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Research Article

Francesco Aletta, Andrea Gemma, Livia Mannini, and Sergio Maria Patella*

Comparing pre- and post-pandemic greenhouse gas and noise emissions from road traffic in Rome (Italy): a multi-step approach

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Abstract: This study presents the results of a traffic simulation analysis and emissions (greenhouse gas and noise) assessment comparing pre-pandemic (2019) and post-pandemic (2022) periods. The estimation of road traffic demand is based on conventional data sources and floating car data; next, the traffic simulation procedure was performed providing road network traffic volumes, which are the input for the emission models. The diffusion of teleworking, e-commerce, as well as the digitization of many processes, services and activities, lead to a significant change in urban mobility. Results show a significant though still not complete resumption of commuters travel activity (−10% compared to pre-pandemic period) in the morning peak-hour. This translates into an 11% reduction of greenhouse gas emissions and a 0.1% increase in noise emissions.

Keywords: COVID-19, Italy's coronavirus epidemic; pre-pandemic era, post-pandemic era, traffic simulation, noise mapping, greenhouse gas (GHG) emissions, urban noise pollution

1 Introduction

On March 11th, 2020, the Italian Government led by Prime Minister Giuseppe Conte decided to impose a national "lockdown" (the 'stay at home' decree), restricting people's mobility, except for essential work or health reasons, in response to growing concerns about the COVID-19 pandemic situation in the country [1].

The mobility restriction led to a drastic reduction of urban traffic volumes, with a consequent strong decrease in road congestion, pollutant and noise emissions [2–10]. Moreover, the lockdown imposed by the Italian Government resulted in unprecedented increase in teleworking [11].

Recent scientific literature suggests that, in the "post-covid" era, previously office-based workers around the globe would like teleworking to become more prominent [12], and it is generally accepted that teleworking leads to a reduction in traffic, at least during the morning commuting peak-hour [13, 14]. Recent observations reveal that the total number of Italian teleworkers in 2022 is 3.6 million [15], corresponding to 15.5% of the Italian workforce. In addition, the emergency has given a boost to e-commerce, which has led to a reduction of costumers' trips towards shops and shopping centres [16] and an increase in last-mile deliveries. Click & collect and proximity commerce also have gained momentum during the pandemic [17]. In the Italian context, the pandemic has also accelerated the ongoing digitalization of public administration and the introduction of "Smart Governance", bringing citizens closer to digital opportunities, with the possible effect of reducing people's travel needs.

The research presented in this paper aims at understanding to what extent teleworking arrangements, e-commerce and digitalization affect peak-hour road traffic volumes and related emissions (greenhouse gas and noise). To this end, traffic simulations and emissions assessments were run in two different periods: pre-pandemic (October 2019), and post-pandemic (October 2022). The remainder of the paper is organized as follows. Section 2 outlines the methodology used for passenger road transportation demand, traffic simulation and emissions (GHG and noise). Section 3 presents and discusses the results of the study. Section 4 concludes and summarizes the paper, including remarks for future research developments.

***Corresponding Author: Sergio Maria Patella:** Faculty of Economics, Universitas Mercatorum, Piazza Mattei 10, Rome, 00186, Italy; Email: sergiomaria.patella@unimercatorum.it
Francesco Aletta: UCL Institute for Environmental Design and Engineering, The Bartlett, University College London, Central House, 14 Upper Woburn Place, London WC1H 0NN, United Kingdom
Andrea Gemma, Livia Mannini: Department of Engineering, Roma Tre University, Via Vito Volterra 62, Rome, 00146, Italy

2 Methodology

The first step of the methodology was to evaluate the morning peak-hour (8:30-9:30 am) traffic demand both for October 2019 (last pre-pandemic year) and October 2022 (first post-pandemic year). Road traffic Origin-Destination matrices were estimated through conventional and emerging traffic data collection technologies (such as automatic counts and probe vehicles), according to the procedure defined by Carrese *et al.* [18] and Nigro *et al.* [19]. To capture the demand variation between 2019 and 2022 a Floating Car Data (FCD) analysis was performed. Floating Car Data are collected through black boxes, installed by insurance companies, that record the position, speed, and type of vehicles at regular intervals between 30 and 60 seconds. Through the analysis of these data, it is possible to reconstruct users' travel behaviour and to estimate traffic demand.

