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The effect of electrified mobility on the relationship between traffic conditions and energy consumption[1]

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ABSTRACT

Decreasing road transport's harmful effects on environment and health and reducing road accidents are major policy priorities. A variety of technologies could drastically improve air quality, reduce energy consumption and CO_2 emissions of road vehicles: in this respect, a prominent trend leverages Electric Vehicles (EVs), supported by improved performance and energy efficiency through connectivity and automation. A noteworthy research question in the transition from Internal Combustion Engine Vehicles (ICEVs) to the alternative technologies, is to understand how Intelligent Transport Systems and other traffic –related measures can contribute to the reduction of fuel consumption and greenhouse gas emissions. In fact, a widely acknowledged tenet assumes that congestion removal or mitigation in presence of ICEVs implies also a reduction of transport-related externalities. This paper explores whether this effect still holds for EVs, by performing an analysis of energy consumption over different vehicle trajectories, under both congested and free-flow conditions. Calculations are carried out using two vehicle simulators: the VT-CPEM (Virginia Tech Comprehensive Power-based Energy consumption model) model for EVs and the CO_2MPAS (CO_2 model for Passenger and commercial vehicle Simulation) vehicle simulator for the ICEVs, for both electric and conventional cases passengers and freight/commercial powertrains have been analysed. Results are presented on real and simulated data related to four powertrain-vehicle combinations, in terms of general trends of energy/fuel consumption versus speed. Interestingly, results show that, differently from ICEVs, the relationship between congestion and energy consumption underlying EVs can change with higher energy consumption connected to an increased average traffic speed.

Keywords: Energy Consumption, Fuel Consumption, Congestion, Traffic, Free Flow, Electric Vehicles.

GLOSSARY

- CAVs: Connected and Automated Vehicles
- CONG: Congested
- CO_2MPAS: CO_2 model for Passenger and commercial vehicle Simulation
- EVs: Electric Vehicles
- EFVs: Electric Freight Vehicles
- FF: Free Flow
- GHG: Greenhouse Gas
- ICEVs: Internal Combustion Engine Vehicles
- LC ICEVs: Light Commercial Internal Combustion Engine Vehicles
- NGSIM: Next Generation SIMulation
- PEVs: Plug-in Electric Vehicles
- PHEVs: Plug-in Hybrid Electric Vehicles
- SL: Speed Limit
- VT-CPEM: Virginia Tech Comprehensive Power-based Energy consumption model
- WLTC: World-wide harmonized Light duty Test Cycle

1. INTRODUCTION

Connected and Automated Vehicles (CAVs) represent one of possible technologies to improve energy efficiency of transport systems: indeed, CAVs aim firstly at increasing users' comfort and safety and secondly at reducing energy consumption and vehicle emissions by driving more efficiently than a human driver. In this respect, automation without connectivity could decrease road capacity because of more risk-averse automated driving setups, yielding larger headways (Makridis et al., 2018); however, the envisaged reduction of road accidents improves overall network performance, as accidents are major causes for bottlenecks. With the support of connectivity, CAVs might in theory allow for smaller headways thanks to shorter reaction times, with a consequent *ceteris paribus*[2] positive effect in reducing traffic congestion. For ICEVs (Internal Combustion Engine Vehicles), lower congestion implies lower energy consumption and lower emissions, see e.g. (Litman, 2017), (Wadud et al., 2016), (Barth and Boriboonsomsin, 2008) and (Treiber et al., 2008), thus leading reasonably to argue that connected and automated ICEVs are effectively able to reduce traffic externalities. The reason why low congestion levels also imply low energy consumption in ICEVs (Internal Combustion Engine Vehicles) is that the efficiency of internal combustion engines deteriorates in the presence of recurrent, highly transient, acceleration/deceleration phases (stop and go conditions). The vehicle powertrain efficiency increases with the speed, because of higher load, hence consumption decreases when travelling at constant speed, up to a certain speed limit, above which the vehicle powertrain

[2] The *ceteris paribus* concept should be intended by considering that improvement of traffic conditions is only a potential effect, due to the complexity of transport system phenomena. By way of example, the rebound effect – also referred to as the Braess' paradox in the transport community – shows that seeking congestion reduction by increasing system capacity usually attracts further transport demand, with a possible deterioration of the system level-of-services in the long run.

reaches its peak efficiency and any further increases in speed increases also fuel consumption. In addition, modern vehicles, especially in the attempt to meet CO_2 emission targets set in several countries, adopt a variety of technologies (such as variable valve timing, regenerative breaking energy, coasting technologies, start-stop system, and so on) to improve their fuel consumption performances.

Plug-in Electric Vehicles (PEVs)[3] represent another prominent technology towards improved sustainability and lower emissions. Indeed, alternative powertrains such as PEVs represent a promising technology for the propulsion of vehicles thanks to higher efficiency and potentially effective contribution to the decarbonisation of transport, as well as air quality improvements in urban areas. However, whether this holds for any specific conditions in which the vehicle operates it is still a vastly unexplored field. Obviously, PEVs can be easily coupled with vehicle connection/automation and, in general, they can be applied in the context of policies aimed at reducing traffic congestion. In this respect, the efficiency of hybrid and electrified powertrains has a very different pattern with respect to ICEVs, being approximately constant over large intervals in the vehicle operational range. This makes the relationship between traffic congestion and PEVs consumption much less straightforward than for ICEVs: thus, any claims on the environmental effectiveness of traffic-related measures in presence of PEVs should be supported by an investigation of the underlying relationship between traffic conditions and fuel/energy consumption.

[3] The U.S. DOE (Department Of Energy of the United States) defines as Plug-in Electric Vehicles (PEVs) both the (i) Plug-in Hybrid Electric Vehicles (PHEVs) parallel/blended (e.g. Toyota Prius Plug-in) and series, also named Extended Range Electric Vehicles (EREVs) (e.g. Chevy Volt); and (ii) Electric Vehicles (EVs) (e.g. Nissan Leaf). In this paper exclusively Electric Vehicles (EVs) for passengers applications have been analysed. Addionally, Electric Freight Vehicles (EFVs) have been studied.

In this light, main objective of this paper is to perform a preliminary investigation of this research question. For this aim, the energy/fuel consumption of four different types of vehicles and concerned powertrains (including passengers and freight/commercial powertrains) has been simulated in various traffic scenarios, including both free-flow and congested traffic conditions, to explore the general trend of energy/fuel consumption vs. speed in such case studies. Specifically, for EVs and Electric Freight Vehicles (EFVs), the tank-to-wheel calculation of on-board energy consumption/recovery has been performed with the Virginia Tech Comprehensive Power-based Energy consumption model (VT-CPEM) (Fiori et al., 2016), whilst for ICEVs and Light Commercial (LC) ICEVs the CO_2 model for Passenger and commercial vehicle Simulation (CO_2MPAS) ("CO2MPAS: Vehicle simulator predicting NEDC CO2 emissions from WLTP — CO2MPAS 1.6.1.post0 documentation," 2018, Fontaras et al., 2018) has been applied. Preliminary results show that, in contrast with a rather wide common belief, the relationship between energy consumption and traffic conditions for EVs is appreciably different from the relationship between fuel consumption and traffic conditions underlying ICEVs. In this light, results presented in this paper aim at stimulating a broader discussion on the impact of vehicle electrification on the overall energy consumption of the transport sector.

The remaining of the paper is organized as follows: Section 2 reports on a short literature review, Section 3 illustrates the methodology and all concerned details on the approach and on used vehicle simulators, Section 4 describes analysed case studies, Section 5 shows experimental results and, finally, Section 6 draws conclusions and research prospects.

2. LITERATURE REVIEW

Energy consumption of a vehicle can generally achieve high variability (Pavlovic et al., 2018), depending on several external factors, such as vehicle and road characteristics, environmental conditions, traffic conditions, and so on (Fontaras et al., 2017). In particular, the relationship between traffic conditions and environmental externalities has been the subject of several research efforts, from both policy and technical viewpoints.

By way of example, from a policy perspective, (Gerboni et al., 2017) presented a conceptual link between two families of models - energy and transport - showing the importance of accurate ICT-based data exchange between the models and the relevance of a comparison between present and future policy implementations. Indeed, both energy strategy makers and transport planners need supporting tools for a better assessment of the impact of alternative policies and to set realistic targets for the transport sector. From a technical perspective, (Li et al., 2017; Qi et al., 2017) developed a mesoscopic energy consumption estimation for EVs to evaluate its integration with eco-routing applications. Barth and Boriboonsomsin (Barth and Boriboonsomsin, 2008) underlined that fuel consumption and CO_2 emissions for ICEVs can be lowered by improving traffic conditions, specifically by reducing traffic congestion. The authors analysed traffic congestion and its impact on CO_2 emissions using detailed energy and emission models and linking them to real-world driving patterns and traffic conditions. Results show for a typical traffic scenario in Southern California that CO_2 emissions can be reduced by up to almost 20% by applying different traffic management strategies. Similar conclusions are reported, amongst others, by (Mascia et al., 2017), (Beevers et al., 2016), (Stevanovic et al., 2009), (Demir et al., 2014), and (Boriboonsomsin et al., 2012).

