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Energy demand estimation method for a charging station at workplace

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ABSTRACT

Energy demand increase due to large deployment of electric vehicles combined with volatile decentralized renewable energy production is bringing up new challenges in the transmission network. Power quality issues might be avoided taking advantage from the flexibility offered by the charging process to match the local renewable energy production. However, the potential benefits from a controlled electric vehicle charging process could be optimally exploited only if electric vehicles energy demand is reliably evaluated.

This study proposes a detailed methodology to evaluate the load of a working place charging station, in order to further optimally design a second life battery storage system for ancillary services provision. In details, the electric vehicles energy demand has been estimated using a multiple linear regression model that links the vehicles battery energy consumption with microscopic driving parameters (such as speed and acceleration). In particular, the model inputs are typical driving cycles performed by the employees to reach the working place. These representative speed profiles have been reconstructed with a Markov chain-based method using real-world collected data.

The proposed approach allows to predict the battery energy consumption with a Mean Absolute Error less than 18% and with a correlation coefficient R^2 of 99%.

Keywords: Electric Vehicles, Energy Consumption Prediction, Markov chain theory, Multiple Linear Regression

NOMENCLATURE

dE	Mechanical Energy [kWh]
m	Total vehicle mass [kg]
m_f	Fictive mass of rolling inertia [kg]
g	Gravitational acceleration [m/s^2]
f	Vehicle coefficient of rolling resistance [-]
ϑ	Road gradient angle [°]
ρ	Air density [kg/m^3]
C_x	Drag coefficient of the vehicle [-]
A	Vehicle equivalent cross section [m^2]
v_{EV}	Vehicle speed [km/h]
v_w	Wind speed [km/h]
ds, s	Distance driven [km]
Aux_t	Time scaling term
k	Segment (micro-trip) of a trip
K	Number of segments in a trip
a	Acceleration
t	Time
B_x	Regression coefficients
CMF_k^p	Positive Constant Motion Factor
CMF_k^n	Negative Constant Motion Factor
ε	Error term
n	Number of data points in micro-trip k

1. INTRODUCTION

Market diffusion of electric vehicles (EVs) is undergoing very rapid growth. The International Energy Agency measured a 40% year-on-year increase on EV sales and, according to a Sustainable Development Scenario, foresees a 36% annually growth in the global EV stocks until 2030 [1]. These projections suggest that EVs are likely to play an important role for power systems in the near term. However, several difficulties for the distribution system operator (DSO) at regional and/or local levels could arise from non-uniform EVs charging demand and increasing charging power level. In order to avoid voltage and frequency drops, grid congestion, increase of electricity costs and overload on the local electrical components, several studies in literature proposed the deployment of smart charging strategies [2][3][4][5][6]. From the aforementioned works it emerges that a key aspect for implementing an effective charging strategy is the proper modelling of the energy demand at the charging station. Most of the time this is estimated using a probability distribution function (uniform or log-normal) evaluated from available historical data. For example, authors in [7] have used driving patterns from the National Household Travel Survey to simulate workplace charging station under various scenarios, while in [8] and [9] uncertainties in battery initial and final states of charge, arrival and departure time, EV models mix at the station road characteristics and traffic conditions have been taken into account.

Thus, while great efforts have already been done to model the uncertainties due to EVs connection and dwelling time, there is still a lack of studies focusing on a proper estimation of the EV consumption for smart charging applications. Usually, the vehicles energy demand is modelled throughout a probability function defining the load profile of an overall parking lot. Even though this approach allows to catch the uncertainties globally, it could led to an ineffective prediction of the charging station load due to missing details related to the impact of each user driving behavior and habits [10].

This study proposes a systematic modeling of the electric load for EV charging stations taking into account, differently from most of the available papers in literature, real driving patterns of EVs users. The input of the model are velocity profiles over time obtained from GPS data. In order to preserve the privacy of the EV owners a driving cycle reconstruction method with the aim to generate representative speed profiles equivalent to the real ones has been implemented. In particular, Markov chain theory has been used to this end.