Following an initial pre-processing phase, designed to remove acquisition errors about position and speed, the drivers' trajectories were reconstructed by analysing GPS data, engine on/off state and movements. Then, for each trajectory, the total distance travelled, total travel time and intermediate stops times were calculated. It was necessary to remove short stops, such as when dropping off passengers, since they could mislead the estimation of actual origin and destination of the trips.

Using the trajectories reconstructed, the total vehicle kilometres travelled (VKT) during the peak-hour and the number of monitored vehicles (n) were calculated, respectively, for heavy and light vehicles in the different years. Based on the official data released by the Automobile Club Italia (ACI), concerning the composition and numerosity of the vehicle fleet, the percentage of detected vehicle was calculated, distinguishing between two vehicular classes: heavy (P_H) and light vehicles (P_L). Then, the detected sample was extended to the universe, and in the same way also the VKT, considering the passenger-car equivalent factor (c).

Finally, the demand variation (Dv) was calculated as follows:

$$Dv = \frac{\dfrac{\left(\frac{VKT_{L22}}{P_{L22}} + c\frac{VKT_{H22}}{P_{H22}}\right)}{\left(\frac{n_{L22}}{P_{L22}} + c\frac{n_{H22}}{P_{H22}}\right)}}{\dfrac{\left(\frac{VKT_{L19}}{P_{L19}} + c\frac{VKT_{H19}}{P_{H19}}\right)}{\left(\frac{n_{L19}}{P_{L19}} + c\frac{n_{H19}}{P_{H19}}\right)}}$$

This formulation addresses a critical issue experienced in the use of FCD data, *i.e.*, the variability of the number of vehicles observed, which, even if slowly, changes between successive years according to the marketing ability of insurance companies. For this reason, the ratio of VKT was normalized by the number of vehicles monitored.

The demand variation was used to update the Origin-Destination demand matrix using the previously calibrated 2019 matrix as a starting point.

Origin-Destination matrices were loaded onto the traffic network of Rome, which was modelled with about 1,400 centroids (zones) and about 82,000 directional road links; of these, about 63,000 are intra-urban links. Traffic simulation was performed through a static deterministic equilibrium assignment with the Emme/4 software. The assignment problem is defined as follows [20]:

$$\min z(f) = \sum_a \int_0^{f_a} t_a(f)df$$

$$\sum_{p\in P^{OD}} F_p^{OD} = d_{OD} \forall O, D$$

$$f_a = \sum_O \sum_D \sum_{p\in P^{OD}} F_p^{OD} \delta_{a,p} \forall a$$

$$F_p^{OD} \geq 0 \forall p \in P^{OD}, O, D$$

where:
f_a is the vehicular flow on the link a; F_p^{OD} is the flow on the path p connecting the Origin-Destination (O-D) pair; $\delta_{a,p}$ is 1 if link a is part of path p, 0 otherwise. As for the volume-delay functions $t_a(f_a)$, the usual Bureau of Public Roads (BPR) [21] were used for highway and freeway links:

$$t_a = t_a^0 \left(1 + \alpha \left(\frac{f_a}{C_a}\right)^{\beta}\right)$$

where:
t_a^0 is the free flow time of link a; α and β are characteristic parameters of the road segment; C_a is the capacity of link a. As for urban links, where time spent at intersections is an essential component of the link travel time, Doherty-type functions were used [22]:

$$t_a = \begin{cases} 0.5T_C\left(1 - \frac{g}{T_C}\right)^2 + \frac{K}{\frac{g}{T_C}S}\left(\frac{\frac{f_a}{\frac{g}{T_C}S}}{1-\frac{f_a}{\frac{g}{T_C}S}}\right) & \text{if } \frac{f_a}{\frac{g}{T_C}S} \leq Z \\ 0.5T_C\left(1 - \frac{g}{T_C}\right)^2 + \frac{K}{\frac{g}{T_C}S}\left(\frac{\frac{f_a}{\frac{g}{T_C}S}}{1-\frac{f_a}{\frac{g}{T_C}S}}\right) - \frac{\gamma_1}{\frac{g}{T_C}S} + \frac{\gamma_2 f_a}{\left(\frac{g}{T_C}S\right)^2} & \text{if } \frac{f_a}{\frac{g}{T_C}S} > Z \end{cases}$$

where:
Z is the limit of the saturation degree (generally between 0.90 and 0.95); γ_1 e γ_2 are parameters that depend on the value of Z (for $Z = 0.95$ we have $\gamma_1 = 209$ and $\gamma_2 = 220$); K is a constant that depends on the law of arrivals at the intersection (generally between 0.55 and 0.60); g is the green traffic light time available for the link a; T_C is the duration of the traffic light cycle; S is the saturation flow, corresponding to

the capacity in the event that the approach always had the green light.

