Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 47 (2020) 211–218

Transportation Research Procedia

www.elsevier.com/locate/procedia

22nd EURO Working Group on Transportation Meeting, EWGT 2019, 18-20 September 2019, Barcelona, Spain

Energy consumption of electric vehicles: models' estimation using big data (FCD)

Antonello Ignazio Croce[a], Giuseppe Musolino[b]*, Corrado Rindone[b], Antonino Vitetta[b]

[a]*Dipartimento di Ingegneria Civile, dell'Energia, dell'Ambiente e dei Materiali Università Mediterranea di Reggio Calabria, Feo di Vito Reggio Calabria 89122, Italy*

[b]*Dipartimento di ingegneria dell'Informazione, delle Infrastrutture e dell'Energia Sostenibile Università Mediterranea di Reggio Calabria, Feo di Vito Reggio Calabria 89122, Italy*

Abstract

The paper presents a framework to estimate energy consumption of Electric Vehicles (EVs) by combining: (a) the use of models derived from traffic flow theory and from mechanics of locomotion and (b) the great amount of Floating Cara Data (FCD) from available Information and Communications Technology (ICT) devices. Existing energy consumption models may be classified into aggregate vs. disaggregate, according to the level of aggregation of variables related to driver, vehicle, and infrastructure. The proposed models have a hybrid nature: the aggregate component allows to estimating the values of vehicular speed and acceleration on a road link; the disaggregate one allows to estimating the discrete variability of EVs' energy consumption inside a spatial-temporal domain. The energy consumption models are estimated using traffic data extracted from FCD.
The proposed framework is structured into four steps: FCD processing, estimation of vehicular speeds and accelerations, estimation of resistance/energy consumption. The framework is applied in a pilot study area, composed by the backward (sub-)urban area of the port of "Porto delle Grazie" of Roccella Jonica (South of Italy). The preliminary results show that the methodology allows relative inexpensive and accurate calculation of EVs' energy consumption and that it can be integrated into Intelligent Transportation System (ITS) applications.

Keywords: energy consumption models; Eletric Vehicles (EVs); Floating Car Data (FCD); passenger mobility

* Corresponding author. Tel.: +39-0965-1693-272; fax: +39-0965-1693-247.
E-mail address: giuseppe.musolino@unirc.it

10.1016/j.trpro.2020.03.091

1. Introduction

The term Well-To-Wheel (WTW) commonly indicates in literature the overall chain from production to consumption of energy. The chain includes two processes: (a) the Well-To-Tank (WTT) process, which considers the amount of energy required to make fuel available from the primary energy source to the vehicle tank; (b) the Tank-To-Wheel (TTW) process, which considers the necessary amount of energy to move a vehicle over a given distance.

Focusing on the TTW process, the paper presents a framework to estimate energy consumption of passenger Electric Vehicles (EVs) by means of models derived from traffic flow theory and from laws of vehicles locomotion. Big data (e.g. Floating Car Data - FCD) analysis allows making available a great amount of observed traffic data that can be used to calibrate the models.

The literature related to models on vehicle energy consumption is mature. Existing models may be classified according to different criteria: methods of calculation of energy, the level of aggregation of variables. The widespread presence of Information and Communications Technology - ICT (e.g. mobile phones, GPSs) allows the collection of potentially valuable information on travel patterns and transport networks. The possibility to consider them as a replacement or complement of data obtained from traditional survey methods depends on the ability to select, filter and process the great amount of available spatial-temporal data. Focusing on FCD, today their potentialities in providing position and speed of road vehicles are commonly recognized.

The paper presents a framework to estimate energy consumption of EVs by combining: (a) the use of models derived from traffic flow theory and from laws of vehicles locomotion, and (2) the great amount of FCD available from ICT (i.e. GPS) devices. The models have a hybrid nature in relation to the two above mentioned classes. The steady-state component allows to estimating the average values of vehicular speed for each class of links of the road network, which is function of vehicular flow. The (quasi-)dynamic component allows to estimating the energy consumption of a EVs in a discrete spatial-temporal domain, according to the average values of speed, acceleration and traction/resistance. The energy consumption models are estimated using traffic data extracted from FCD, after a process of filtering, integration and conversion. This structure of models allows relative cheap and accurate calculation of energy consumption of EVs and it can be integrated into Intelligent Transportation System (ITS) applications.