For the purposes of the paper, few studies have introduced already the concept that a migration from conventional ICEVs to electrified powertrains may change the relationship between traffic conditions and vehicle energy consumption. In this respect, amongst others, (Fontaras et al., 2008) and (Gardner et al., 2013) highlighted that, for both hybrid and plug-in hybrid vehicles, the tank-to-wheel energy consumption on a per-kilometre basis is lower in within-city driving cycles and higher in highway driving cycles, that is the opposite of a conventional internal combustion engine vehicle. However, a more thorough investigation of this research question is still missing in the literature.

This paper aims at filling this gap, leveraging and extending a previous work by (Fiori et al., 2017), whose aim was the evaluation of the impact of route selection on energy consumption of electric vehicles, based on empirical second-by-second Global Positioning System (GPS) commute data and traffic micro-simulation data. The study found that EVs and conventional ICEVs exhibit different fuel/energy-optimized traffic performances, thus leading to recommendation of different routing paths. More specifically, simulation results indicated that a faster route can increase EVs energy consumption, whilst significant energy savings can be observed when EVs utilize a longer travel time route due to energy regeneration. Interestingly, regenerated energy was greatly affected by facility types and congestion levels and, in turn, it can influence significantly EVs energy efficiency. As a side note, this opens room for an in-depth exploration of eco-routing strategies for alternative powertrains.

3. METHODOLOGY

The paper aims at analysing the relationship between energy/fuel consumption and traffic conditions based on an empirical approach, primarily because of the inherent difficulties underlying a theoretical approach able to cover satisfactorily the wide range of concerned technology configurations and traffic conditions. The proposed empirical approach takes advantage of different available sources of real-world vehicle activity data and calibrated vehicle simulation models for different vehicle technologies, thus covering a broad range of vehicle operating conditions, case studies and types of vehicles. Overall, empirical results allow exploring – at least qualitatively – the general relationship between energy consumption and traffic conditions for both ICEVs/LC ICEVs and EVs/EFVs and to explore concerned policy implications.

The methodology adopted in the paper leverages two main aspects, respectively the vehicle activity data and the calculation of vehicle energy/fuel consumption, illustrated in the next sub-sections.

3.1. Vehicle activity data

The soundness of the proposed empirical approach highly depends upon availability of a rather broad set of data, sufficiently representative of different contexts and traffic conditions. For this aim, the paper considers the following four data sources:

- two sets of real "reconstructed" vehicle trajectory data:
    - the **NGSIM** dataset collected in US (in the remainder of the text labelled as NGSIM) ("U.S. Department of Transportation. Federal Highway Administration. Next Generation Simulation (NGSIM) program, https://www.its-rde.net/index.php/rdedataenvironment/10023; [accessed 08 November 2017]," 2017), eventually reconstructed by (Montanino and Punzo, 2015)
    - the MULTITUDE dataset collected in **Naples** (Italy), and described in (Punzo et al., 2005)
- simulated trajectory data using the Aimsun traffic simulation model (Barceló and Casas, 2005) calibrated for a freeway scenario in **Antwerp** (Belgium).
- average speed profiles resulting from the analysis of 1 million kilometres of real-world trajectory data in the **WLTC** dataset ("Development of the World-wide

harmonized Light duty Test Cycle (WLTC) and a possible pathway for its introduction in the European legislation - EU Science Hub - European Commission," 2015).

Each of these datasets consists of one or more vehicle trajectories on the same origin-destination pair. For the purposes of the paper, all traffic conditions should be covered, from congestion (i.e. traffic speed affected by traffic flow) to saturation (unstable flow, i.e. stop-and-go conditions). In this respect, the first two datasets were built to perform analysis of longitudinal interactions among vehicles, the third represents a simulation scenario with heavy traffic conditions and the fourth is an artificial[4] vehicle trajectory used in laboratory for the certification of vehicles' energy consumption and pollutant emissions. As a result, the first dataset is the only embedding an almost free-flow trajectory. Thus, a free-flow trajectory has been generated and added to each dataset to cover the set of all traffic conditions: such free-flow trajectory assumes a vehicle reaching and keeping constant either its maximum speed of the trajectory itself or the road speed limit where available/applicable. Additional information on the different datasets is reported in Section 4.

3.2. Calculation of energy/fuel consumption

For the purposes of the paper, each trajectory in the vehicle activity datasets illustrated in the previous section should be associated with a energy/fuel consumption related to different vehicle types/configurations, that is:

[4] An average speed profile is an artificial vehicle trajectory constructed to be representative of average driving conditions from a series of real-world observations. It is usually used to derive various types of information related to vehicles performance (e.g. fuel consumption, pollutant emissions, electric range, etc.) under standardized conditions (e.g. by using it to test a vehicle on a chassis-dynamometer in a lab or to perform a vehicle simulation).

- a C-segment electric vehicle (e.g. Nissan Leaf, Chevrolet Bolt),
- a C-segment gasoline ICE vehicle (e.g. Ford Focus, Toyota Auris),
- a light commercial electric freight vehicle (e.g. Renault Kangoo Z.E., Nissan e-NV 200),
- a light commercial diesel ICE vehicle (e.g. Renault Kangoo, Nissan NV 200).

The main characteristics of the vehicles simulated are reported in Table 1.

Table 1: Vehicles main characteristics.

	EV	**EFV**	**ICE**	**LC ICE**
Weight [kg]	1595	1628	1220	1270
Air drag coefficient	0.28	0.35	0.28	0.35
Battery capacity [kWh]	24	22	-	-
Engine capacity [cm^3]	-	-	1600	1600
Fuel used	Electricity		Gasoline	Diesel

The two light commercial vehicles have been simulated with two different payloads, to understand the potential impact of different weight conditions. At a glance, a summary of all case studies simulated in the present study is presented in Table 2, resulting from intersection of vehicle activity data and types of vehicles. Further information on simulated trips, case studies, and vehicles characteristics/performances is provided in the remaining of the paper, where needed. Importantly, already calibrated vehicle simulation models have been applied to calculate energy/fuel consumption of concerned vehicles in each trajectory, as illustrated in the next sub-section.

3.2.1. Vehicle simulators

The vehicle simulators applied in this work are the CO_2MPAS vehicle simulator, developed by the Joint Research Centre of the European Commission, for estimating the fuel consumption of the ICEVs/LC ICEVs (Ciuffo and Fontaras, 2017; Tsiakmakis et al., 2017) and the VT-CPEM vehicle energy consumption model, developed by (Fiori et al., 2016), for estimating the energy consumption of the EVs/EFVs.

The interested reader might refer to the above literature references for in-depth technical details of each simulator. At a glance, CO_2MPAS is a backward-looking longitudinal-dynamics CO_2 and fuel-consumption simulator for light-duty M1 & N1 vehicles (cars and vans), especially created to *estimate and type-approve CO_2 emissions* of vehicles by simulating NEDC conditions based on the emissions measured during WLTP tests, according to the *EU legislation* ("Regulation (EU) No 1014/2010," 2018). CO_2MPAS is an open-source project developed in Python-3.5 (Van Rossum and Drake Jr, 1995) and licensed through the European Public License scheme, and currently adopted by dozens of technical services and type-approval authorities in charge of the emission type-approval of vehicles in Europe. Evidence collected from the official use of CO_2MPAS during the type-approval of vehicles shows that the model is able to estimate fuel consumption of internal combustion engine vehicles equipped with any kinds of specific technology, with an unbiased error of ± 4% in 75% of the cases (Ciuffo and Fontaras, 2017; Fontaras et al., 2018).

The VT-Comprehensive Power-based EV Energy consumption Model (VT-CPEM) is a backward highly-resolved power-based model. Specifically, the model requires as inputs the instantaneous speed and the vehicle characteristics, and produces as output the energy consumption (EC) [kWh/km] by the vehicle for a specific drive cycle, the instantaneous power consumed [kW], and the state of charge (SOC) of the electric battery [%] at the end of the simulation. This model accurately estimates the energy consumption, producing an average error of about 6% relative to empirical data (Fiori et al., 2016).

Table 2: Overview of case/scenario characteristics.