The paper is organized as follow: the EVs energy consumption model and the driving cycle reconstruction method are presented in section 2, the achieved results are shown and discussed respectively in section 3, and section 4.

2. TRIP ENERGY CONSUMPTION MODEL

This study aims at evaluating the electric energy demand at a workplace, specifically at the research center “ENEA La Casaccia” located in Rome (Italy), with the ultimate objective to properly design a second life battery storage system to provide ancillary services to the electric grid. Two main categories of parameters have been used to develop the proposed methodology. The first category includes the arrival and dwelling time of the employees at the workplace, and an estimation of the distance driven in urban and extra-urban road during daily commute. These information have been collected for some specific users for an entire year with the aim to fully characterize the variability of the daily energy demand of the charging station. Example of the available data is reported in Table 1. The second category, instead, consists of GPS data and battery output current measurement of the missions of a specific EV under different operating conditions (urban, extra-urban road). From the available data typical real driving parameters and energy consumption values have been extrapolated. The procedures implemented to reconstruct the representative driving cycles and evaluate the battery energy consumption are further described in the next sections.

Table 1 – Example of information gathered at the ENEA La Casaccia parking.

User	Distance Driven [km]		Day of the Year	Time Arrival	Dwelling Time [h]
	Urban	Extra-Urban			
1	2.82	101.69	9	08:44	7.49
2	80.94	19.65	7	07:23	9.26
3	31.23	17.78	8	09:28	10.6
⋮	⋮	⋮	⋮	⋮	⋮

2.1 Driving Cycle reconstruction

In literature there are mainly two approaches to build representative driving cycles. The first one is based on the combination of various driving modes (such as idle speed, acceleration, deceleration and constant speed) and it is the methodology used for example for the definition of the European Test Cycle (ECE) and New European driving cycle (NEDC). The second one is usually called "real-world cycle" as being derived from actual driving data [11]. This allows to consider specific characteristics, like road and traffic conditions, as well as driving habits of the specific user and location under study. In this work a procedure based on the second approach has been used, namely the Markov chain method. Several works have proven the effectiveness and the reliability of this methodology in reflecting specific real driving conditions [11–13] and in dealing with the random property of driving cycles [14].

The Markov chain-based reconstruction method mainly includes 3 steps: data collection, driving cycle reconstruction and driving cycle evaluation. For the first step, GPS data of a Nissan Leaf vehicle (having technical characteristics compatible with common vehicles used by the research center employees) have been collected under different operating conditions. Velocity and acceleration have been selected to define the vehicle dynamic state. Historical driving cycles have been encoded discretizing the speed and acceleration with a resolution of 2 km/h and 0.2 m/s^2, and 1 km/h and 0.2 m/s^2 respectively for extra-urban and urban roads.

The Markov property claims that future states of a systems depend only on the current one. The probability of transition from one vehicle dynamic state to another in a time unit is defined on the basis of the Transition Probability Matrix (TPM) [14], which is calculated using real-world driving data of the EV.

The procedure to build a driving cycle is therefore the following. First of all, the driving cycle is initialized to the initial state of zero velocity and acceleration. Then, the Roulette Wheel Selection algorithm is used to generate the random following state number and the process continues until a representative number of step for the driving cycle have been reached.

In order to verify the representativeness of the generated driving cycles with respect to the real ones a comparison of the Speed and Acceleration Probability Distribution (SAPD) with the original data has been performed. As Figure 1 illustrates, the generated SAPDs (right side of the Figure) are consistent with the original ones (left side of the Figure). A further confirmation derives from the evaluation of the Mean Squared Errors (MSE) between the generated and original SAPDs, which are for both Urban and Extra-Urban case below the 1%.