The remaining part of the paper is structured as follows. A brief state of the art is reported in section 2. The proposed framework is presented in section 3. Section 4 reports the prototypal experimental results for a link belonging to a road category; they could be extended for all links' categories and for the whole road network. Both sections 3 and 4 are subdivided into four parts; each of one describes a step of the framework (see Fig.1). Conclusions and developments are reported in section 5.

2. State of the art

The literature on energy consumption models of road vehicles may be classified according to different criteria (Fiori and Marzano, 2018; Praticò et al., 2012; Wu et al., 2015). A first criterion considers forward and backward models. Forward models start from the engine and "work forwards" towards the wheels in order to identify component interactions that affect energy consumption levels and vehicle performances. Backward models compute the amount of traction required at the wheels and ''work backward" towards the engine; in this case, vehicle energy consumption is estimated from drive cycle (driver behavior), vehicle (traction at the wheels) and infrastructure (geometry) characteristics. Another criterion of classification is based on the level of temporal aggregation. Models may be steady-state (or aggregate), and dynamic (disaggregate). Steady-state models need fewer input data (e.g. average speed on a link, consumption per unit of travelled distance), than dynamic models (e.g. instantaneous speed/traction profile of vehicle on the link). However, the former ones provide aggregate results that do not take into account the variability of driver behavior, vehicle and infrastructure characteristics, as the latter does.

The widespread use of ICT (e.g. mobile phones, GPSs) allows the collection of potentially valuable information on travel patterns and transport networks (see Chilà et al., 2016; Bonnel and Munizaga, 2018). The possibility to consider them as a replacement or complement of data obtained from traditional survey methods depends on the ability to select, filter and process the great amount of available spatial-temporal data. Focusing on FCD, today their potentialities in providing positions and speeds of road vehicles are commonly recognized (Croce et al., 2019).

As far as concern EVs, they seem to be one of the promising solutions to reach global Sustainable Development Goals (SDGs). The economic studies predict in the next future a progressive replacement of the internal combustion engine vehicles with EVs. Today the market offers several types of EVs that may be classified according to the criterion of propulsion systems and energy sources: battery electric vehicle; hybrid electric vehicle, plug-in hybrid electric vehicle, extended range-electric vehicle (Ehsani et al., 2005; Chan 2007; Shaukata et al., 2018).

The research contribution of the paper regards the integration of energy consumption models and FCD in order to pursue two connected objectives. The first concerns the benefits' maximization of using energy consumption models, in order to increase their capacity to analyze and forecast the effect of the relatively greater mass of EVs with respect to the road traffic and geometry-related characteristics. The second concerns the reduction of costs necessary to build the above models. The execution of surveys to obtain traffic data (vehicular flows, densities, speeds and accelerations) is expensive. Big data concerns observations of large sample of population and long observation periods about people and freight mobility. But they are sparse and noisy. Therefore, a great effort is necessary to filter, integrate and convert them into traffic and infrastructure performances estimates.

3. Proposed framework: specification of steps

The proposed framework is structured into four steps (see Fig. 1): FCD processing (step 0), vehicular speeds estimation (step 1), vehicular accelerations estimation (step 2), resistance/energy consumption estimation (step 3). Step 0 is the first; step 3 is the last; steps 1 and 2 are in parallel. The framework requires some preliminary operations connected to study area delimitation, road graph building, and link classification.

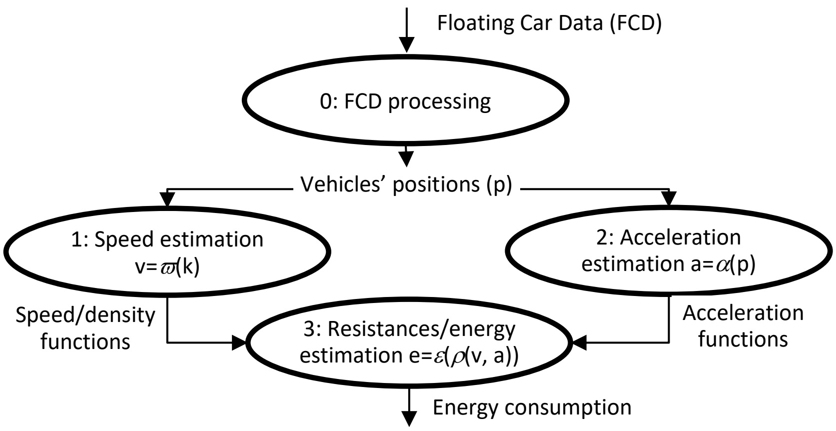

Fig. 1. Framework for energy consumption estimation of EVs from FCD.