The output of the traffic simulation (*i.e.*, traffic volume, the travel time, and speed for every link of the road network) was used for GHG and noise emissions assessment.

The GHG emissions assessment was performed following the Well-to-Wheel (WTW) approach, which consists of two components: Well-to-Tank (WTT) and Tank-to-Wheel (TTW) analysis. The former refers to the production, processing and delivery of a fuel or energy vector. The latter refers to the use of the power source during driving. Emission factors by vehicle type and context (highway or urban road) are shown in Table 1 and were taken from previous research [23]. Table 2 shows the vehicle fleet composition circulating in the metropolitan city of Rome in 2019 and 2021 (vehicle fleet data are not yet available for the year 2022).

Table 1: Emissions factors per unit distance travelled

	kqCO2eq/km	
	Urban road	**Highways**
ICEV gasoline	0.309	0.171
ICEV diesel	0.284	0.182
LPG	0.261	0.200
CNG	0.376	0.212
HEV gasoline	0.068	0.171
HEV diesel	0.067	0.182
BEV	0.068	0.078

Table 2: Vehicle fleet composition circulating in Rome in 2019 and 2021 [24, 25]

	Year 2019		Year 2021	
Propulsion	**n°**	**%**	**n°**	**%**
ICEV gasoline	1,424,986	49.45	1,323,413	48.58
ICEV diesel	1,148,833	39.86	1,019,479	37.42
LPG	266,739	9.26	247,251	9.08
GPL	21,235	0.74	23,238	0.85
HEV gasoline	19,259	0.67	94,717	3.48
HEV diesel	201	0.01	5,214	0.19
BEV	703	0.02	10,805	0.40
TOTAL	2,881,956	-	2,724,117	-

Table 3: Italian generation mix, reference year 2020 [32]

Energy source	Share (%)
Renewable sources	45.04
Coal	6.34
Natural gas	42.28
Petroleum oil	0.48
Nuclear	3.22
Other sources	2.64

Well-to-Tank GHG emissions from the use of battery electric vehicles (BEVs) strongly depends on each country's electricity generation mix [26–30]. For a proper comparison between the pre-pandemic (2019) and the post-pandemic period (2022), it should be considered the impact of the war in Ukraine on Italian generation mix since Italy gets around 40% of its natural gas from Russia [31]. However, for data availability reasons, this study referred to the same Italian generation of the year 2020 for both periods (Table 3).

Traffic simulation data –*i.e.*, the flow and the speed at single-link level– were used to assess noise emissions for the whole road network, as per the guidelines provided within the Common Noise Assessment Methods in Europe (CNOSSOS-EU) [33]. In Chapter III, the CNOSSOS-EU document defines a four-vehicle type classification framework, with equations and coefficients for the calculation of their corresponding sound power emissions: Category 1 - Light motor vehicles; Category 2 - Medium heavy vehicles; Category 3 - Heavy vehicles; Category 4 - Powered two-wheelers (actually, a Category 5 has been set up for future technological developments, but no further information is available at the moment). Since the traffic demand was simulated as equivalent-vehicle trips (using passenger cars as the reference vehicle) the same was done for the noise emissions calculation and only Category 1 vehicles as per the CNOSSOS-EU were considered with the same flows on the links of the network. According to the CNOSSOS-EU protocol, the noise emission of a traffic flow on a given link of a network can be characterized as the directional sound power of a line source, per metre, per frequency, based on the cumulative sound emissions of individual vehicles, as a function of speed. The directional sound power per metre per frequency band of the line source $L_{W',eq,line,i,m}$ (expressed in dB) is calculated based on a traffic flow of Q_m vehicles of category m with a known average speed v_m [33]. Several assumptions were made to simplify the calculations applied within the CNOSSOS-EU method, which have also been previously implemented in literature [2, 24]. Links with traffic volume = 0 were excluded from the calculations, as they would not contribute to actual noise emissions.