Case	**Traffic Characteristics**		**Vehicle powertrain**	**Payload**
	Condition	**Average speed (km/h)**		
NGSIM	Congested	15.4 (std. dev. 0.32)	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
	Free-flow	87.5	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
Naples	Congested	22.2	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
	Speed-Limit	50	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg

Antwerp	Congested	41.5 (std. dev. 1.81)	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
	Free-flow	90	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
WLTC	Congested	46.5	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg
	Free-flow	77.9	EV	-
			ICEV	-
			EFV	0 and 300kg
			LC ICEV	0 and 300kg

4. DETAILED DESCRIPTION OF CASE STUDIES

4.1. NGSIM real trajectory data (NGSIM)

The Next Generation Simulation (NGSIM) program was initiated by the United States Department of Transportation (US DOT) Federal Highway Administration (FHWA) in the early 2000's (“U.S. Department of Transportation. Federal Highway Administration. Next Generation

Simulation (NGSIM) program, https://www.its-rde.net/index.php/rdedataenvironment/10023; [accessed 08 November 2017],” 2017). The Next Generation SIMulation project is the only data source that provide public access to complete sets of all vehicle trajectories observed in a time-space domain. NGSIM vehicle trajectory data were collected in four sites (two highway segments and two arterials) through synchronized video cameras, mounted on top of high buildings adjacent to the roadway, recording all vehicles passing through the study area (see Figure 1 (left)). Post-processing of images finally gives vehicle positions on the road section every 0.1 seconds.

Overall, NGSIM data is well-acknowledged as one of the most valuable source of microscopic traffic data and have been widely used by scientists worldwide to advance research in traffic flow theory. However, in recent years, some researchers collected substantial proofs demonstrating that such data are largely affected by measurement errors, potentially jeopardizing credibility of many studies based on them (Punzo et al., 2011). (Montanino and Punzo, 2015, 2013) deeply investigated these issues and proposed a multi-step procedure to reconstruct vehicle trajectory data, and applied it to the NGSIM I80-1 dataset. The “reconstructed” NGSIM I80-1 dataset, publicly available on the US FHWA ITS Public Data Hub, has been used in this study. For the simulations carried out in this paper, 19 out of more than 2000 overall NGSIM trajectories have been selected as representative of 19 different congested case studies, with an average speed of 15.4 km/h and a standard deviation of 0.32 km/h. Each of the 19 trips has a duration higher than 90 seconds. A further trajectory, showing approximately constant speed (average 87.5 km/h) throughout the road stretch, has been also selected as representative of a free-flow situation. The length of all trajectories is approximately 400 meters (see Figure 1 (right)).

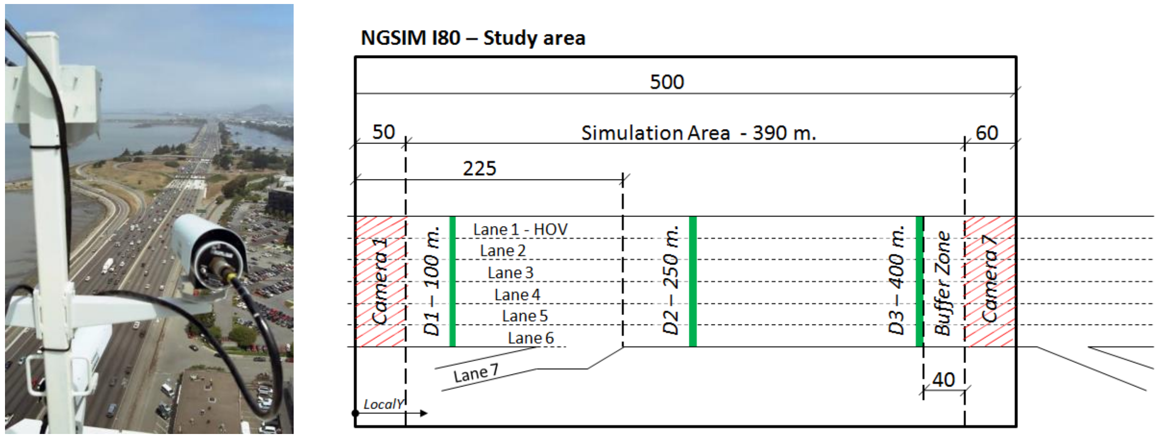


Figure 1: (left) digital video camera mounted on top of a building that overlooks I-80 is recording vehicle trajectory data ("U.S. Department of Transportation. Federal Highway Administration. Next Generation Simulation (NGSIM) program, https://www.its-rde.net/index.php/rdedataenvironment/10023; [accessed 08 November 2017]," 2017) and (right) schematic representation of the NGSIM I80 scenario (simulation starts in x = 50 m and ends at x = 440 m). Virtual detector D1 is located at x = 100 m, D2 at x = 250 m, and D3 at x = 400 m (Montanino and Punzo, 2015).

Figure 2 presents at a glance the 20 reconstructed trajectories selected from the NGSIM database.

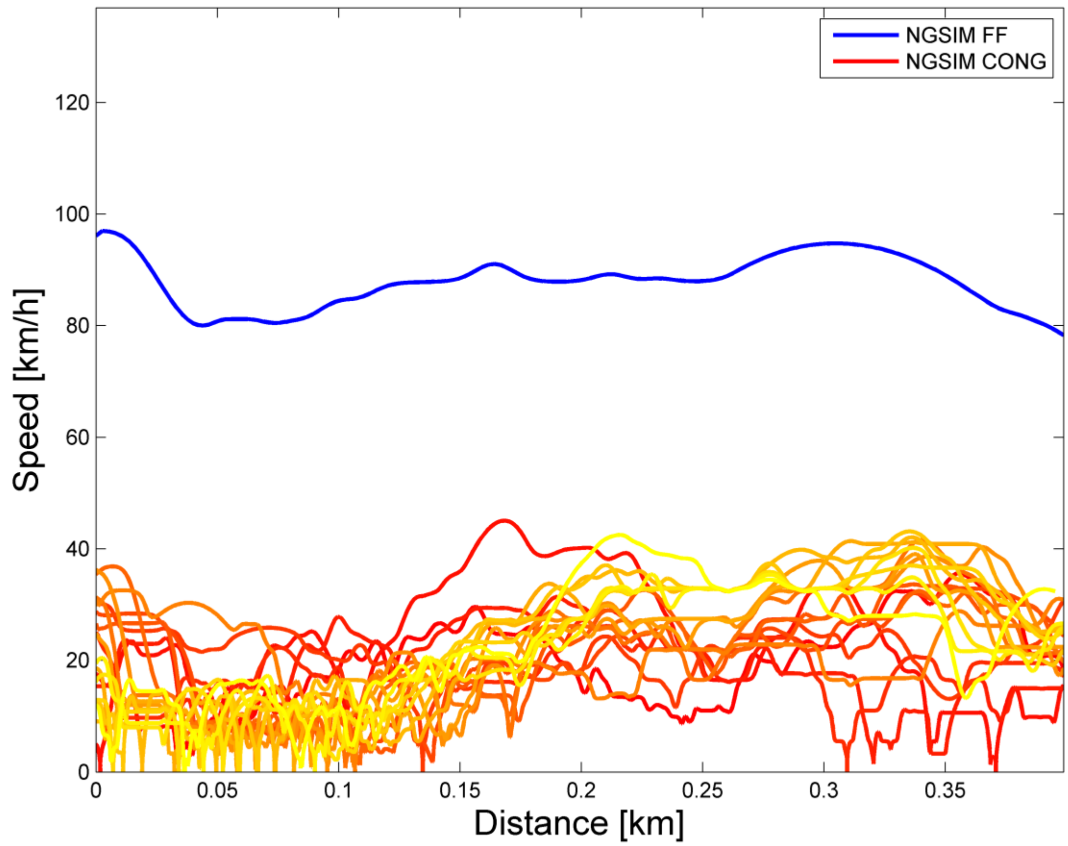


Figure 2: Speed profiles in the case n. 1: NGSIM "reconstructed" trajectory data. Different colours are used to help the reader distinguishing the different trajectories in the NGSIM CONG set.

4.2. MULTITUDE real trajectory data (Naples)

The EU project MULTITUDE ("MULTITUDE Project," 2018) made available to the scientific community a series of vehicle trajectories collected to carry-out vehicle longitudinal interaction analyses, namely car-following experiments. Specifically, the trajectory applied in the present study was collected in the context of a data acquisition campaign in the city of Napoli (Italy) (Punzo et al., 2005). Such trajectory is representative of a congested scenario, with an average speed of 22.2 km/h, and the corresponding free-flow trajectory has been generated by considering that the concerned road speed limit was 50 km/h. The main interest in analysing this trajectory lies in its higher length with respect to the NGSIM dataset, that is 1850 meters versus 400 meters. Figure 3 illustrates both the congested and the corresponding free-flow trajectories.

