level values. This can be attributed to two main factors: i) the presence of stochastic events (such as ambulances pass-byes and cars honking) that affecting the measured values and simultaneously not forecastable by the models; ii) the presence of a second seasonal pattern in the data (namely a weekly one), difficult to include in ARIMA models without compromising the computational load.

The missing values were replaced by the respective forecasted noise levels allowing the reconstruction of the time series for the four sensors. The process has not strongly altered the statistic main parameters related to the original (with missing values) and the reconstructed series (Table 2).

Table 2. Statistical parameters of the noise Time Series.

	NS1		NS2		NS3		NS4	
	Original Series	Reconstructed Series	Original Series	Reconstructed Series	Original Series	Reconstructed Series	Original Series	Reconstructed Series
Mean [dBA]	68.66	68.58	69.47	69.37	62.76	62.69	64.33	64.24
St. Dev. [dBA]	4.68	4.71	5.77	5.77	5.18	5.17	5.86	5.86
Median [dBA]	68.81	68.77	69.20	69.20	62.52	62.47	64.36	64.35
Min [dBA]	55.93	55.11	55.11	54.66	50.19	50.19	49.27	49.27
Max [dBA]	90.85	90.85	98.13	98.13	83.08	83.08	87.53	87.53
Skew	-0.23	-0.24	0.26	0.24	0.26	0.25	0.16	0.15
Kurtosis	0.26	0.21	0.43	0.42	0.05	0.03	0.25	0.23

3.2. Noise Levels Trends and Correlation with Mobility Data

The trend, seasonal, and random components were extrapolated from the reconstructed series. The measured values were plotted against the fitted ones (obtained as the product between the trend and the seasonal values), as presented in Fig.4.
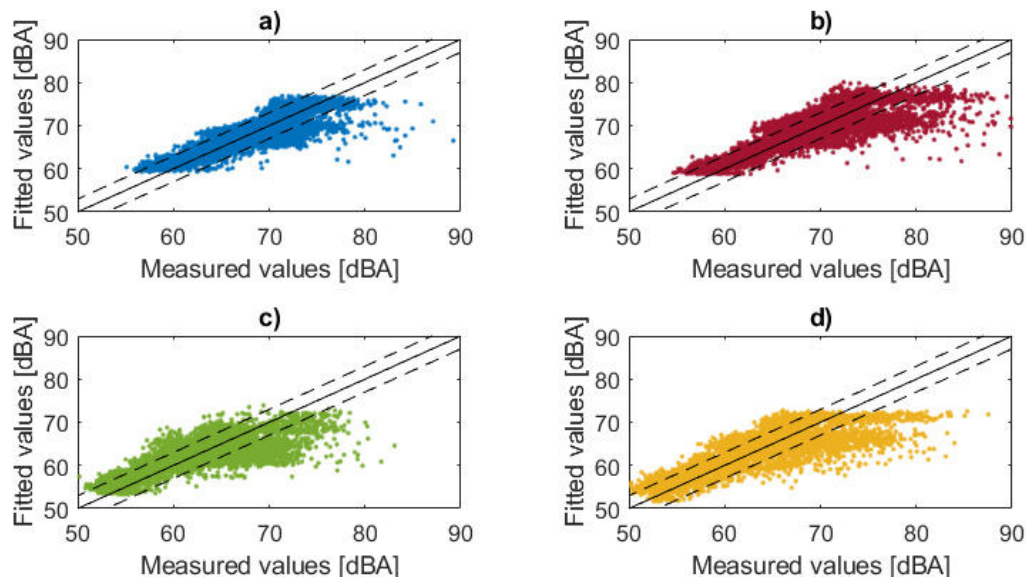

Fig. 4. Decomposition fitting goodness evaluation for: a) NS1; b) NS2; c) NS3; d) NS4.

The results show that 82%, 70%, 68%, and 74% of points are within the region identified by bisector ± 3dBA for NS1, NS2, NS3, and NS4, respectively. Moreover, the statistical parameters related to the random values (identically equal to the ratio between the measured and fitted values) are presented in Table 3.

Table 3. Statistical parameters of the random components.