Step 0: FCD processing.

A sequence of operations, such as data filtering and elaboration, allows to obtain, as output, the spatial-temporal *vehicles' positions*, p, associated to each link of the road network from the available FCD set.

By processing the information on p, the following outputs are calculated for each class of links, denoted with c.

Step 1: vehicular speeds estimation.

Vehicles' positions, p, are the inputs for the estimation of *average speed of vehicles*, v_c, depending on the vehicular density, k_c, obtained from vehicles' positions:

$$v_c = \varpi(k_c) \qquad \forall c \qquad (1)$$

The link speed-density function requires that stationary conditions of traffic flow hold. Preliminary, the values of density, k_i, and average speed, v_i, on link i are estimated.

The average vehicular density on link i (of length L_i), k_i, adopted for the estimation of (1), is calculated as:

$$k_i = (\Sigma_j\, n_{j,i}(T, \Delta t_j) \bullet \Delta t_j) / (T \bullet f \bullet L_i) \qquad \forall i \qquad (2)$$

with

- T, given period of time (T should be as small as possible in order to let density be correctly defined);
- Δt_j, time interval of group of vehicles positions j, which lies between the instant of detection of a vehicle position on link and the next instant of detection included in the FCD set (generally the vehicle positions are detected every minute (j=1; Δt_1= 1 minute), but this time interval could be greater than 1 minute for different reasons (j>1), up to several minutes);
- $n_{j,i}(T, \Delta t_j)$, number of vehicle positions of group j, detected on link i inside T, whose next position is present in the FCD set after a time interval Δt_j;
- $f\in[0,1]$, is the ratio between the detected vehicles (i.e. equipped with GPS) and the whole number of circulating vehicles in the study area (penetration rate).

The weighted average speed of vehicles travelling on link i, v_i, is calculated as:

$$v_i = (\Sigma_j\, (\Sigma_{p\in i}\, v_{p,i} \bullet \Delta t_j) / (n_i \bullet \Delta t_j)) \qquad \forall i \qquad (3)$$

with

$v_{p,i} = d_p(\Delta t_j) / \Delta t_j$, average speed of vehicles' position p of group j, travelling on link i, whose next position is detected after Δt_j;

$d_p(\Delta t_i)$, distance covered by vehicle p during time interval Δt_j;

$n_i = \Sigma_j\, n_{j,i}(T, \Delta t_j)$, number of vehicle positions detected on link i inside T.

The values of k^*_c and v^*_c of (1) are calculated as the weighted averages of k_i (2) and v_i (3):

$$v^*_c = \Sigma_{i\in c}\,(v_i \bullet n_i) / \Sigma_i\, n_i \qquad \forall c \qquad (4)$$

$$k^*_c = \Sigma_{i\in c}\,(k_i \bullet n_i) / \Sigma_i\, n_i \qquad \forall c \qquad (5)$$

The speed-density curves (1) related to link i, or the class c, are estimated from the available speed and density values calculated respectively with (2) and (3), or with (4) and (5).

Step 2: vehicular accelerations estimation.

Statistical analyses allow obtaining, as output, the *average acceleration* of vehicles on a link belonging to class c:

$$a_c = \alpha(\mathbf{g}_c) \qquad \forall c \qquad (6)$$

where $\mathbf{g}_c$ is the vector of geometric and functional characteristics of links belonging to class c.

The average acceleration of vehicles p travelling on links belonging to class c, a^*_c, is calculated as:

$$a^*_c = \Sigma_{p\in c}\, a_p / P_c \qquad \forall c \qquad (7)$$

with

$a_p = \Delta v_p(\Delta t_j) / \Delta t_j$, discrete acceleration of detected vehicle, p, inside time period Δt_j;

$\Delta v_p(\Delta t_j)$, discrete variation of speed of detected vehicle, p, travelling on links belonging to class c during Δt_j;

P_c, number of vehicles p travelling on links belonging to class c.