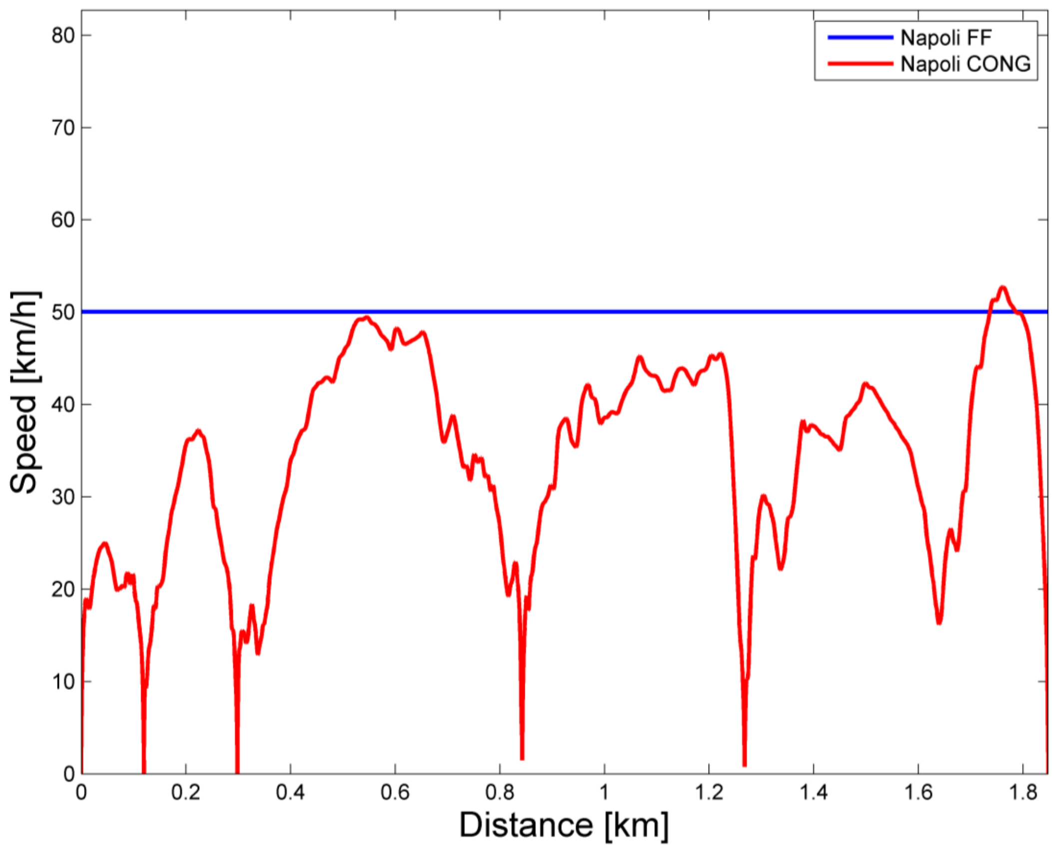


Figure 3: Speed profiles in the case n. 2: Naples (Italy) trajectories.

4.3. Aimsun simulated trajectory data (Antwerp)

To increase the number of trajectories included in the present study, a further set of vehicle trajectories was derived using a traffic simulation model of the ring road of Antwerp (Belgium), characterized by highly congested traffic conditions. The concerned network is implemented in the Aimsun commercial micro-simulation software ("AIMSUN: https://www.aimsun.com/; [accessed 08 November 2017]," 2017) (see Figure 4). For the needs of the present paper, a single origin-destination pair has been selected in the ring road, with a distance from origin to destination of approximately 4225 meters. The driving behaviour implemented in the model is a modified version of the Gipps car-following model (Gipps, 1981). The trajectory selection procedure used in this work is heuristic and threshold-based on vehicles' delay time when traveling from the origin to the destination point. The free flow profile was chosen randomly from the set of trajectories having a delay time lower than 3 seconds, while the 23 congested trajectories were chosen randomly from the set of trajectories having a delay time of more than 200 seconds. Notably, the average speed, of the free flow profile, is 90 km/h and in the remaining 23 trajectories that the average speed is 41.5±1.81 km/h. Albeit simplistic, such trajectory selection procedure can be considered reasonable enough to support the research objectives of the present paper. Overall, Figure 5 illustrates the 24 trajectories (23 congested plus a free-flow) for the Antwerp case study.

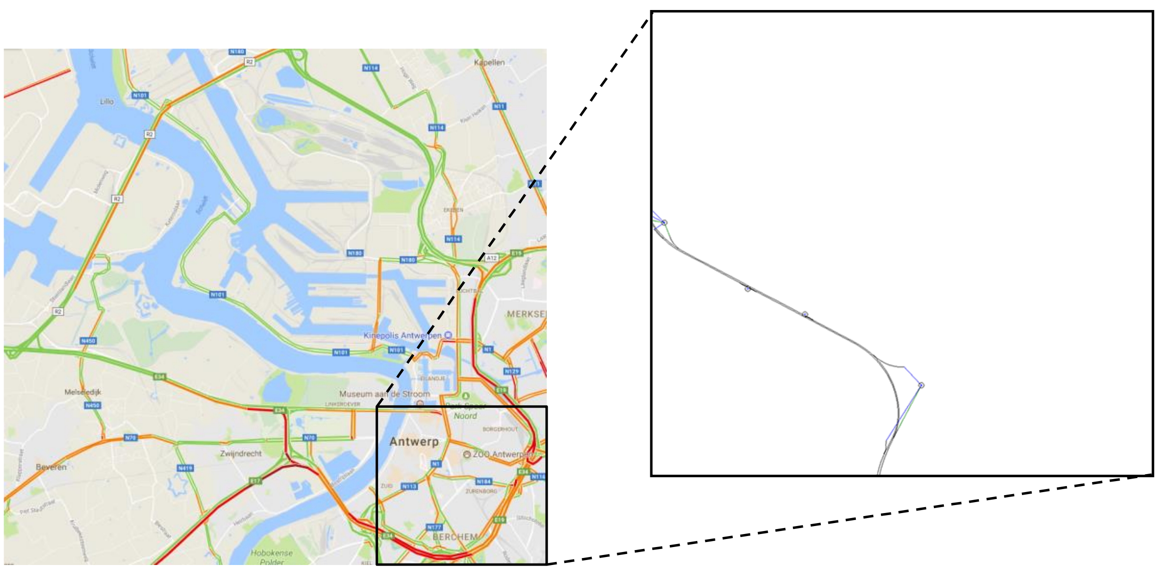


Figure 4: (left) network of the ring road of Antwerp (screenshot from Google Maps) and (right) network exported from the simulation software. Simulated trajectories were selected on the highlighted path .

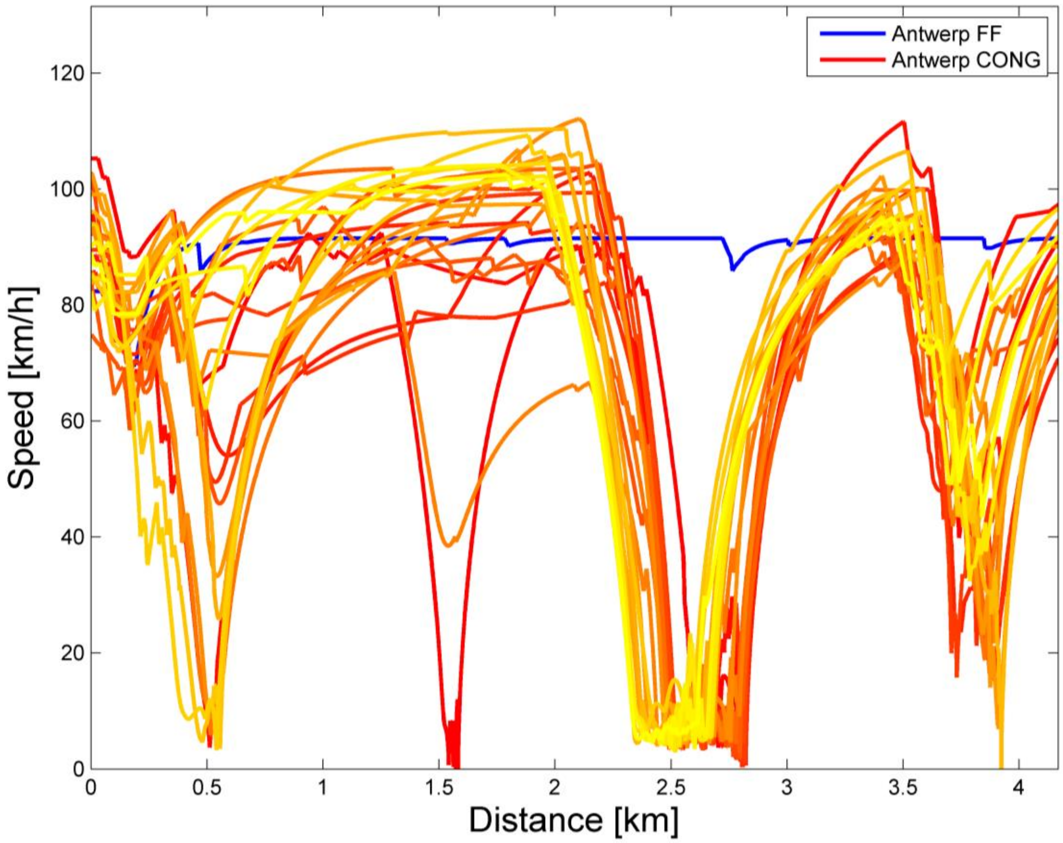


Figure 5: Speed profiles in the case n. 3: Antwerp (Belgium) simulated trajectory data. Different colours are used to help the reader distinguishing the different trajectories in the Antwerp CONG set