	Mean	St. Dev.	Median	Skew	Kurtosis
NS1	1	0.04	0.99	1.59	6.44
NS2	1	0.05	0.99	1.73	5.52
NS3	1	0.05	0.99	1.14	2.06
NS4	1	0.06	0.99	1.32	2.22

The trends extracted from the hourly time series of the four sensors are shown in Fig.5. The first Covid-19 case confirmed in Portugal occurred on March 2, 2020; since the virus rapidly spread, the government progressively implemented measures (e.g., school closures), having declared the maximum alert level and then the emergency state on March 12 and March 18, 2020, respectively. Several limitations were imposed, namely the closure of schools, universities, bars, restaurants, cinemas, theaters, commercial and working activities. Moreover, the number of trips had to be limited to the essential (e.g., to go to grocery shops, pharmacies, or emergencies only). The restrictions were maintained until May 18, 2020, when commercial activities and schools were allowed to re-open. The lockdown had also repercussions on noise levels trends recorded. Particularly, the noise levels trends sharply dropped by 6.7, 7.4, 7,5, and 7.2 dBA from the 1st to the 31st of March for NS1, NS2, NS3, and NS4, respectively. The trend functions maintained almost constant in April, with the exception of NS4, where the noise levels tended to rise up starting from the last days of March. In May, with the progressive removal of the restrictions, the noise trends gradually rose; specifically, they increased from the beginning of May to the end of August by 2.5, 3.3, 4.2, and 3 dBA for NS1, NS2, NS3, and NS4, respectively. However, note that the noise levels did not reach the pre-Covid-19 levels during the study period.
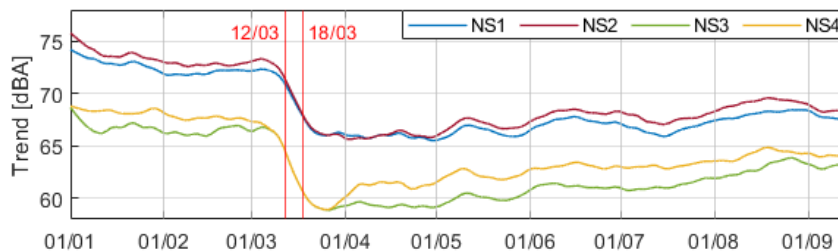

Fig. 5. Noise levels trends.

Bearing in mind that nowadays, the first source of environmental noise in Europe is represented by the road transportation sector, followed by railways, airports, and industries (European Environment Agency, 2020), the significant drops in the noise levels trends can be attributed to the traffic flows reductions in the city. To support this assumption, statistical tests were performed to verify if a monotonic relationship between noise levels and traffic volumes exists (at 95% confidence level), and Spearman correlation coefficients between them were computed. The analysis was limited to the time interval between January 1 – June 30, 2020, due to the unavailability of traffic volumes data after the aforesaid period. Considering that the null hypothesis is that there is no monotonic relationship between the variables, results show that, for all the cases, the p-values were lower than the chosen significance level, and therefore, a monotonic relationship between the variables subsists. The correlation coefficients are given in Table 4; they assume positive and moderate-to-high values. Usually, larger correlation values are obtained for sensors in close physical proximity (e.g., NS1 and IL3) and associated with the main traffic flows in the area. Thus, from the above-discussed facts, the assumption that the decreasing of the noise levels between March-May 2020 is associated with the reduction of the traffic volumes seems to be confirmed.

Table 4. Spearman correlation coefficients between noise levels and traffic volumes.

	IL1	IL2	IL3	IL4	IL5
NS1	0.74	0.79	0.80	0.70	-
NS2	0.75	0.80	0.82	0.72	-
NS3	0.70	0.69	0.68	0.62	-
NS4	-	-	-	-	0.79

4. Conclusions

The Covid-19 disease and the measures adopted to contrast its spreading have been affecting environmental indicators, in which the noise is included. In this paper, the city of Porto was selected as case study, and data from

four noise sensors and five inductive loop detectors were analyzed, with the purpose to assess the noise evolution during the first lockdown period (March-May 2020).

First, the unrecorded noise levels were imputed through seasonal ARIMA models. The forecasting goodness of the models (tested by comparing the measured and the forecasted values) revealed their adequacy in imputing missing values. Then, the trend, cyclic, and random components were extracted from the noise series through the STL decomposition, and the goodness of the process was evaluated by comparing the measured and the fitted values.

Results showed that the noise trends drastically dropped during March 2020, with a reduction ranged between 6.7 and 7.5 dBA, and then they gradually rose again after the removal of the limitations. Finally, the Spearman correlation analysis revealed positive and moderate-to-high coefficients between noise and traffic volume series, suggesting that noise reduction can have been caused by the diminution of road traffic flows in the examined time periods.

The attention to the evolution of environmental parameters, and consequentially also of noise, during the lockdown periods involved in turn debates on the mobility policy implications. The monitoring of noise and the parameters correlated to it (namely fleet composition, traffic average speeds, congestion levels) on a local scale appears to be, nowadays, crucial. If on one side, policies that aim to face the problem with the introduction of acoustic barriers and traffic limitations in specific points and changing of road pavements remain valid, on the other side, the Covid-19 related crisis opened also other types of discussions. In fact, the role of micromobility (i.e., bikes, e-scooters, pedestrians) to stem noise and traffic-related problems seems to be reinforced; however, it necessary requires redesigns of cities layouts and has to be subjected to further studies.

Acknowledgments

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