The average acceleration (6) of vehicles p travelling on links belonging to class c, is estimated from the vector of geometric and functional characteristics and acceleration calculated with (7). The whole values of acceleration are grouped into a histogram of frequency according to predefined intervals.

Step 3: resistances / energy consumption estimation.

(3.a) The whole *resistances* on a vehicle p, $r_{tot,p}$, are calculated as (valid for every link):

$$r_{tot,p} = \rho\,(v_p, a_p) = r_{roll,p} + r_{aero,p} + r_{slope,p} + r_{inertia,p} \qquad \forall p \tag{8}$$

with

$r_{roll,p} = m_p \cdot g\,(a + b \bullet v_p)$, rolling resistance; (9)

$r_{aero,p} = 1/2 \bullet \rho \bullet c_x \bullet s_p \bullet v_p^2$, aerodynamic resistance; (10)

$r_{slope,p} = \alpha \bullet m_p \bullet g \bullet i$, slope resistance; (11)

$r_{inertia,p} = \beta \bullet m_p \bullet a_p$, inertial resistance; (12)

where m_p, mass of vehicle p; g, gravity acceleration; a and b, parameters; ρ, air density; c_x, coefficient of aerodynamic shape; s_p, front surface of vehicle p; i, link slope; $\alpha>0$, percentage of energy recovered downhill ($i<0$); $\beta>0$; percentage of energy recovered under braking ($a_p<0$), if the vehicle is supposed to be electric (EV).

(3.b) The *energy consumption* of a vehicle p is estimated on the base of $r_{tot,p}$ (from step3.a):

$$e_p = \varepsilon(r_{tot,\,p}) \qquad \forall p \tag{13}$$

where e_p is equal to

$$e_p = \gamma \bullet r_{tot,p} \qquad \forall p \tag{14}$$

with γ, increase of electricity consumption due to accessory installations (i.e. air conditioning).

4. Proposed framework: application and preliminary results

The framework has been tested in the backward (sub-)urban area a touristic port, called "Porto delle Grazie", located in Roccella Jonica (South of Italy). There is a general objective of local administrations, which is the design of optimal transport services for passenger mobility to be operated by means of a fleet of EVs (see Musolino et al., 2019). A potential catchment area (Fig. 2) on the landside of the port (study area) has been identified, including several coastal and hilly municipalities. The road network of the study area has been built and the links have been classified into five different classes: freeway, primary road of type 1, primary road of type 2, secondary road, urban road. Each class has been identified by its own geometrical and functional characteristics. The steps of the proposed framework, reported in section 3, have been applied, and the preliminary results are reported in the following paragraphs.

4.1. FCD processing (step 0)

FCD are available for a wide region, including the study area, in a period 4 weeks (about 5.31 millions of vehicle positions). Several filtering operations were executed on the available initial database (see Table 1). Temporal filtering consisted of selecting positions travelling during the weekdays (about 3.65 millions). Spatial filtering consisted of-the elimination of the positions of the vehicles outside the study area (about 0.38 million). Cinematic filtering consisted of selecting positions with speed greater than zero (about 0.30 million). Topological filtering (or map matching) allowed to associate the vehicles' positions to the main links of the road network, previously identified (about 0.15 million, which are about 2.8% of the total points).

The map matching was carried out after building a road graph, which represents a portion of the existing road facilities. After classifying the links of the graph according to their functional and geometric characteristics (see table 2), it was possible to associate an average speed to each link class. Starting from the filtered FCD data (in time and space) (table 1), two selection criteria were applied: (1) distance of vehicle position, p, from a link lower than a predefined threshold; (2) minimum difference, in absolute value, between the observed speed of the vehicle, p, and the average speed associated to the link class (topological filtering, table 1). The association of vehicle position, p, to a link is conditioned upon the satisfaction of both criteria (see details in Croce et al., 2019).