4.4. Average speed profile data (test-cycle or driving-cycle) (WLTC)

The World-wide harmonized Light duty Test Cycle (WLTC) (Tutuianu et al., 2015) is the most recent artificial driving-cycle trajectory developed for legislative purposes. The process leading to its development has been motivated by the willingness to achieve a single cycle representative of driving conditions in different contexts and therefore suitable for introduction in the vehicle certification process all around the world. An average speed profile is an artificial vehicle trajectory constructed to be representative of average driving conditions from a series of real-world observations. It is usually used to derive various types of information related to vehicles performance (e.g. fuel consumption, pollutant emissions, electric range, etc.) under standardized conditions (e.g. by using it to test a vehicle on a chassis-dynamometer in a lab or to perform a vehicle simulation). Several test-cycles are available in the literature for different purposes (research, vehicle benchmark, official type-approval, etc.). For an overview of different driving cycles, the interested reader can refer to the following on-line source: ("Emission Test Cycles," 2018). The WLTC has been developed under the UNECE framework and resulted from the analysis of almost 1 million kilometres of real-world activity data collected in several countries (Tutuianu et al., 2015).

The WLTC trajectory is divided in four different phases: low, medium, high and extra-high speed, for a total duration of 1800 seconds. For the purposes of the paper, the corresponding free-flow trajectory has been constructed by using the maximum speed of each phase as an hypothetical road speed limit, and by setting at each stop a speed equal to 0 km/h. Overall, the WLTC congested scenario has an average speed of 46.5 km/h, against an average speed for the free-flow condition of 77.9 km/h. The corresponding trajectories are depicted in Figure 6.

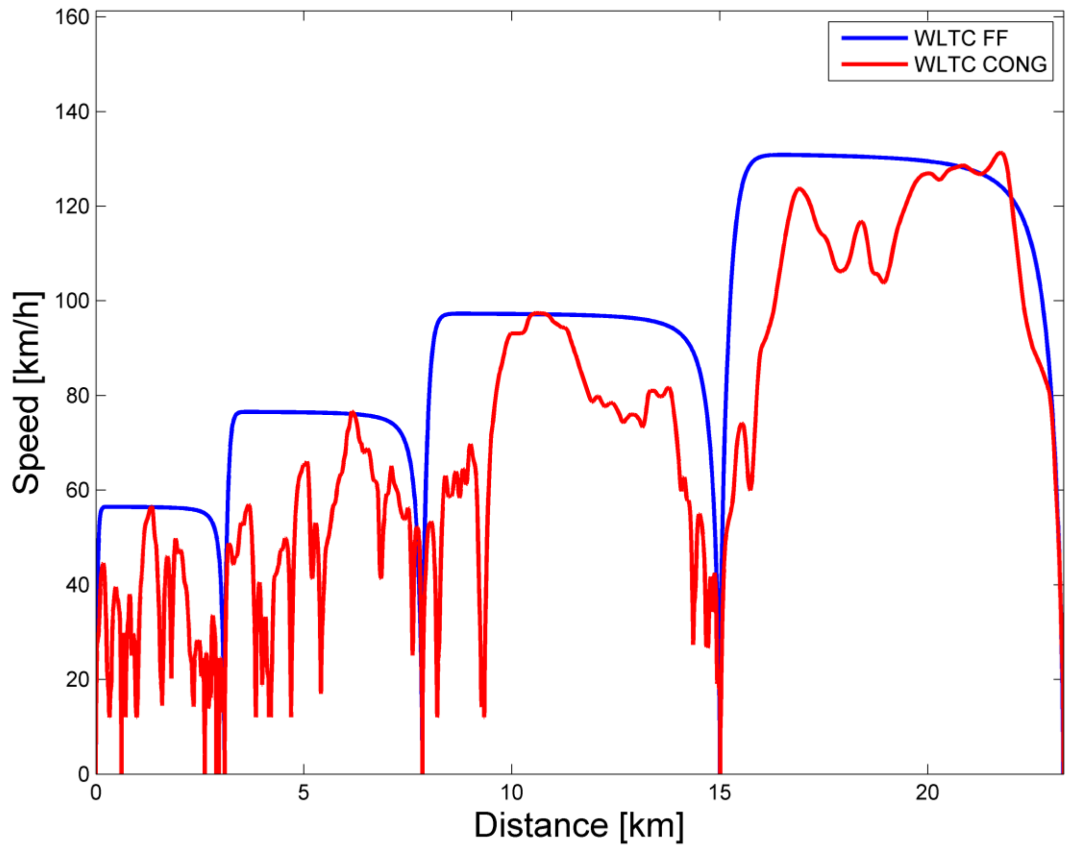


Figure 6: Speed profiles in the case n. 4: WLTC.

4.5. Summary statistics of vehicle trajectory datasets

For the sake of completeness, Table 3 summarizes relevant kinematic statistics for each trajectory dataset.

Table 3: Summary of kinematic statistics per trajectory dataset is reported

		NGSIM		**Naples**		**Antwerp**		**WLTC**	
		CONG	FF	CONG	SL	CONG	FF	CONG	FF
Duration (s)	mean	93.75	16.5	300.1	133	367.69	166.7	1801	1075
	std dvn	2.05				16.19			
Distance (km)	mean	0.40	0.40	1.85	1.85	4.23	4.17	23.26	23.26
	std dvn	0				0			
Average speed (km/h)	mean	15.35	87.5	22.17	50	41.54	90	46.50	77.88
	std dvn	0.32				1.81			
Maximum speed (km/h)	mean	37.27	96.7	52.71	50	102.44	91.5	131.30	130.83
	std dvn	4.96				5.99			
Standard deviation of speed (km/h)	mean	9.93	4.7	16.32	0	36.59	3.6	36.04	35.45
	std dvn	1.61				2.60			
Min acceleration (m/s2)	mean	-3.66	-0.46	-3.59	0	-3.95	-0.36	-1.50	-0.94
	std dvn	0.70				0.58			
Maximum acceleration (m/s2)	mean	2.47	0.25	2.75	0	1.20	0.16	1.75	1.75
	std dvn	0.25				0.20			
Standard deviation of acceleration(m/s2)	mean	0.88	0.14	0.83	0	0.66	0.04	0.53	0.44
	std dvn	0.12				0.08			

5. EXPERIMENTAL RESULTS

5.1. Detailed results for each trajectory dataset

The four different powertrains described in Section 3.2 have been tested on the four case scenarios illustrated in Section 4. As already mentioned, the VT-CPEM and CO_2MPAS vehicle simulators have been respectively applied for the electric (EV) and internal combustion engine (ICE) powertrains to calculate their energy/fuel consumption and related emissions.

Experimental results are presented separately for free-flow (FF) and congested (CONG) trajectories for each dataset, separately for EVs and ICEs and by type of vehicle (passenger, light commercial/freight). In the case of freight vehicle, also a case study with a payload of 300 kg has been simulated. Overall, Figure 7 and Figure 8 report respectively results of the experiments for the EVs and the ICEVs. Notably, the standard deviation of energy/fuel consumptions is reported only for the NGSIM and the Antwerp congested cases, being the only with adequate number of trajectories.

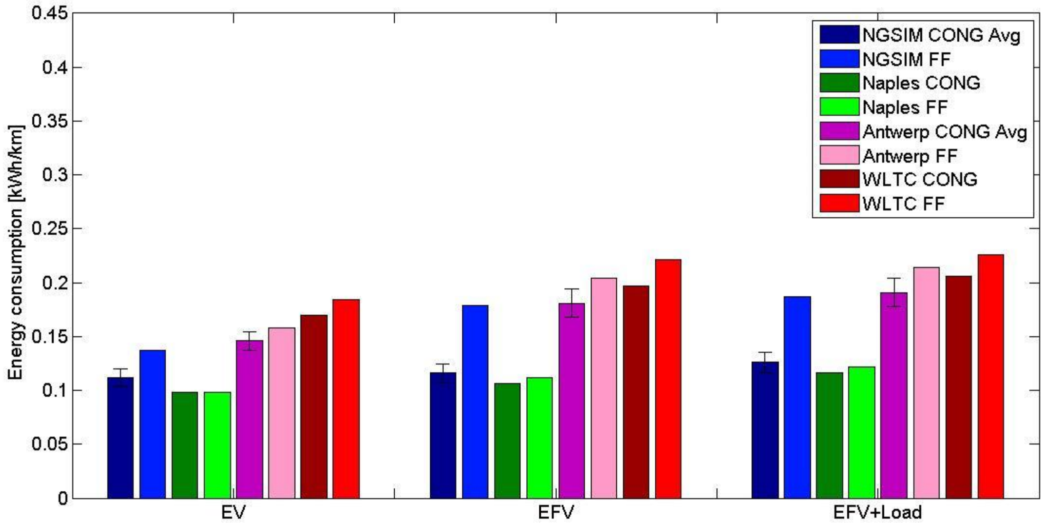


Figure 7: Energy consumptions of the EV and EFV on the 4 scenarios analysed in congested (CONG) and free flow (FF) conditions. Also, for the EFV the case with a payload of 300 kg has been analysed.

