Analyzing Network-wide Energy Consumption of Electric Vehicles in a Multimodal Traffic Context: Insights from Drone Data

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Short summary

The environmental benefits and driving range of electric vehicles are closely related to their energy consumption. In this paper, we analyze the energy consumption characteristics of electric mobility systems in a multimodal urban traffic context by establishing the aggregated relationships between macroscopic fundamental diagram (MFD) dynamics and network-wide energy consumption. To do this, we utilize a data-based approach, combining vehicle trajectories collected by a swarm of drones in the downtown areas of Athens, Greece, during the pNEUMA experiment with microscopic energy consumption models. We assume all the trajectories are driven by electric vehicles yet maintain the same behavior observed in the pNEUMA dataset. Preliminary results show well-defined relationships between aggregated traffic parameters and energy consumption at a network level. The total energy consumption of electric cars and buses in the network increases linearly with vehicle accumulation under uncongested traffic conditions. At the same time, the energy consumption per distance traveled by electric buses significantly decreases as the spatial mean speed increases. While for electric cars, the impact of spatial mean speed on energy consumption is marginal, especially when the average speed is above 10 km/h.

Keywords: Electric mobility, Energy consumption, pNEUMA dataset, Macroscopic fundamental diagram.

1 Introduction

Climate change, mainly caused by carbon dioxide emissions from human activities, severely threatens human health and the planet's ecosystem (Zhang et al., 2020). The transportation sector could play an essential role in climate change mitigation, as the sector is responsible for the highest energy consumption in 40% of countries globally and contributes to approximately 15% of total greenhouse gas emissions (IEA, 2022). It is worth mentioning that road transportation is the largest source of transport emissions, accounting for 69% of the sector's overall emissions (IPCC, 2022). This situation will be even more alarming in the decades to come as the trend toward motorization continues (Gao & Newman, 2018).

The electrification of vehicle fleets has been widely recognized as a crucial path to decarbonizing and alleviating fossil fuel dependency in the road transportation sector. Battery electric vehicles (EVs) represent an advanced and promising technology that offers an opportunity to increase energy efficiency and achieve 'zero emissions' compared to their traditional fossil fuel-powered counterparts (Xie et al., 2020). However, EVs are not truly 'zero emissions' from the life cycle perspective as they consume electrical energy, and the indirect emissions produced by the electricity generation are non-negligible, especially where carbon-intensive grids operate. This highlights that the environmental benefits provided by EVs are directly dependent on their energy consumption. Moreover, energy consumption determines vehicle driving range, and the limited driving range remains one of the significant barriers to the massive adoption of EVs. In this context, optimizing EVs' energy consumption plays a vital role in advancing the development of a more sustainable transportation system while concurrently alleviating concerns surrounding range anxiety for EVs.