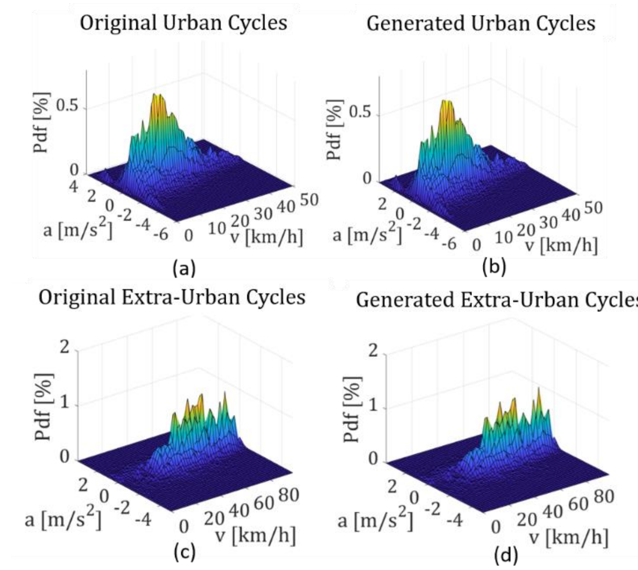

Figure 1. Speed and Acceleration Probability Distribution Function of orginal urban cycles (a), generated urban cycles (b), orginal extra-urban cycles (c), generated extra-urban cycles (d).

2.2 *Energy Consumption Estimation Method*

Several energy consumption estimation models have been proposed in literature with the purpose of EV drivetrain design and optimization, range prediction, energy-efficient routing allocation and charge impact estimation on the electricity grid [15–18]. Generally, two approaches are the most common used: statistical models based on physical principles, or machine learning techniques. In order to preserve the physical interpretability of the results and the computational simplicity, the first framework has been adopted in this study, implementing a Multiple Linear Regression (MLR) model. Moreover, as De Cauwer et al. claimed in [17], since any statistical model is based on real-world measured data, the external influences are implicitly present in the dataset and, therefore, the resulting model is not calibrated only on some specific operating conditions.

The MLR framework has been evaluated as in [17] starting from the physical modeling of the forces acting on the vehicle in motion. The mechanical energy dE required at the wheel to cover a distance ds could be expressed as:

$$dE = \frac{1}{3600}\left[mg(f\cos\vartheta + \sin\vartheta) + \frac{1}{2}\left(\rho C_x A\frac{(v_{EV} + v_w)^2}{3.6}\right) + (m + m_f)\frac{dv_{EV}}{dt}\right] ds \qquad (1)$$

The terms on the right-hand side of eq. (1) represent respectively the rolling resistance, potential energy, aerodynamic losses, and inertial energy. Assuming in a first order approximation the rolling resistance coefficient, drag coefficient, air density and vehicle mass constant, and neglecting the wind speed contribution, the energy consumption can be described as a linear combination of the kinematic parameters ds, $v^2 ds$, $\frac{dv}{dt}ds$, and $h = ds \cdot \sin\vartheta$. Due to the lack of elevation information in the reconstruction process, the contribution given by potential energy (term proportional to h) has been neglected in this study. However, being the elevation variation of the territory around the research center limited, the assumption does not significantly affect the results. To represent the consumption of the auxiliaries, the formula has been extended with a time-linear dependent term. Therefore, the corresponding linear expression of eq. (1) is:

$$E_{EV} = B_1 s + B_2 v_{EV}^2 s + B_3 a\, s + B_4 h + B_5 Aux_t t \qquad (2)$$

The coefficients B_1, B_2, B_3, B_4 and B_5 could then be evaluated applying a MLR analysis on the real-world driving and battery energy consumption data. In particular, the regression analysis is performed splitting the trips into shorter segments (k), evaluating the energy consumption on these segments and combining them for the estimation of a full trip energy demand [17]. Accordingly, eq. (2) could be rewritten as:

$$E_{TRIP} = \sum E_{segments} = \sum_{k=1}^{K}\left[B_1\,\Delta s_k + B_2\left(\sum_{i}^{n} v_{EV,i}^2\right)\Delta s_k + B_3(CMF_k^p)\Delta s_k + B_4(CMF_k^n)\Delta s_k + B_5\Delta t_k + \varepsilon\right] \qquad (3)$$

With $$CMF_k = \frac{\sum_{i=2}^{n}|v_{EV,i}^2 - v_{EV,i-1}^2|}{\Delta s_k} \qquad (4)$$

The constant motion factor (CMF) is the sum of the change in kinetic energy per unit distance and it replaces the acceleration term in eq (2). Positive and negative changes in kinetic energy have been separated into two terms: CMF_s^p and CMF_s^n respectively.

