

Fuzzy-Probabilistic Estimation of the Electric Vehicles Energy Consumption

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Abstract. This paper presents a framework and methodology to characterize the uncertainty of the consumption in the Electric Vehicles (EVs). A Fuzzy Logic (FL) is implemented to obtain an interval of the probability that the energy consumption may take. The framework assumes the availability of Information and Communication Technology (ICT) technology and previous data records. A case study is presented using a fleet of 30 EVs considering a smart grid environment.

Keywords: Communications · Electric vehicles · Fuzzy logic · Smart grid

1 Introduction

Currently, more than 90 % of the energy used in the transportation sector is provided by oil source [1]. Oil will continue to be a major fuel for decades, but reducing this dependence on a single source is very risky because oil is a fossil source, as such, does not last forever. Other problem is the enormous quantity of CO² produced by the vehicles moved with fossil fuels that is prejudicial to the planet. With the increasing concern over global climate change, policy makers are promoting renewable energy sources (RESs) to reduce this problem. According to the reference [2], a partial solution to solve this problem can be mitigated by 2 measures: the first one is the use of decentralized RES, and the second is the application of next-generation plug-in vehicles, which include plug-in hybrid electric vehicles (PHEV) and electric vehicles (EVs), with vehicle-to-grid (V2G).

If we do a direct comparison, EVs convert about 59–62 % of the electrical energy from the grid to power at the wheels, the conventional gasoline vehicles only convert about 17–21 % of the energy stored in gasoline to power at the wheels [3]. In [4] it is discussed the social and technical barriers to the V2G transition, namely what policymakers need to achieve to enable a successful implementation. However, the introduction of EVs represents an unprecedented interaction between transportation and the electricity grid. The electricity grid and EVs are highly dependent due to the fact that the energy to charge the batteries comes from the grid [5]. With the increased use of the EVs the planning of the electrical infrastructures is more demanding [6], mainly due to the level of the uncertainties introduced. The impacts of the EV penetration in the grid were studied in [7] and [8].

The variability in EV's energy consumption has a high impact at the user level and the electricity system. For example, to the user this situation difficult the planning of the

periods that the EV need to charge. In what regards system's impacts, daily charging of an EV would double of a typical household electricity consumption. With a significant penetration level at the distribution system, this could result in high variations in energy demand.

Due to improvements in Information and Communication Technology (ICT) big data will be available for smart grid operators [9]. Real-time records regarding EVs' location, time of charge, energy charged, charged rate and trip consumptions, could be maintained in appropriate data storage systems, e.g. a computer cloud. This data can be processed to be useful for operators in a later stage.

This paper proposes one methodology to model the uncertainties of the consumptions in the EV. The methodology presented in this paper depends on the availability of ICT technology and historical data records to obtain the probabilistic consumptions. Its ultimate goal is to be used with realistic data. EV's are very sensitive to parameters which can influence their energy consumptions, such as: driving conditions, auxiliary systems' impact (for example, electrically driven air conditioning, driver's aggressiveness and braking energy).

Recent works on the available literature use a different types of methodologies to model similar problems, for example. In [10], an EV demand model for load flow studies is developed, the model considers the EV demand has PQ buses with stochastic characteristics using Queueing Theory as a function of the charging time. The method only considers one type of vehicle in the case study and does not represent a load pattern along the day or a set of scenarios for the EV. This method has been applied in [11] to developed a probabilistic constrained load flow with the presence of EVs. The work considers the full charge and discharge power of EVs in a specific region, allowing the calculation of power flow with probabilistic constraints. However the two methods mentioned above do not consider the different types of battery capacity of the EVs. In reference [12] a Fuzzy Logic (FL) control strategy is developed for an energy management system of an EV with dual source power (battery and super capacitor). This dual source architecture is proposed in order to satisfy the EVs energy requirements, improving the EVs efficiency and the performance of the overall system. In [13] MATSim is used to obtain the arrival and departure time of each trip and the associated energy consumption for each vehicle. Based on that reference sample, a generation of different samples of driving patterns for each vehicle was made. The trip departure time and trip duration are uniformly distributed 30 min around their reference values and the trip consumption is also assumed to be uniformly distributed 1 kWh around the reference value. With these distributions is possible generate different realizations of driving patterns for each individual vehicle. However, the chosen distributions are just exemplary distributions, in practice the aggregator would need to collect data from its PEV customers to find appropriate models for their stochastic behavior. In [14], a Bootstrap technique is used to model the charging temporal uncertainties for the Plug-In Electric Vehicles (PEV). Initially, using the Bootstrap method, an input sample is generated, representing the different scenarios for the behavior of PEVs, with the various initial battery state-of-charges and arrival and departure times of the PEVs. The GA-based optimization model is used to generate 25 independent observations of the daily system peak demand and their corresponding hourly load tap charging

schedules to make up the original sample, which are then used to generate a large number of Bootstrap samples in order to demonstrate the central limit theorem.

Taking into account the current literature this work proposed a framework and respective methodology to support the estimation of the fuzzy-probabilistic curves of the EVs' energy consumption. This information can be used to make an accurate planning of the journey and obtain an adequate pattern of the EV demand. This can be useful for power system operators and EVs' energy management systems in order. This methodology was tested with a realistic case study that represent one year for weekdays and weekend behavior.

This paper is organized as follows: after this introductory Sect. 2 presents the proposed framework based on FL, Sect. 3 presents the case study and finally Sect. 4 presents the conclusions.

2 Methodology

This section presents the developed framework and methodology.