3 Results

Assuming that the total mileage (vehicle kilometres travelled – VKT) can be split proportionally to the fleet composition (Table 2), one can calculate GHG emission by using factors shown in Table 1. The results of the traffic simulation as well as GHG emissions are shown in Table 4. Morning peak-hour traffic volumes decrease by 10% when comparing the year 2022 with 2019, and this corresponds to an 11% reduction of GHG emissions. Such a reduction could be attributed to the growth in telecommuting and e-commerce and to a minor extent to the replacement of internal combustion engine vehicles with electric vehicles (hybrid or full electric). For sake of completeness, it should be noted that a reduction of customer trips is associated to an increase in the traffic of couriers and vans for home delivery [16]. Since this study focuses on passenger mobility, the environmental impact of urban freight distribution was neglected. An interesting future development is to consider freight traffic by performing a multiclass assignment; and thus, explicitly taking into account the contributions of different vehicular classes on the road network links. The first results of the analysis of the FCD show that the percentage of commercial vehicles' mileage (VKT) increased significantly between 2019 and 2022, by about 9%.

As for the noise emissions of the traffic flow, these were calculated following the sections III.2.1, III.2.3, III.2.4, and Appendix III-A of the CNOSSOS-EU protocol for each link of the road network (excluding those with volume = 0) as a source line with a directional sound power per metre, by one-octave frequency band (63 Hz – 8 kHz) [33]. Such values were subsequently integrated into a single $L_{W',eq,line,m}$ value. Figure 1 and Figure 2 show the distributions of sound power values of the road network links for the 2019 and 2022 simulations, respectively: visual inspections of the two samples suggested noise emissions to be non-normally distributed, and indeed numerical analysis confirmed the distributions to be positively kurtosed. Therefore, for the sake of statistical comparison, a non-parametric approach was sought. Comparisons for noise emissions were conducted separately for Urban roads and Highways. Data are medians unless otherwise stated. For Urban roads, noise emissions in 2022 were slightly higher than in 2019 for 84.5% of the network links. A Wilcoxon signed-rank test determined that there was a statistically significant median increase in $L_{W',eq,line,m}$ value (0.1 dB) in 2022 (78.6 dB) compared to 2019 (78.5 dB), $z = -128.397$, $p < .001$. Likewise, for Highways, noise emissions in 2022 were slightly higher than in 2019 for 88.0% of the network links. A Wilcoxon signed-rank test determined, similarly, that there was a statistically significant median increase in $L_{W',eq,line,m}$ value (0.1 dB) in 2022 (78.7 dB) compared to 2019 (78.6 dB), $z = -81.831$, $p < .001$. Furthermore, following the traffic simulation approach, a similar calculation was performed to explore the change in noise emissions between 2019 and 2022. Table 5 shows the sound power levels change, clustered as per road type (*i.e.*, Urban roads or Highways). It is worth highlighting that "summing" dB-values as per the traffic flows simulation is not a commonly used method, and it only provides an indication of decibels "leaving or entering" the network; yet other studies have also proposed this approach [2, 24]. Table 5 confirms a similar trend as per the distributional analysis, with almost no change in terms of decibels emitted on the network, and even very marginal increases from 2019 to 2022, +0.1% for both Urban Roads and Highways (and for the network as a whole).

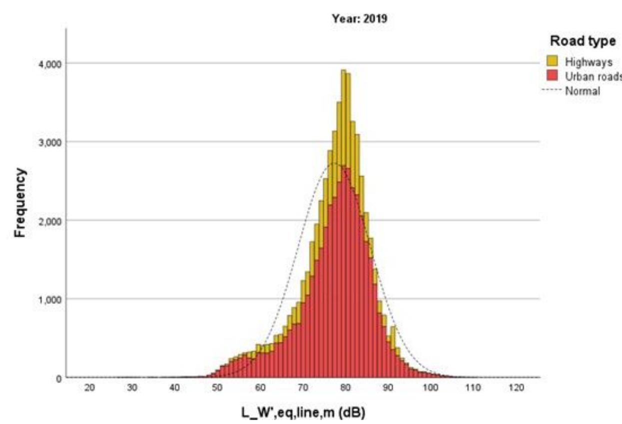

Figure 1: Distributions of the directional sound power per meter values for 2019 simulation; bars stacked by road type