The split of the full trips into shorter segments is crucial for the accuracy of the proposed method. Indeed, the simplified linear representation of the energy consumption expressed in eq. (3) requires a minimum level of data points aggregation for accuracy, but over-aggregation of the predictors could lead to loss of estimation variability [17]. In this study, each segment has been identified by a so-called "micro-trip" (i.e. a sequence of driving data between successive stops). From the driving data generated with Markov chain approach, two distinct sets of micro-trips have been individuated: urban micro-trips (if maximum speed was below 50km/h) and extra-urban micro-trips. A complete trip has then been evaluated throughout the concatenation of urban and extra-urban micro-trips until the total distance covered satisfies the distance

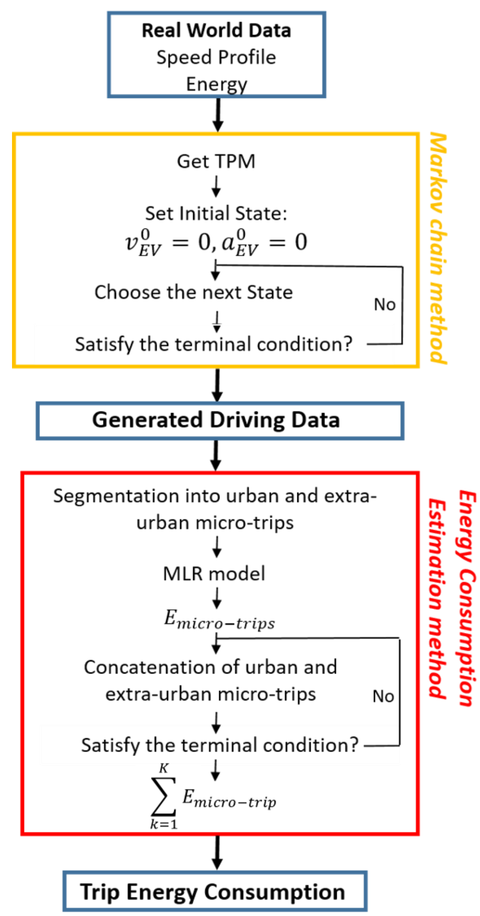

Figure 2. Overview of the proposed model for energy consumption prediction.

registered during the experimental campaign for the research center worker in urban and extra-urban roads (Table 1). An overview of the proposed method is given in Figure 2.

3. RESULTS AND DISCUSSION

The MLR analysis based on the segmentation process presented in the previous section has been performed using the fit linear regression function in Matlab. Results in terms of regression coefficients and corresponding p-values are showed in Table 2. All the p-values below 10^{-5} indicate which terms are more significant.

It can be seen that the energy predictions points mainly lie on the 1:1 line in the observed vs predicted data plot for the micro-trips, thus validating the accuracy of the energy consumption model and confirming the choice of the selected predictors.

A greater bias between the predicted points and the 1:1 line can be observed in Figure 4. This can be explained considering that the energy prediction errors in the micro-trips are not symmetrically distributed, thus they tend to sum up together when recombined to trips.

Some performance indicators for MLR energy consumption model have been calculated and shown in Table 3. Although all the values calculated for the complete trips are lower than the single micro-trips ones, both the correlation and the R^2 are above 98%, confirming the accuracy and the reliability of the energy consumption model in predicting a trip energy demand.

	Intercept	Rolling Resistence (B_1)	Aerodynamic (B_2)	Positive Acceleration (B_3)	Negative Acceleration (B_4)	Auxiliaries (B_5)
Coefficient	0.00332516	0.169241356	-6.37E-06	0.029709581	0.000242606	-0.0001648
p-value	<0.2	< 0.0001	< 0.05	< 0.0001	< 0.0002	< 0.2

Table 2 – Results of the MLR analysis for the complete trip energy consumption estimation

Figure 3 and 4 shows the regression plots for the single micro-trips and the complete trips, respectively.