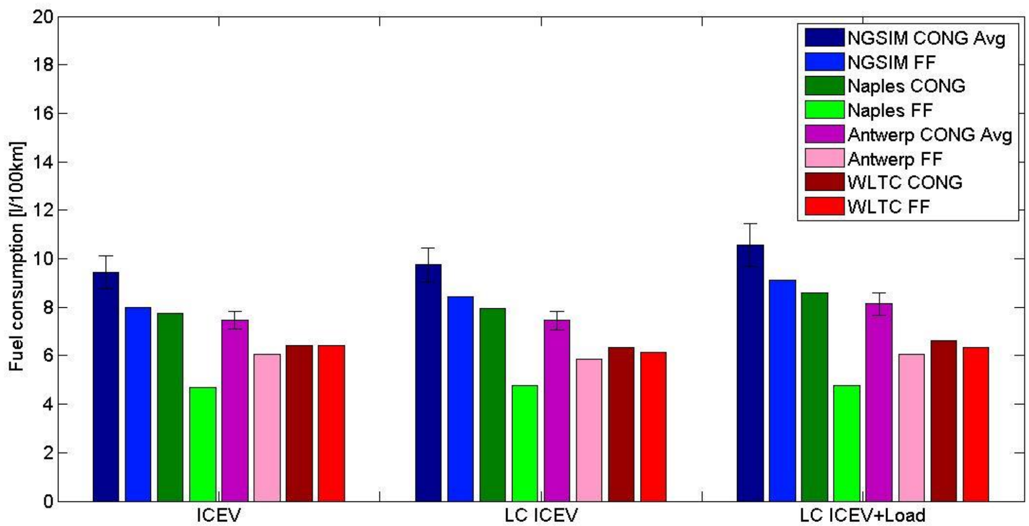


Figure 8: Fuel consumptions of the ICEV and LC ICEV on the 4 scenarios analysed in congested (CONG) and free flow (FF) conditions. Also, for the LC ICEV the case with a payload of 300 kg has been analysed.

In particular, for the NGSIM case these values are 0.008, 0.009 and 0.009 kWh/km respectively for EV, EFV and EFV with additional load, and 0.677, 0.707 and 0.888 l/100km for ICEV, LC ICEV and LC ICEV with additional load, respectively. Similarly, the standard deviation of energy/fuel consumptions for the Antwerp dataset leads to 0.009, 0.013 and 0.013 kWh/km for EV, EFV and EFV with additional load, respectively, and 0.907, 0.960 and 1.116 l/100km for ICEV, LC ICEV and LC ICEV with additional load, respectively.

Table 4 illustrates the relative difference of energy/fuel consumption between the congested case and the corresponding free-flow case, for all datasets.

Table 4: Overview of the results achieved

Case	**Vehicle characteristics**		**Energy consumption impact congestion vs. free-flow (in %)[5]**
	Vehicle	**Payload**	
NGSIM, congested	EV	-	-18
	ICEV	-	18
	EFV	-	-35
	LC ICEV	-	16

[5] The percentage values reported in this table represent the decrease (-) or the increase (+) of the energy/fuel consumption in the congested case compared with the free flow scenario. For example, for the NGSIM data the EV energy consumption decreases of the 18% in the congested case compared with the free flow one, while the ICEV fuel consumption increases of the 18% in the congested scenario compared with the free flow one.

	EFV	300kg	-33
	LC ICEV	300kg	16
Naples, congested	EV	-	0
	ICEV	-	65
	EFV	-	-6
	LC ICEV	-	66
	EFV	300kg	-5
	LC ICEV	300kg	80
Antwerp, congested	EV	-	-8
	ICEV	-	23
	EFV	-	-11
	LC ICEV	-	27
	EFV	300kg	-11
	LC ICEV	300kg	35
WLTC, congested	EV	-	-8
	ICEV	-	0
	EFV	-	-11
	LC ICEV	-	3
	EFV	300kg	-9
	LC ICEV	300kg	4

Interestingly, in the NGSIM reconstructed dataset, the energy consumption for EVs and EFVs is lower in congested conditions with respect to free-flow conditions, with a percentage different equal to -18% for EVs and -35% for EFVs. The impact of additional payload on the EFVs just reduces a little bit this difference, yielding a -33% between congested and free-flow conditions. On the contrary, ICEV, LC ICEV and LC ICEV with load provide an increase of fuel consumption of respectively 18%, 16% and 16% in congested conditions with respect to free-flow conditions. In the second case (Naples), the energy consumption for passenger EVs is the same in the two cases (0%), whilst EFV and EFV with the additional payload in the congested conditions are respectively -6% and -5% with respect to the free-flow case. On the contrary, a very significant difference can be observed between congested and free-flow conditions for traditional ICEVs, ranging from +65% for passenger ICEVs to 80% for ICEV with load. Similar trends can be observed also for the Antwerp and WLTC scenarios, whose percentage reduction in energy consumption between congested and free-flow conditions is very similar also in magnitude, whilst the corresponding percentage increase in fuel consumption is remarkably higher for the Antwerp scenario with respect to the WLTC.

As a summary, results show that a trend seems to exist for electric vehicles, that is *congested conditions are characterized by lower energy consumption if compared with free flow conditions on the same case scenario*; this difference slightly decreases as the onboard load in light commercial vehicles analysed increases. This phenomenon can be explained rather straightforwardly because of the combined effect of (a) higher and more constant efficiency of electric motor/generator and electric devices (inverters, batteries etc) with respect to ICEVs, and (b) the energy recovered during braking, that allows reducing energy consumption especially when congested situations occur.

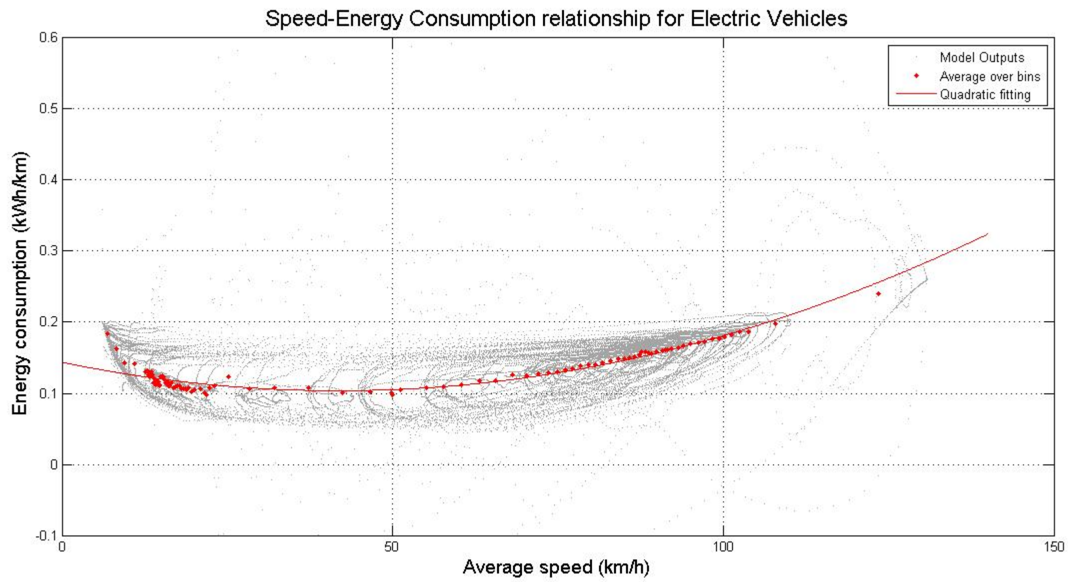
The analysis of the ICE and LC ICE vehicles indicates an opposite trend: congested conditions are characterized by higher fuel consumption if compared with free flow conditions on the same case scenario, with also an higher range of variation with respect to EVs (up to 80% and up to -35% for ICEVs and EVs, respectively). Similar, yet slightly higher gaps can be observed for ICEVs in Naples and Antwerp cases with respect to the NGSIM and WLTC cases. Interestingly, the same trend does not hold for the WLTC, where the observed difference between free-flow and congested conditions is marginal. This can be explained by the fact that the range of dynamics in the WLTC is much broader than in the other cases and therefore only marginal gains in efficiency can be achieved.

