Human Mobility, AI assistants, and urban emissions: an insidious triangle

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Abstract

Transportation remains a significant contributor to greenhouse gas emissions, with a substantial proportion originating from road transport and passenger travel in particular. Today, the relationship between transportation and urban emissions is even more complex, given the increasingly prevalent role and the pervasiveness of AI-based GPS navigation systems such as Google Maps and TomTom. While these services offer benefits to individual drivers, they can also exacerbate congestion and increase pollution if too many drivers are directed onto the same route. In this article, we provide two examples from our research group that explore the impact of vehicular transportation and mobility-AI-based applications on urban emissions. By conducting realistic simulations and studying the impact of GPS navigation systems on emissions, we provide insights into the potential for mitigating transportation emissions and developing policies that promote sustainable urban mobility. Our examples demonstrate how vehicle-generated emissions can be reduced and how studying the impact of GPS navigation systems on emissions can lead to unexpected findings. Overall, our analysis suggests that it is crucial to consider the impact of emerging technologies on transportation and emissions, and to develop strategies that promote sustainable mobility while ensuring the optimal use of these tools.

Keywords

Human Mobility, Climate Change, GHG emissions, Social AI

1. Introduction

Assessing Greenhouse Gas (GHG) emissions and air pollution is essential to mitigating climate change and promoting human health. Among various sources of emissions, transportation ones significantly increased since 1970, with 11.9% of global GHG emissions in 2016 originating from road transport, 60% of which from passenger travel [1, 2]. Additionally, transportation emissions contribute to non-CO_2 pollutants such as nitrogen oxides, ozone, particulate matter, and volatile organic compounds, significantly impacting climate change and threatening human health [1]. Achieving Sustainable Development Goals (SDGs) by 2030 requires urgent action towards reducing cities' per capita environmental impact [3].

When examining the impact of transportation on urban emissions and welfare, it is essential to consider the impact of Artificial Intelligence (AI) on human mobility. GPS navigation systems, such as Google Maps and TomTom, have become ubiquitous features in transportation and offer significant benefits to individual drivers. However, they can also create congestion and increased pollution when too many drivers are directed on the same route [4, 5, 6]. The town of Leonia in New Jersey is a notable example of this phenomenon. In 2017, navigation apps repeatedly directed drivers onto Leonia's narrow, hilly streets, causing significant congestion [6]. As a result, the police had to close dozens of streets to non-residents during rush hour periods, effectively taking most of the town out of circulation for popular traffic apps. The unintended consequences of well-intentioned navigation apps pose a significant challenge to transportation planning and require careful consideration in urban policy development.

This article presents examples of how vehicular transportation and mobility-AI-based applications impact urban emissions. In Section 2, we examine the spatial patterns of vehicle-generated emissions and how to design more efficient emission reduction scenarios through realistic simulations. In Section 3, we demonstrate how studying the impact of GPS navigation systems on emissions can reveal unexpected results. By evaluating the impact of mobility and AI-based applications on emissions, we aim to provide insights into the potential for mitigating transportation emissions and developing poli-

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cies that promote sustainable urban mobility.

2. Understanding urban emissions

Existing methods to measure vehicles' emissions vary widely in their level of detail and generalizability. Some methods rely on small samples of vehicles with high spatio-temporal resolutions but limited generalizability due to their sample size. For example, particulate sensors and portable emissions measurement systems provide accurate emissions measurements in real-world driving conditions but are limited in scope [7, 8, 9]. In contrast, studies using odometer readings provide estimates for entire regions but lack instantaneous speed and acceleration data [10, 11, 12, 13].

GPS traces offer a trade-off between these two extremes, providing high spatio-temporal resolution and the ability to estimate emissions using microscopic models while covering a representative fraction of the vehicle fleet [14]. Several studies have used GPS traces to investigate the relationship between emissions and the urban environment, vehicle miles travelled and fuel consumption, trip rates and travel mode choice, and more [15, 16, 17, 18, 19]. Overall, using GPS traces provides a valuable tool for understanding the impact of vehicles on the environment and implementing strategies to reduce emissions.

Despite the variety of literature, it remains unclear what statistical patterns characterize the distribution of emissions per vehicle and road, how these distributions change over time and space, and how this information can be used to simulate emission reduction scenarios. While studies have reported that the distribution of emissions from on-road remote sensing sites across vehicles is skewed [20, 21], this finding has been questioned due to the limitations of this type of measurement [22].