Most studies so far have focused on minimizing the energy consumption of EVs from two perspectives. One is adopting an eco-driving strategy, which provides drivers with recommendations for modifying their driving behavior to avoid the high energy consumption caused by aggressive driving patterns (Y. Zhang et al., 2022; Donkers et al., 2020; Bingham, 2012). The other is developing an eco-routing strategy, which incorporates the energy-saving potentials when planning routes for electric vehicle operation (Ahn et al., 2021; Basso et al., 2019; Fiori et al., 2018). Although these strategies are efficient and reliable, their real-world application is limited in terms of scope, as they typically apply to a few routes or trips and a single transportation mode. While several studies have investigated the impact of eco-routing and eco-driving strategies on network-wide energy consumption, they mostly resorted to traffic simulators and used the simplest energy consumption models (e.g., energy consumption is linear to distance) for algorithm simplicity (see e.g., Rakha et al., 2012; Hiermann et al., 2019)). Moreover, to the best of our knowledge, no study yet has analyzed the energy consumption characteristics of EVs in a multimodal traffic network. In this paper, we address this gap, combining real multimodal traffic data with microscopic energy consumption to analyze the network-wide energy consumption of electric mobility systems. Existing vehicle energy consumption models can generally be classified as either macroscopic or microscopic (Othman et al., 2019). Macroscopic models use a single value (i.e., energy per unit distance or time) to roughly calculate the energy demand of vehicles. On the other hand, microscopic models provide a more accurate estimation of energy consumption based on high-resolution driving profile data; however, such data are not easily obtained, especially on a large scale. To overcome this, some studies have used macroscopic fundamental diagram (MFD)-based traffic models to estimate network-wide vehicle environmental externalities (e.g., CO_2 emissions). The MFD describes the well-defined relationships between network production, accumulation, and speed (Geroliminis & Daganzo, 2008). Shabihkhani & Gonzales (2014) proposed an analytical model to estimate the network emissions leveraging the relationship between MFD and the driving cycle. They further evaluated this model in an idealized homogeneous network. Saedi et al. (2020) developed a network-wide emission modeling framework by combining the network fundamental properties with the microscopic emission model. This framework was applied to an urban network through simulation. Recently, Barmpounakis et al. (2021) combined large-scale drone data with the MOVES emission model to establish the relationships between network accumulation, speed, and vehicle emissions. They referred to this relationship as the emission-MFD. However, these studies only focused on traditional fossil fuel-powered vehicles, and the impact of electrified technology on network-scale energy consumption is still unclear.

In this paper, we focus on analyzing the network-wide energy consumption characteristics of electric vehicles in a multimodal urban traffic context. We do so by utilizing a data-based approach, combining high-resolution vehicle trajectory data collected by a swarm of ten drones in the central business district of Athens, Greece, during the pNEUMA experiment (Barmpounakis & Geroliminis, 2020) with microscopic energy consumption models. This allows us to estimate the large-scale vehicular energy consumption and further investigate the aggregated relationship between network-wide energy consumption and macroscopic fundamental diagram dynamics. We refer to this aggregation relationship as energy consumption-MFD, following the naming method proposed in Barmpounakis et al. (2021). The analysis conducted in this paper paves the foundation for optimizing the energy consumption and environmental footprint of electric vehicles in multimodal traffic networks.

The reminder of this paper is organized as follows. In Sect. 2, we describe the pNEUMA dataset and the data processing method. We also briefly introduce the microscopic energy consumption models utilized for different vehicle types. In Sect. 3, we discuss the preliminary results on the aggregated energy consumption at the multimodal urban network. In Sect. 4, we draw the main findings of this paper.

2 Methodology

In this section, we first introduce the pNEUMA dataset and describe the data pre-processing method. We then present the energy consumption models utilized for electric vehicles.

Data source and pre-processing

The pNEUMA experiment was conducted in the central business district of Athens, Greece, in October 2018 (Barmpounakis & Geroliminis, 2020). This experiment collected nearly half a million naturalistic vehicle trajectories in a 1.3 [km^2] urban area using a swarm of ten drones during morning peak hours (8:00 - 10:30) over four weekdays. Figure 1 shows the overview of the whole study area and the subareas flown by each drone. The pNEUMA dataset records

Figure 1: Study area of the pNEUMA experiment and drone-assigned subareas and flight routes (Barmpounakis & Geroliminis, 2020).

vehicle trajectory information in 0.04-second time intervals, including longitude, latitude, speed, longitude acceleration, latitude acceleration, and timestamp. Due to the multimodal urban traffic characteristics in the selected study area, six vehicle types are recorded in the dataset: car, taxi, bus, motorcycle, medium vehicle, and heavy vehicle. In this paper, we focus on three vehicle types, i.e., car, taxi, and bus.