5.2. Detection of general trends

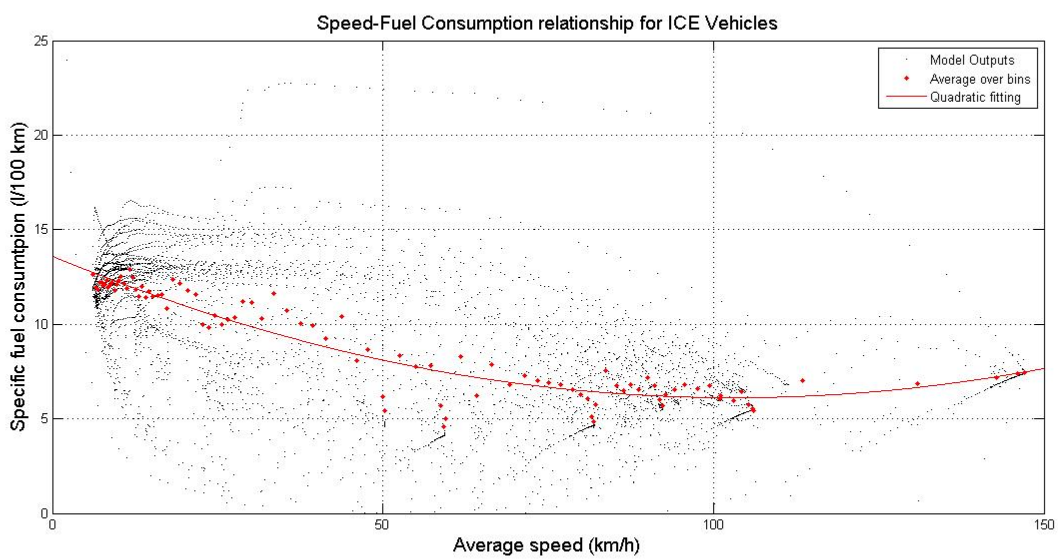
This section aims at identifying possible general trends in the relationship between average speed over a road segment and concerned energy/fuel consumption respectively for both electric and conventional vehicles. For this aim, all trajectories applied in this paper have been split randomly into 300 metres-long “elemental segments”, whose number for each trajectory depends upon the length of the trajectory itself. Specifically, each trajectories longer than 300 metres generated a number of elemental segments equal to 10 times the rounded ratio between the length of the trajectory and 300 metres, and the starting point of each elemental segment has been identified by randomly selecting a starting point in the original trajectory in between the beginning and the length of the trajectory minus 300 metres. Notably, the selection of the random starting point was carried out by means of the low-discrepancy Sobol sequence of quasi-random numbers (Sobol, 1976), to ensure maximization of the coverage of each trajectory through elemental segments. The above procedure allowed generating a total of 3000 elemental segments from the entire database of trajectories. Each elemental segment has been associated with an average speed, a specific fuel consumption (in l/100km) for each of the three internal combustion engine vehicles (ICEV, LC ICEV, LC ICEV with load) and a specific electric energy consumption (in kWh/km) for each of the three electric vehicles (EV, EFV, EFV with load). Importantly, the length of 300 metres has been set after a few tests as the one allowing for enough stability of the fuel/energy consumption calculation.

The resulting empirical relationships between speed and fuel/energy consumption are plotted in Figure 9. Within each chart, light-grey points represent fuel/energy consumption values for each of the 3000 segments. The bold-red points represent the average fuel/energy consumption of the segments with similar average speed. Overall, 100 red points are considered, each representative of one percentile of the average speed distribution, that is each red point in Figure 9 represents 30 segments in each percentile of the speed distribution. As a result, a general trend can be defined based on a quadratic regression line calibrated using a least-square regression method on these representative red points; concerned coefficients of these regressions are reported in Table 5.

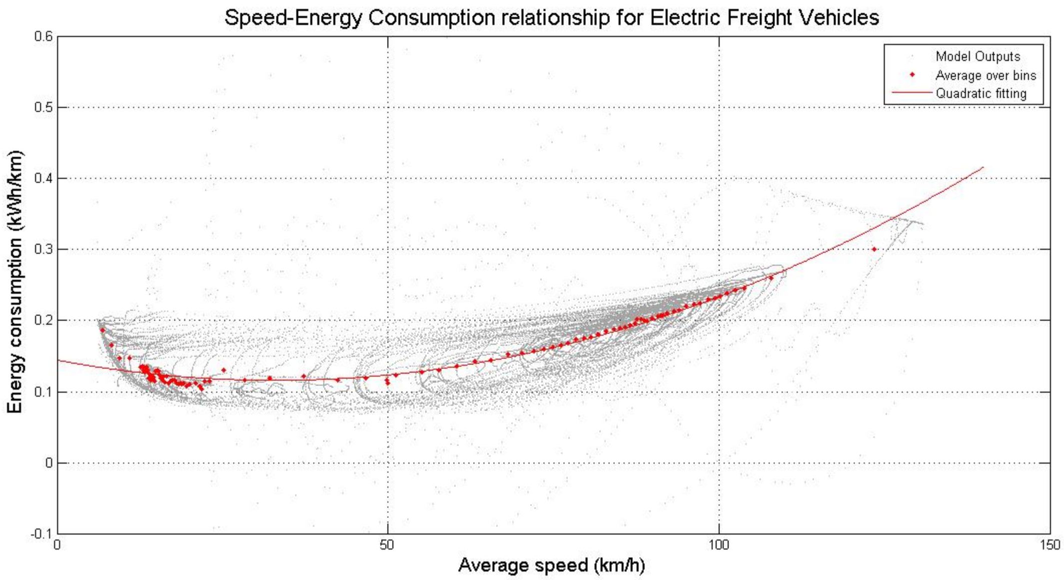
A visual inspection of the resulting trends in Figure 9 highlights the inherent differences in energy/fuel consumption patterns between electric and internal combustion engine vehicles. In particular, the energy consumption of electric vehicles is fairly constant for an average speed in between 0 km/h and 50 km/h, and tends to increase gradually as the speed increases over this range. This leads to a clear indication that, independently of traffic conditions, higher energy consumption is expected as the average speed increases. Conversely, internal combustion engines exhibit the expected U-shaped relationship (Fontaras et al., 2014, 2008), confirming the general assumption that fuel consumption achieves its minimum for speeds around 100km/h (the specific real value depends upon the specific configuration of the vehicle technology) and then increases in both lower speed ranges (due the inefficiency of the thermal engine in the stop-and-go regimes) and higher speed ranges (due to the significant increase in the resistances to the vehicle motion).



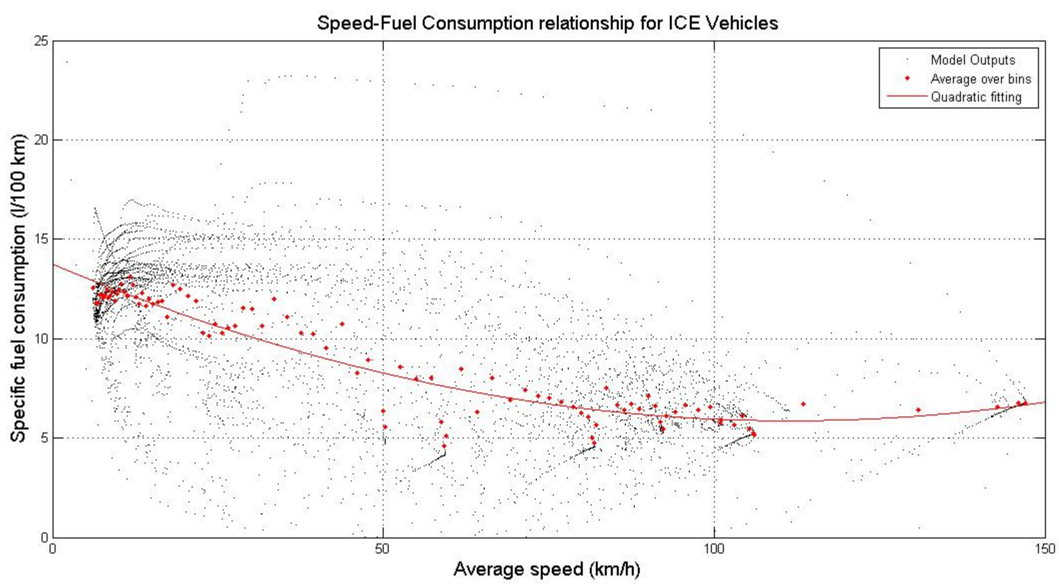
(a) – Electric Vehicles (EVs)