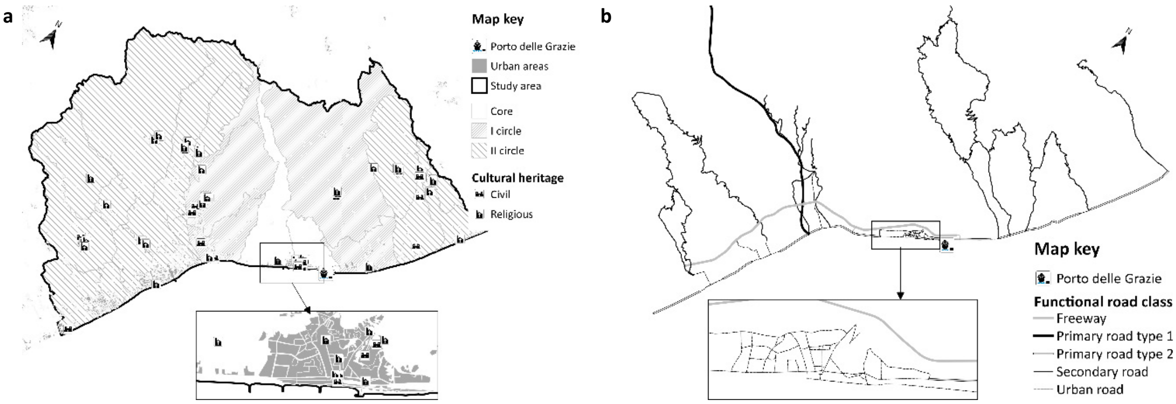

Fig. 2. (a) Potential catchment area; (b) and main roads.

Table 1. Filtering operations on FCD data

		Temporal	Spatial	Cinematic	Topological	%
Week	Total points	Points in the weekdays	Points in the study area	Points with speed>0	Points on the road network	
1	1,031,984	764,669	87,700	67,869	32,452	22.1%
2	1,045,594	772,674	82,948	63,155	31,395	21.4%
winter	2,077,578	1,537,343	170,648	131,024	63,847	43.5%

Table 2. Estimation of link characteristics (avr. and st.dev.) for each link class

Class	Typology	Links	Length [Km]		Width [m]		N. Lanes		Slope [%]	
			avr.	st. dev.	avr.	st. dev.	avr.	st. dev.	avr.	st. dev.
1	Freeway	7	5.62	1.55	7.50	0.00	2.00	0.00	0.05	0.06
2	Primary of type 1	15	2.01	1.58	3.50	0.00	1.00	0.00	0.09	0.19
3	Primary of type 2	4	5.06	3.79	3.50	0.00	1.00	0.00	2.03	0.95
4	Extra-urban	40	4.98	5.17	2.98	0.40	1.00	0.00	1.93	2.75
5	Urban	115	0.32	0.47	3.15	0.63	1.00	0.00	0.43	5.88

4.2. Vehicular speeds estimation (step 1)

Step 1 is preliminary applied on a link belonging the class 3, by using (3) and (4). It could be extended to all links of the class, by using (4) and (5), and to all classes for evaluations regarding the whole network.

From the set of vehicles positions, p, obtained after several filtering operations of initial FCD data (see Table 1), it is possible to estimate the values of speeds and densities related to each link i from (2) and (3), and then to each link class c, from (4) and (5).

The averages speeds-densities scatterplot for a link belonging to class 3 (see Table 2) is depicted in Fig. 3 (left), as a result of the application of (2) and (3). The estimated values concern an average working day inside the two available winter weeks. The following values are assumed: T=1 min, f=0.02, L= 2.42 km. The estimated speed-density points seem to lie exclusively in the stable region of the curve. Therefore, at this stage of the research, a linear specification of the stable branch of the speed-density curve is considered. The calibrated value of free speed is v_0=72.55 (km/h) and the speed reduction per unit of density is -1.65 (km/veic x km/h). The value of R^2 is equal to 0.4252. The absolute average speed error is about 6 km/h and the relative standard deviation is about 6 km/h. These results are due to the low FCD penetration rate (f=0.02), as reported in Klunder et al. (2017).

Once the values of average speeds and densities for each link i are available, the values of average speeds and densities values of average speeds and densities for each class c by applying (4) and (5).