Extensive pre-processing of the empirical dataset is necessary because measurement errors were detected during the observation period of some drones. We follow the pNEUMA dataset preprocessing method proposed by Hamm et al. (2022), removing the records in the last 2 minutes of each drone flight from the dataset. In addition, we filter some unreasonable records based on the mechanical properties of vehicles and the real-world driving conditions in downtown areas. For example, bus records with instantaneous acceleration greater than 3.5 $[m/s^2]$, car records with average travel speeds higher than 80 $[km/h]$, and vehicle records with zero instantaneous speed and acceleration throughout the whole trajectory (probably are parked vehicles).

Microscopic energy consumption modeling

According to the information reported in (Barmpounakis et al., 2021), during the pNEUMA experiment in Athens, the fuel type of taxis and buses was diesel, and the fuel type of cars was gasoline. For the analysis in our paper, we assume all three vehicle types are electric-powered, yet they maintain the same behavior as that observed in the pNEUMA dataset. We adopt the VT-CPEM (Virginia Tech Comprehensive Power-based Energy consumption Model) to calculate the energy consumption of electric cars/taxis (Fiori et al., 2016). For electric buses, we use the microscopic power-based energy consumption model (Ma et al., 2021). Both models belong to the microscopic backward-looking longitudinal dynamic models, which estimate vehicles' energy consumption based on the calculation of tractive force. In particular, these models produce the energy consumption in units of $[kwh/km]$ and the instantaneous energy consumption in units of $[kw]$ using the instantaneous speed profile as the input. Such input data can readily be provided by the pNEUMA dataset. Previous studies have widely utilized these models and demonstrated their accuracy in estimating the energy consumption of vehicles in the urban traffic context (Ahn et al., 2020; Ma et al., 2021). For the mathematical details of these models, interested readers could refer to the above references.

It is also worth mentioning that road grade has a significant influence on the energy consumption of electric vehicles (Liu et al., 2017). The city of Athens is surrounded by mountains, resulting in relatively large terrain fluctuations. Therefore, the impact of road grade on vehicle energy consumption should not be omitted. In this paper, we use the Shuttle Radar Terrain Mission (SRTM) digital elevation model to obtain road elevation information and then calculate the road slope between every two consecutive records in the dataset (Farr et al., 2007).

3 Results and discussion

In this section, we describe the empirical results regarding two aggregated relationships in the network, specifically, (i) the relationship between accumulation and network-wide total energy consumption; and (ii) the relationship between spatial mean speed and network-wide energy consumption per distance traveled. Before showing the results, we discuss how we calculate the network fundamental properties and network-wide energy consumption.

In this paper, we use vehicle trajectory data collected from 8:30 to 11:00 on October 24th. After pre-processing the dataset as described in the previous section, we gathered records of 36282 vehicle trajectories. Among them are 34820 trajectories of private cars and taxis and 1462 trajectories of buses. We consider 1 minute as the time interval T for aggregating the MFD dynamics and energy consumption results. For each time interval, the accumulation n_r and the spatial mean speed of cars v_r (including private cars and taxis) in the network r are determined as:

$$n_r = \frac{\sum_{i=1}^{N_{car}} tt_i}{T} \tag{1}$$

$$v_r = \frac{\sum_{i=1}^{N_{car}} td_i}{\sum_{i=1}^{N_{car}} tt_i} \tag{2}$$

where N_{car} $[veh]$ is the number of cars circulating in the network during the given time interval; tt_i $[s]$ is the time spent by car i in the network during the time interval, and td_i $[m]$ is the distance traveled by car i during the time interval.

The total energy consumption of car traffic in the network for each time interval is determined as:

$$EC_r = \sum_{i=1}^{N_{car}} ec_i \tag{3}$$

where ec_i $[kWh]$ is the energy consumption of car i during the time interval.

The energy consumption per distance traveled $[kWh/veh.km]$ is calculated with Eq. 4:

$$ECD_r = \frac{EC_r}{\sum_{i=1}^{N_{car}} td_i} \cdot 1000 \tag{4}$$

Regarding the traffic dynamics and energy consumption of buses, we use the same equations for calculations.