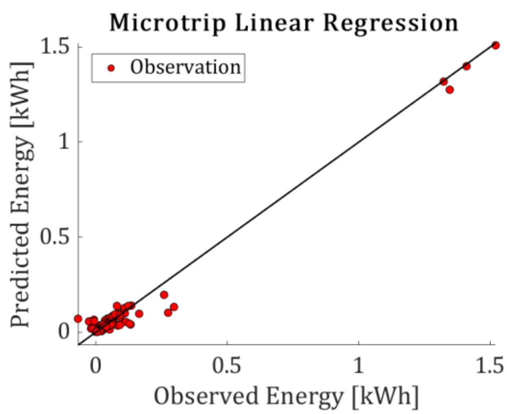

Figure 3. Regression plot for the energy prediction over the micro-trips

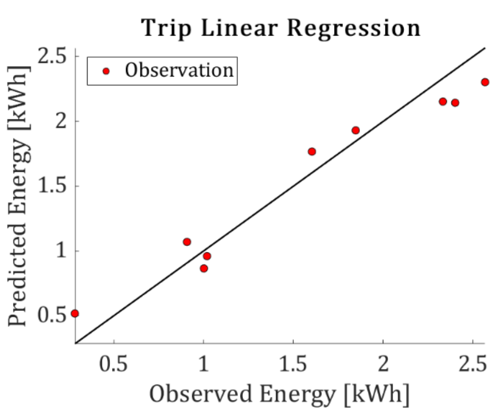

Figure 4. Regression plot for the energy prediction over the complete trips.

	Correlation	RMSE	MAE	R^2
Micro-trip	0.9917	0.0252	0.0108	0.9846
Trip	0.9800	0.1841	0.1711	0.9886

Table 3 – Correlation Evaluation Parameters

In the end, matching the results of energy consumption estimation for the EVs reaching the working place with their registered time of arrival, it is possible to evaluate the energy demand profile over time. This it has been done for all the days of the year. Then, to identify a reference energy demand considering

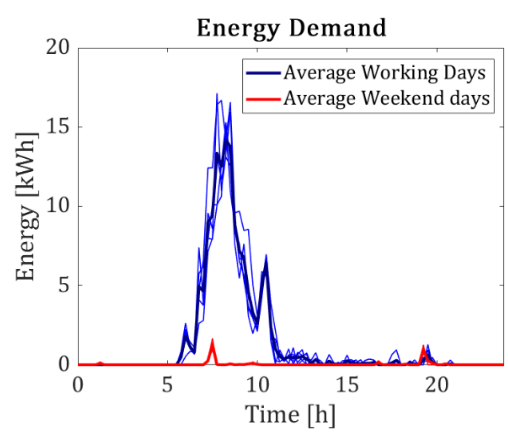

Figure 5. Average energy demand profile for working days (blue lines) and weekend days (red line) at the EV charging station

uncertainties, a cluster analysis has been carried out. As shown in Figure 5 two main patterns can be recognize: energy profile for working days (from Monday to Friday) and weekend (Saturday and Sunday). These profiles can be used to design a second life battery energy storage system and optimally control the charging process to provide ancillary service to the grid.

4. CONCLUTIONS

A detailed and reliable estimation of the EVs energy charging demand is essential to optimally design an EV charging station. Indeed, matching the information of energy magnitude with EV presence profile in time at a parking lot, it is possible to define the size of an electrical storage system to better fit the users' requirements and provide ancillary services to the grid.

This study proposed a comprehensive methodology to estimate the EVs energy demand based on a Multiple Linear Regression model. To preserve the privacy of the users' data, a Markov chain-based method has been implemented to reconstruct representative real-driving cycles with a Mean Squared Error below the 1% with respect to the original ones.

Moreover, the accuracy of trip energy estimation for the implemented MLR model has been validated by the achievement of a correlation coefficient between the real and the predicted energy consumption above the 98%. The obtained results confirm the reliability with which the overall charging station energy demand profile has been calculated.

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