4.3. Vehicular accelerations estimation (step 2)

The availability of filtered vehicles positions, p, (see Table 1) allowed to estimate the values of average accelerations for each link class c from (7). A curve of cumulative frequency of average acceleration for vehicles travelling on all links belongs to class 3 (see Table 2) is depicted in Fig. 3 (right), as result of the application of (7). The figure shows also the tabulated values (a_{min}, a_{max}, a_{vrg}) of five classes of accelerations obtained from the cumulative frequency, which are associated to five discrete locomotion regimes (in term of acceleration) of vehicles along the road links. The application of (7) could be repeated for each link class c, obtaining five curves of specific cumulative frequency of average accelerations.

a **b**

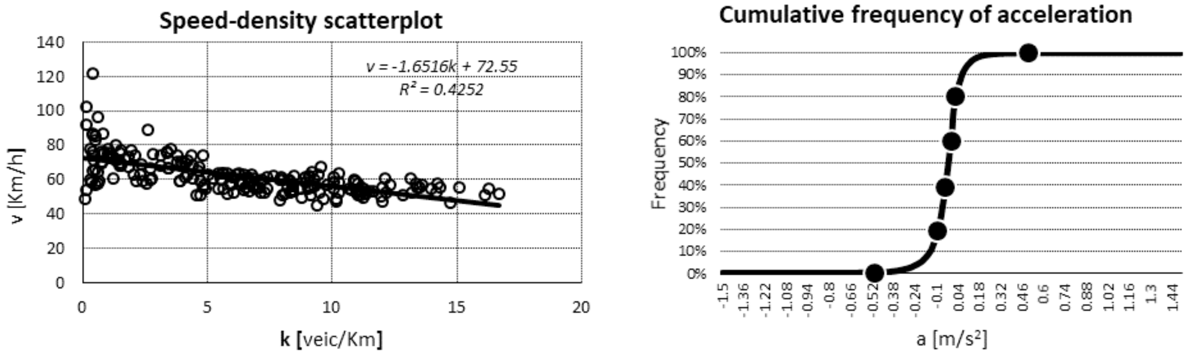

Fig. 3: (a) Speed-density scatterplot for a link of category 3; (b) and average vehicles' acceleration profiles for link category 3.

4.4. Resistance/energy consumption estimation (step 3)

The application of (8) allowed to estimating the values of *total resistances of* an Electric Vehicle (EV) travelling on the link in each of the 24 hours of the average working day (see steps 1 and 2). The EV considered is a Renault Zoe, that has the following characteristics: m=1468 kg, c_x=0.25, s= 1,5 m^2. The characteristic of the link is i=0.3%. The values of the parameters are: g= 9,8 m/sec^2, ρ= 1,25; a=0.0025 , b=0.000025, α=0,6, β=0,5.

The values of speed, v_p, in (9) and (10) are, at this stage, the average values of speed on the link i of vehicles travelling at each hour. For what concerns the value of acceleration in (12), the average values, a_{vrg}, for each of the five classes defined in Fig. 3.b are considered, in order to represent five different acceleration regimes of the vehicle along the link. Fig. 4 (left) presents the estimation of temporal profile (every hour) of the total, rolling, aerodynamic, slope and inertial resistances of an EV on the considered link.

Finally, the application of (14) led to the estimation of the values of energy consumption of an EV, travelling on the link in each of the 24 hours of the average working day considered in steps 1 and 2. The value of γ=1.25.

By assuming that all vehicles travelling on the link are EV, it is possible to estimate the temporal profile of the total amount of energy consumed by multiplying the value of e_p, obtained from (14), per hour and the value of vehicular flow in the same hour. The vehicular flow is calculated by multiplying the average hourly values of speeds and densities, from the linear speed-density function calibrated in step 2 (see Fig. 3, left). Fig. 4 (right) presents the estimation of temporal profile (every hour) of energy consumption and speed of all vehicles (assumed to be EV) travelling on the link.

5. Conclusions

The paper presents a framework to estimate energy consumption of EVs, based on a hybrid (steady-state/quasi-dynamic) system of models. A great effort has been made to filter, integrate and convert FCD into traffic estimates (such as vehicular densities, speeds and accelerations), in order to be suitable for models' calibration.