Macroscopic relationship between accumulation and total energy consumption

Figure 2 depicts the total energy consumption of cars and buses in the network as a function of accumulation (i.e., energy consumption-MFD). The value of each blue or green data point in the figure represents the aggregated energy consumption of cars or buses in the network over a given period (i.e., 1 minute). For electric cars, we observe that when the accumulation is smaller than 1600 $[veh]$, the total energy consumption increases roughly linearly with the increase in accumulation. This is because when the car traffic in the network is not heavy, the total energy consumption of the system increases correspondingly with the number of vehicles in the network. However, when the traffic conditions become congested, the additional effects of congestion make the relationship between car accumulation and energy consumption non-linear (refer to the blue points in Figure 2 (a) when the accumulation is larger than 1600 $[veh]$). This is because heavy traffic leads to congestion and lower speeds, which means that cars spend more time traveling the same distance. As a result, the energy consumed by cars in the network further increases. We also observe that for electric buses, the total energy consumption shows a growing trend with the increase in accumulation. Considering the empirical dataset has a limited range of obervations, especially for public transport vehicles, our empirical enegry conusmption-MFD may only represent the aggregated relationship between accumulation and total energy consumption during a part of the network's loading and unloading cycles.

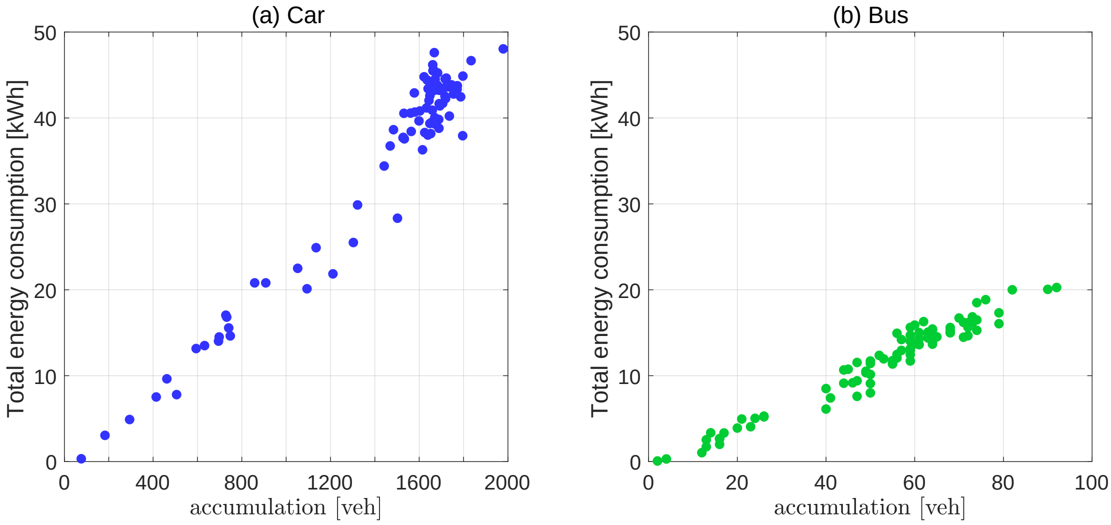

Figure 2: Correlation between total energy consumption and accumulation.

Macroscopic relationship between mean speed and energy consumption

Figure 3 depicts the aggregated relationships between average speed and the energy consumption normalized for distance on a network scale. We observe that when the average speed is lower than 10 km/h, the energy consumption of electric cars decreases with the increase in average speed. However, this decreasing trend tends to be minimal, and the energy consumption of electric cars is basically constant when the average speed is higher than 10 km/h. In contrast, the energy consumption of electric buses significantly decreases as the average speed increases (at least within the typical speed range for buses in the pNEUMA dataset). The different relationships between mean speed and the energy consumption of electric cars and electric buses could be attributed to their differences in vehicle configurations, such as motor power, vehicle mass, drag resistance coefficient and rolling resistance coefficient. Electric cars are lightweight and aerodynamically efficient, which results in approximately constant energy consumption over a wide range of speeds. In comparison, electric buses are heavy and have high rolling resistance. As the speed increases, the rolling resistance reduces, while the aerodynamic drag resistance only slightly increases, leading to decreasing energy consumption.