2.1. Emissions patterns

In a recent study [23], we analyse anonymous GPS trajectories describing 423,018 trips from 16,715 private light-duty vehicles moving in Greater London, Rome, and Florence throughout January 2017 to compute vehicles' emissions. The trajectories are produced by onboard GPS devices that automatically turn on when the vehicle starts, transmitting a point every minute to the server via a GPRS connection.

We develop a methodological framework to compute vehicles' emissions from their raw GPS trajectories, and we use a microscopic emissions model that estimates the vehicles' instantaneous emissions of carbon dioxide (CO_2), nitrogen oxides (NOx), particulate matter (PM), and volatile organic compounds (VOC) from speed, acceleration, and fuel type.

We find that a few "gross polluters" are responsible for a tremendous amount of emissions in all three cities, and most vehicles emit significantly less. Indeed, the distribution of emissions per vehicle is associated with a Gini coefficient higher than 0.55 for all the cities and pollutants. The top 10% of gross polluters in Florence, Rome, and London are responsible for 47.5%, 50.5%, and 38.5% of the total CO_2 emitted during the month, respectively. The study also finds that the distributions of CO_2 emissions per vehicle of Rome and Florence are well approximated by a truncated power law, while a stretched exponential well approximates London's distribution. This pattern is consistent for other pollutants as well. Similarly, a few "grossly polluted roads" suffer from a significant quantity of emissions, but most suffer significantly less. The distribution of emissions per road is associated with a Gini coefficient higher than 0.64 for all the cities and pollutants, and a truncated power law well approximates it. Figure 1 shows the entire road network of Greater London, with the emissions on each road normalised by the road length to better highlight the differences between the roads.

2.2. Simulation scenarios

We study how electrifying a certain share of vehicles would change the emissions on the three cities' roads. In this setting, even if a vehicle's electrification changes its driver's mobility behaviour, it would not create any emissions.

We find that the electrification of just the top 1% of gross polluters would reduce emissions as much as electrifying 10% of random vehicles. In contrast, the percentage reduction of the overall emissions grows almost linearly when the share of electric vehicles is chosen randomly. A Generalised Logistic Function (GLF) approximates the growth rate when the gross polluters are electrified first. The model gives $R^2 = 0.99$ for Rome, and similar results hold for Florence. In Greater London, the growth starts slowly: there are fewer vehicles with high emissions levels, and electrifying the most polluting vehicles is slightly less effective in reducing emissions than in the other two cities [23].

Given the increasing importance of remote working [25, 26], we also simulate the impact of a massive shift to remote working on reducing vehicle emissions. We assume that this working style eliminates commuting trips. We then perform a simulation in which a growing share of these commuters become home workers, i.e., they no longer travel between their home and work locations (detected from GPS traces).

We find that emissions reduction is more effective when the home workers are gross polluters: remote working for the top 1% gross polluters leads to the same reduction reached if they were $\approx$ 4% random vehicles.