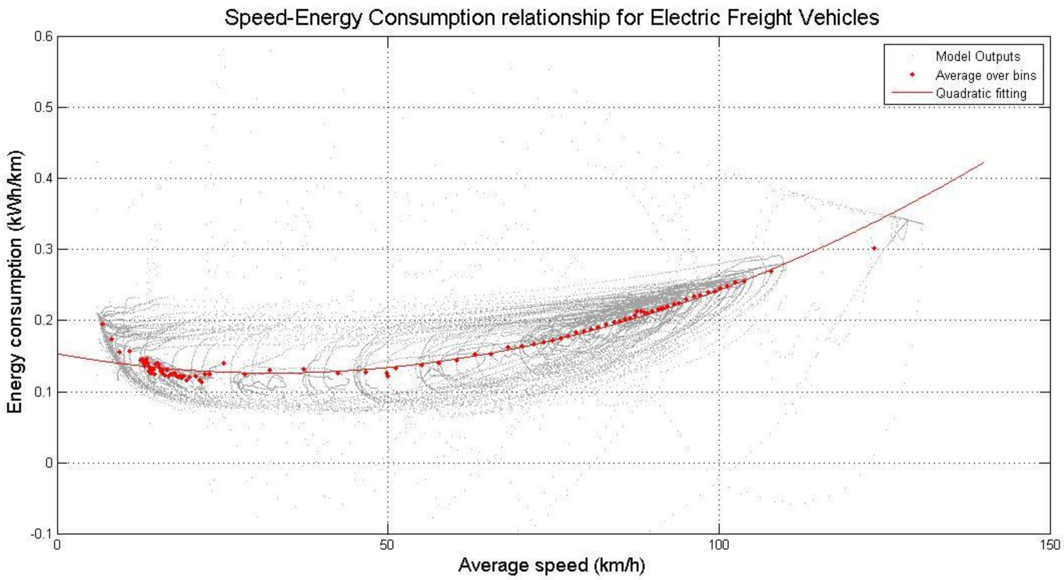
(b) – Internal Combustion Engine Vehicles (ICEVs)



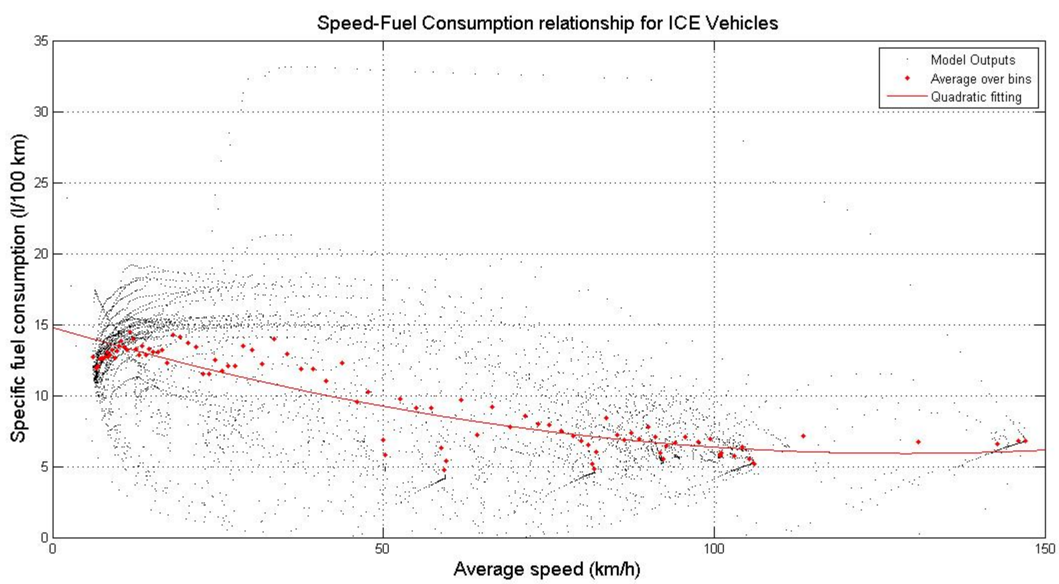
(c) – Electric Freight Vehicles (EFVs)



(d) – Light Commercial Internal Combustion Engine Vehicles (LC ICEVs)



(e) – Electric Freight Vehicles (EFVs) with load



(f) – Light Commercial Internal Combustion Engine Vehicles (LC ICEVs) with load

Figure 9: Energy consumption Vs. Speed evaluated for EVs (a), EFVs (c), EFVs with load(e), ICEVS (a), LC ICEVs (d) and LC ICEVs with load (f). Corresponding coefficients for the different powertrains are reported in Table 5.

Table 5: Fitting of the powertrains analysed.

Fitting curve: $f(x) = p_1*x^2 + p_2*x + p_3$	**Coefficients (with 95% confidence bounds)**	**Fitting - Adjusted R-square**
EV	p_1 = 2.287e-005 (2.043e-005, 2.532e-005) p_2 = -0.001913 (-0.002184, -0.001642) p_3 = 0.1436 (0.1385, 0.1488)	0.8965
EFV	p_1 = 2.623e-005 (2.364e-005, 2.881e-005) p_2 = -0.001729 (-0.002015, -0.001443) p_3 = 0.1444 (0.139, 0.1499)	0.9562
EFV with load	p_1 = 2.569e-005 (2.3e-005, 2.838e-005) p_2 = -0.00167 (-0.001969, -0.001372) p_3 = 0.1533 (0.1477, 0.159)	0.9523
ICEV	p_1 = 7.043e-004 (5.861e-004, 8.225e-004) p_2 = -0.1452 (-0.1604, -0.1301) p_3 = 13.6 (13.22, 13.99)	0.8977
LC ICEV	p_1 = 6.342e-004 (5.087e-004, 7.597e-004) p_2 = -0.1415 (-0.1576, -0.1254) p_3 = 13.76 (13.35, 14.17)	0.8966
LC ICEV with load	p_1 = 5.347e-004 (3.588e-004, 7.106e-004) p_2 = -0.1378 (-0.1604, -0.1153) p_3 = 14.8 (14.22, 15.37)	0.8435

6. CONCLUSIONS

The main objective of the present work was to investigate the relation between energy/fuel consumption and traffic conditions, based on an empirical analysis leveraging real-world, simulated and artificial trajectory datasets. Two specific trends have been detected:

- results show that EVs and EFVs (including a case where 300 kg payload is added to the EFVs) use less energy in the congested scenarios than in free-flow scenarios; the difference in the effects between the two traffic conditions decreases as the payload increases. In particular, a quadratic general trend was estimated for EVs, yielding an almost constant energy consumption up to 50 km/h and then an increase with respect to speed for higher speeds;
- the analysis of the ICE and LC ICE vehicles indicates that an opposite trend occurs: congested conditions are characterized by higher energy consumption if compared with free-flow conditions on the same case scenario but the range of variation it is higher than for EVs. In particular, ICEVs exhibited a different trend, with minimum fuel consumption achieved at around 90 km/h and with a significantly higher fuel consumption both at low and at high average speeds.

The main consequence of these results is that, in presence of a non-negligible share of electric vehicles, the improvement of traffic conditions (e.g. higher speeds and more regular trajectories due to lower congestion levels) might lead to an increase of energy consumption, with likely negative environmental effects depending upon the energy production mix. A case-by-case assessment is thus necessary, based also on the market penetration of each type of vehicle in the current and in the future scenarios under analysis. This implies also need for improving currently available traffic models, especially in the light of a better characterization of vehicles' dynamic especially for EVs.

Overall, the introduction of electrified powertrains in vehicles will alter the well-known relationship between average speed and energy consumption and, in turns, the relationship of this latter with traffic conditions. As a consequence, in a future with a majority of electric vehicles, policy-makers will need to handle an additional layer of complexity in transport planning. Indeed, at that point local pollution will not depend any longer from vehicles, thus policy-makers will need to choose between efficiency of the transport sector (directly connected to the average speed of vehicles) and overall electric energy consumption (with the electricity production system now being responsible for pollution and green-house-gas emissions due to traffic). Notably, this circumstance will be magnified by the spreading of vehicle connectivity and automation, that will be able to achieve an increase in the capacity of the transport system. In this case indeed, higher capacity and a better management of the overall transport system could lead to a substantial increase in the demand for personal mobility which could counterbalance the increased energy efficiency of electric vehicles thus leading to higher levels of energy consumption. In this scenario, without a significant improvement in the electric power production, issues such as electric power availability and pollution due to power generation may become very relevant especially in the future expanded urban contexts. Before arriving at that point it is important to raise awareness on the fact that electric vehicles will change the widely accepted relationship between traffic conditions and energy consumption so that our policies can be prepared to deal with this additional complexity.

It is worth mentioning finally that the simulations carried out in the present paper did not consider comfort heating and cooling and these may increase the energy consumption of the vehicles, especially the EVs, in the congested cases (due to a higher trip duration). A follow-up study will involve these elements as well as will include more vehicle segments for both electric and conventional vehicles to have a complete picture of the new trends occurring with EVs.

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