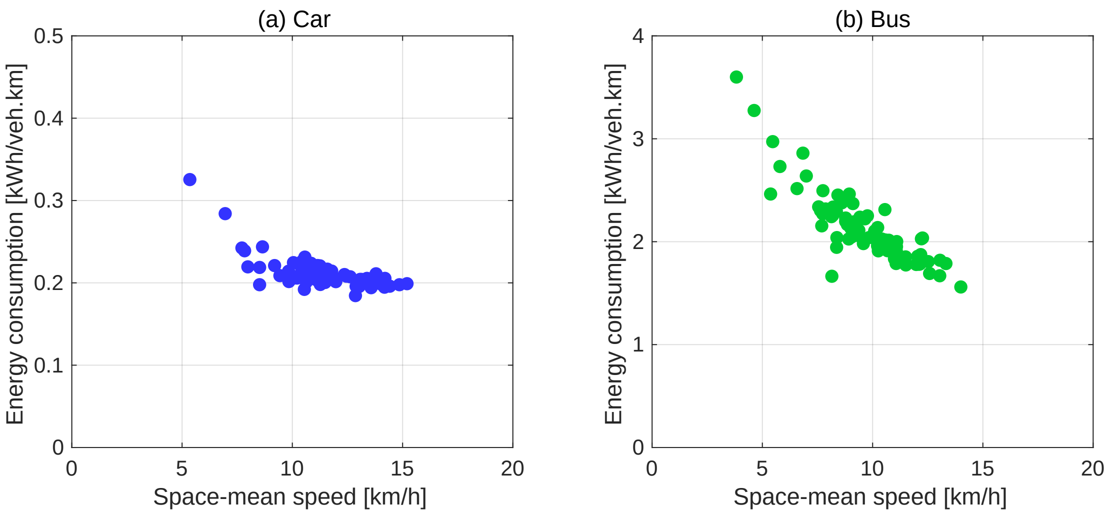

Figure 3: Correlation between energy consumption per distance traveled and spatial mean speed.

4 Conclusions

This paper extends the macroscopic fundamental diagram (MFD) to the energy consumption-MFD by investigating the aggregated relationships between network traffic dynamics and the energy consumption of electric mobility systems in a multimodal urban traffic context. We use a data-based approach, combining naturalistic vehicle trajectories collected by a swarm of drones during the pNEUMA experiment with microscopic energy consumption models. We assume all the trajectories belong to electric vehicles yet maintain the same behavior observed in the pNEUMA dataset. Preliminary results show that well-defined relationships exist between MFD parameters and the energy consumption of electric vehicles (electric cars or buses) at a network level. The total energy consumption of electric cars and buses in the network follows a linear relationship with accumulation under uncongested traffic conditions. When the accumulation exceeds a certain limit (e.g., 1600 $[veh]$ for car traffic in the pNEUMA dataset), the additional effects of congestion make the relationship between accumulation and energy consumption non-linear. We also show that the energy consumption of electric cars decreases as the average speed increases when the average speed is lower than 10 km/h and then tends to be relatively constant even though the average speed further increases. For electric buses, their energy consumption exhibits an obvious decreasing trend with the increase in average speed. These findings provide valuable insights into understanding the network-wide energy consumption characteristics of electric vehicles. In the next phase of our research, we propose to comprehensively analyze the energy consumption distribution of EVs and traditional fossil fuel-powered vehicles across the entire network. On this basis, we could accurately identify the energy consumption hotspots in the network and track the origin of these hotspots. Furthermore, we will also leverage a simulation-based approach to generalize our empirical results and explore viable strategies for mitigating energy consumption hotspots in networks with both electric and fossil fuel-powered vehicles.

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