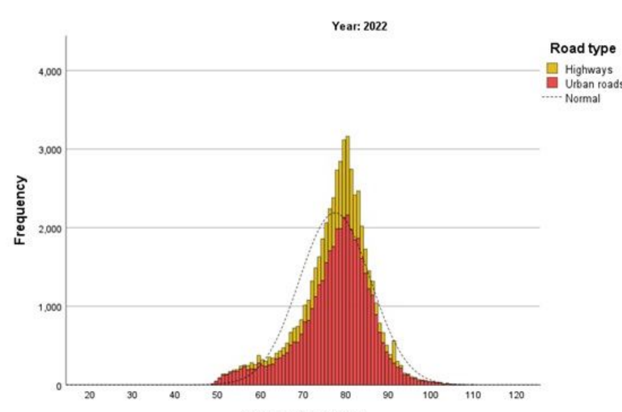

Figure 2: Distributions of the directional sound power per meter values for 2022 simulation; bars stacked by road type

Table 4: Traffic simulation and GHG emissions calculations

	Year 2019		
	Urban roads	**Highways**	**TOT**
VKT [veh•km]	1,870,422	3,230,519	5,100,941
GHG emissions [tCO_2eq]	548,649	575,263	1,123,912
	Year 2022		
VKT [veh•km]	1,681,527	2,907,326	4,588,853
GHG emissions [tCO_2eq]	480,903	515,977	996,881
	Δ (2022-2019)		
VKT [%]	−10.10%	−10.00%	−10.04%
GHG emissions [%]	−12.35%	−10.31%	−11.30%

Table 5: Noise emissions calculations

	Noise emissions (dB)		
	Urban roads	**Highways**	**TOT**
Year 2019	3,233,609	1,032,250	4,338,148
Year 2022	3,240,647	1,033,770	4,352,190
Δ (2022–2019)	+0.1%	+0.1%	+0.1%

While statistically significant, the observed changes in noise emissions are effectively minimal/negligible and of limited practical relevance. The data seems to signal that, at least noise-wise, the situation as of 2022 went “back to normal” pre-pandemic levels. The fact that no noise reductions (and even very small increases) are observed despite reductions of other types of emissions and reduced traffic volumes may be explained by a higher average network speed (leading to increased noise emission). Yet, in terms of distribution of noise emission levels, the 2022 sample (Figure 2) shows a reduced kurtosis compared to the 2019 scenario and seems to tend more towards a normal distribution.

4 Conclusions

This study explored how the COVID-19 pandemic has brought changes to urban mobility by comparing the pre-pandemic (2019) and post-pandemic (2022) road traffic volumes and related emissions. The first evidence of these changes in mobility habits is represented by the diffusion of teleworking, which has become for many companies a structural, and not temporary, working arrangement. The pandemic has also fostered the digitization of many processes, services and activities; among these, e-commerce has the highest implication on urban mobility. Traffic and environmental implications of such changes are evaluated through a methodology that couples transport demand modelling and simulation tools with greenhouse gas and noise emissions assessment.

Our findings indicate that the diffusion of teleworking arrangements, e-commerce, as well as the digitization of many processes, has led to a 10% reduction in morning peak-hour traffic volumes, compared to pre-pandemic period (2019). This resulted into an 11% reduction of greenhouse gas emissions and a 0.1% increase in noise emissions (*i.e.*, no effective changes in noise emissions).

This study confirmed that flexible work arrangements may lead to a reduction in morning peak-hour traffic volumes; however, it is not yet clear whether teleworking causes a reduction only in work-related travels or in total mobility. Some authors found rebound effects from teleworking, since flexible working might generate an increase in frequency and length of non-work-related trips [34–36]. Future research is needed to understand the impact of teleworking on within-day and day-to-day travel patterns and the related environmental issues.

As for the impact of e-commerce on urban mobility, it should be noted that this study focused on the reduction of road passenger trips, neglecting the increase in traffic of couriers and vans for home delivery. Therefore, an important further development, already in progress, is to explicitly consider freight traffic volumes, performing a multiclass traffic assignment. Here the difficulty is to reconstruct the freight Origin-Destination matrix.

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