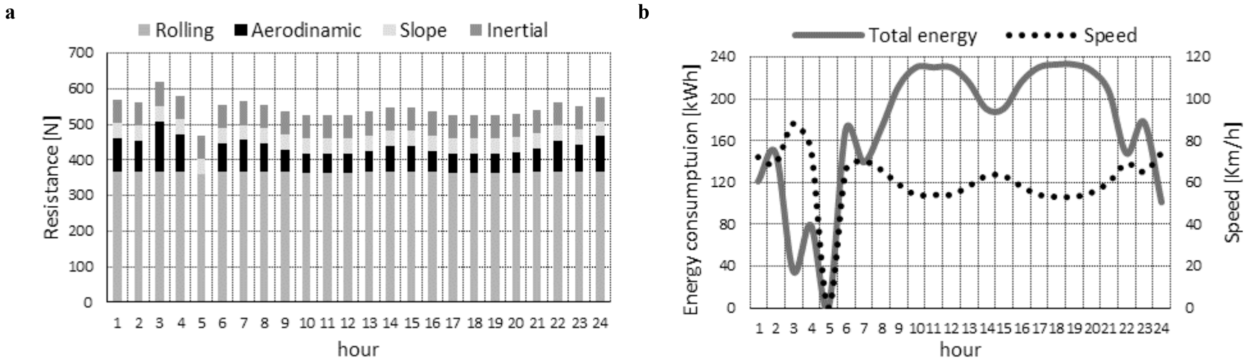

Fig. 4: (a) Estimation of resistances; (b) energy consumption and speed temporal profiles of EVs per hour.

The framework allows, as EVs have limited drive ranges, a quite accurate and inexpensive estimation of their energy consumption, which is a necessary element for transport planners/operators in order to design/implement transport services according to passengers' mobility demand.

The next steps of the research concern: (a) the estimation of link speed-density models (i.e. Drake, Underwood) able to capture the stable and unstable regions; (b) a sensitivity analysis of speeds estimation accuracy based on different values of FCD penetration rates; (c) an experimentation with EVs to obtain observations about energy consumptions profiles, in order to calibrate parameters related to disaggregate energy consumption functions.

Acknowledgements

This research is partially supported by the project GRE.ENE.LOG., funded by Calabria Region via POR CALABRIA FESR - FSE 2014 - 2020, Prog. 2894, Prot. SIAR 52115, date 17/02/2017.

References

Bonnel P., Munizaga M.A., 2018. Transport survey methods in the era of big data facing new and old challenges. Transportation Research Procedia 32 1–15.

Chan, C., 2007. The State of the Art of Electric, Hybrid, and Fuel Cell Vehicles. Proceedings of the IEEE, Vol.95, No.4, pp. 704-718.

Chilà G., Musolino G., Polimeni A., Rindone C., Russo F., Vitetta A., 2016. Transport models and intelligent transportation system to support urban evacuation planning process. IET Intelligent Transport Systems, 10(4), pp. 279-286.

Croce A.I., Musolino G., Rindone C., Vitetta A., 2019. Transport system models and big data: zoning and graph building with traditional surveys, FCD and GIS. ISPRS International Journal of Geo-Information, 8, 187.

Ehsani M., Gao Y., Gay S. E., Emadi A., 2005. Modern electric, hybrid electric, and fuel cell vehicles: fundamentals, theory, and design. CRC PRESS LLC. ISBN 0-8493-3154-4.

Fiori C., Marzano V., 2018. Modelling energy consumption of electric freight vehicles in urban pickup/delivery operations: analysis and estimation on a realworld dataset. Transportation Research Part D, 65, pp. 658–673.

Klunder G.A.,Taale H., Kester L.,Hoogendoorn S. (2017). Improvement of Network Performance by In-Vehicle Routing Using Floating Car Data. Journal of Advanced Transportation, volume 2017.

Musolino, G., Rindone, C., Vitetta, A., 2019. Passengers and freight mobility with electric vehicles: A methodology to plan green transport and logistic services near port areas, Transportation Research Procedia, 37, pp. 393-400.

Praticò F.G., Vaiana R., Gallelli V., 2012. Transport and traffic management by micro simulation models: operational use and performance of roundabouts, Urban Transport: Urban Transport and the Environment in the 21st Century, C. A. Brebbia, J. W. S. Longhurst (eds.) WIT Press, WIT Transactions on Ecology and the Environment.

Shaukata N., Khana B., Alia S.M., Mehmooda C.A., Khana J., Farida U., Majidb M., Anwarc S.M., Jawadd M., Ullaha Z., 2018. A survey on electric vehicle transportation within smart grid system. Renewable and Sustainable Energy Reviews, 81, pp. 1329–1349.

Wu X, Freese D, Cabrera A, Kitch WA., 2015. Electric vehicles' energy consumption measurement and estimation. Transportation Research Part D, 34, pp. 52–67.