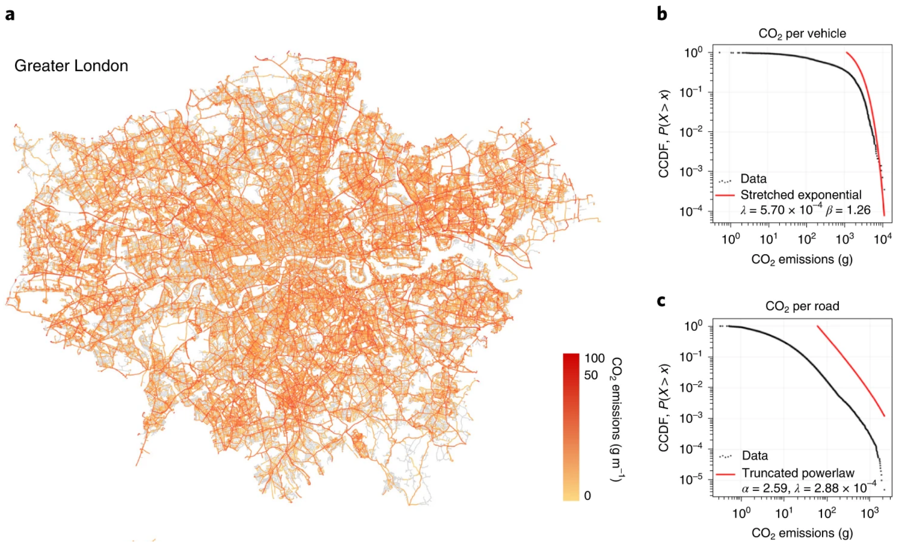

Figure 1: (a) CO_2 emissions (expressed as grams per metre of road emitted during January 2017) on the road network of Greater London. The roads are coloured according to the level of emissions in a gradient ranging from yellow (low emission) to red (high emission). The road network was plotted with the Python library OSMnx [24]. (b) Plot, on the log–log scale, showing $P(X > x)$, i.e., the complementary cumulative distribution function (CCDF; black dots) of the CO_2 emissions per vehicle, together with the best fit (red curve), in Greater London. (c) Plot, on the log–log scale, showing the CCDF (black dots) of the CO_2 emissions per road, together with the best fit (red curve), in Greater London.

Again, a GLF fits emissions reduction when the gross polluters become home workers. Overall, these results demonstrate that targeting specific profiles of vehicles can significantly improve emission reduction policies.

3. Understanding impact of AI

According to preliminary research, the influence of navigation applications on the urban environment is a topic that remains unclear and incomplete, as existing studies produce inconsistent and sporadic outcomes [27, 28]. On the one hand, these apps may contribute to mitigating CO_2 emissions [29]. On the other hand, their usage may increase population exposure to pollution in highly populated regions [30]. Real-time navigation apps provide drivers with optimal routes to reach their destinations, considering the current traffic conditions. However, despite their undeniable practicality, online navigation applications can in principle generate several issues in urban traffic [5, 4]. These apps are usually optimized to minimize individual drivers' travel time without considering the collective impact of the aggregated drivers' behaviour on the city's overall traffic situation. For example, these apps may not factor in whether the recommended routes could handle the additional traffic generated by the app or whether this traffic could pose a risk to safety or lead to further pollution. The impact of a driver's routing choice cannot be evaluated in isolation because it depends on the concurrent choices of other drivers in the city. If too many drivers select the same "eco-friendly" route, the route may become congested, reducing its eco-friendliness. Therefore, a better understanding of the impact of individual routing choices on the urban environment is necessary.

In a recent paper [31], we designed a simulative framework – TraffiCO2 – using the state-of-the-art traffic simulator SUMO [32] to create realistic simulations of traffic under different settings. The simulations were conducted in the city of Milan assuming that vehicles would either adhere to the directions of commercial navigation systems – OpenStreetMap (OSM) and TomTom (TT) – or follow a randomised deviation from the fastest route that emulates the unpredictability and irrationality of human drivers.

We varied the percentage of vehicles of the fleet circulating in Milan that followed a navigation app's suggestions, in order to assess the impact of the rate of routed vehicles on the urban environment. We found that the greater the number of vehicles following the navigation app's suggestion, the higher the total CO_2 emissions in the city: blindly following the recommendations of a navigation app, which are optimised from an individual standpoint, can lead to traffic congestion in some areas of the city, thus leading to spatial polarisation which results in increased travel time and emissions. Conversely, taking “noisy” routes increases the diversity of travelled paths, resulting in a better distribution of traffic on the road network and a decreased travel time and emissions. The fraction of routed vehicles also influenced the spatial distribution of emissions in the city, with more emissions concentrating on the external ring road when more vehicles were routed.

Our results also suggested that introducing randomness into the path generation and suggestion phases could be a solution to avoid suggesting only the optimal paths: route perturbation was beneficial, resulting in shorter travel times and lower emissions in the city.

The study acknowledged that the situation in the real world is more complex, with multiple navigation apps coexisting simultaneously, each with its heuristics and representation of urban reality. The evidence suggests a need for algorithms that can exploit social and collective dimensions while simultaneously meeting individual needs. This challenge requires shifting from an individual to a collaborative and social paradigm, where the choices of non-rational or AI-assisted agents who exploit the system and their impact on the whole society are considered.

4. Conclusion

Urban traffic is a complex system where individual satisfaction is intimately bound to collective happiness, e.g., traffic is smooth for an individual if it is so for everyone. A system where individual interests go hand in hand with collective happiness. There is plenty of room for a better understanding of the impact of individual routing choices on the urban environment, as well as for studying how to design platform architectures and routing recommendations that influence citizens' behaviour towards better aggregated outcomes. The challenge is to turn collective goals into an optimization target, whereby users transparently understand and accept recommendations, which can be individually sub-optimal but produce a more efficient collective outcome. Using (social) norms (such as minimising CO_2 emissions) as targets for collective goals without using them as global constraints might be a way to achieve this goal.

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