2.1 Framework

Figure 1 presents the proposed framework to support the information necessary for the presented methodology and other applications beyond the scope of this paper. In this proposed framework each EV have one processing unit (CPU) with the capacity to process the information in real time, this information can be stored in a memory card

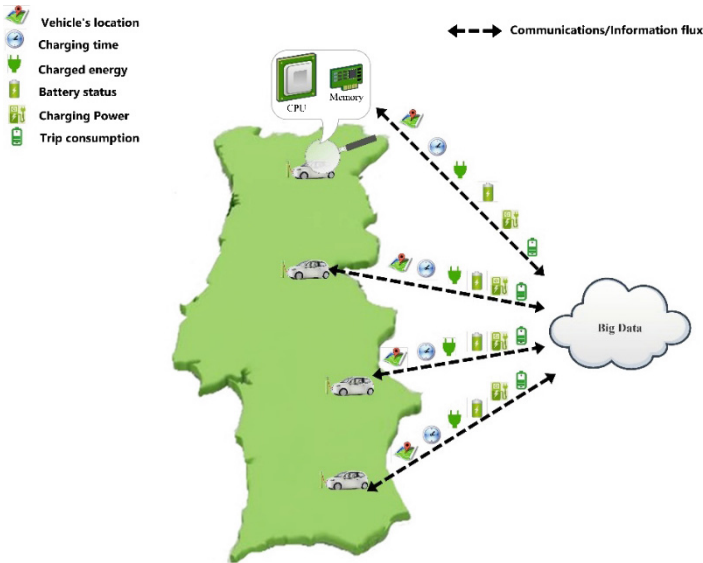


Fig. 1. Framework to support the proposed methodology

and can be transmitted for the cloud (big data), if the EV has an appropriate system with connection to the internet. Several communication technologies are considered as candidates such as WiMAX, WiFi, and power line communications are available for the smart grid system to support the information flux between the EVs and the grid using the Internet Protocol (IP) [15]. The data transmitted over the communication network can be encrypted using a secured TLS cryptographic mechanism. However, this will require an overhead resulting in larger data size to be transmitted. This system in the case of internet connection failure (e.g. driving in tunnels, parking in underground) should have an internal memory system to allow each EV to save the data temporarily. Later, with reconnection, the data can be sent to the cloud, thus preventing previous data from being lost. This implies an individual processing and storage of data with minimal computing requirements in each EV. A centralized process (cloud application) could be available to handle EVs' recorded data in a smarter way, e.g. using big data analytics. Such applications could include real-time traffic alerts, monitoring and rerouting, consumers' patterns identification, EVs' demand forecast, connected vehicles applications including accident avoidance.

The type of data available in each vehicle could be the EVs' location, time of charge, energy charged, charged rate and trip consumptions. This might be regulated by a standard or legal requirement in the future, thus enabling a greater compatibility for the proposed framework. In order to define this standard it would be necessary to consider the types of data to be stored and transmitted, a control access to the data and the transmission mode.

Table 1 shows a very simple data scheme of the information that could be transmitted between the EVs and the cloud applications (see Fig. 1). The values depicted in the table do not consider the overhead of the encryption, the packet's header (typically 20 bytes), and the possible compression of repeated data sequences. The methodology present in this paper depends on the successful treatment and processing of data to attain the expected results.

The first parameter, Vehicle's ID, can provide one number that represent the identification of the client (EV). This ID number can be saved in class int32 format (4 bytes).

Table 1. Proposed data scheme

Data Parameters	Description of data structure		
	Type of data	Data class	Size per record
Vehicle's ID	Identification of EV	int32	4 bytes
Location	GPS location	Double	3×8 bytes
Battery status	Battery capacity; SOC level	int32	2×4 bytes
Connected to outlet	Connected (0/1); Outlet ID	Binary and int32	$1 + 4$ bytes
Charged energy	Charged energy; timestamp	int32 and Double	$4 + 2 \times 8$ bytes
Charge rate	Charging power	int32	4 bytes
Trip consumptions	Energy consumption in the trip; Start and end timestamp	int32 and Double	$4 + 2 \times 8$ bytes

The Location parameter needs to consider a 3 types of data: latitude, longitude and timestamp. The results of this is the GPS location of the EV. The type of data class is double with a size per record of 3×8 bytes, 8 bytes for each type of data. Other important parameter is the trip consumptions, where the types of data records are the energy consumptions in the total trip, the start and end timestamp for this trip. This parameter (energy consumption) can be saved in int32 class format (4 bytes), while the start and end timestamp can be saved in double class format (2×8 bytes).

2.2 Fuzzy-Probabilistic Methodology

The methodology used consists in the use of Fuzzy Logic (FL) to characterize the uncertainty of the consumption data and a probabilistic distribution function.

The term FL was introduced with the 1965 proposal of fuzzy set theory by Zadeh [16], however had been studied since the 1920, as infinite-valued logic [17]. FL is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth. The number of paper dealing, in some sense, with FL and its applications is immense, and the success in applications is evident.

The meaning of fuzzy portrays something vague, uncertain, being used to get one representation of imprecise data [18]. Fuzzy set is very convenient method for representing some form of uncertainty, because this method is a type of logic that recognizes more than simple true and false values. While variables in mathematics usually take numerical values, in FL applications, the non-numeric are often used to facilitate the expression of rules and facts. With FL, this propositions can be represented with degrees of truth. For example, the statement, today is sunny, might be 100 % true if there are no clouds, 80 % true if there are a few clouds, 50 % true if it's hazy and 0 % true if it rains all day. The FL allows an infinite range of values in the range [0, 1], which would indicate the possibility of a statement to be true (1) or false (0), assuming intermediate logical values neither completely true nor false. The process of converting the fuzzy region in a final numeric value is designated by defuzzification and resides in simply calculating the center of gravity of the end region and can be achieved by expression (1):

$$v = \frac{\int_x (x \times t(x))}{\int_x (t(x))} Z \quad (1)$$

Where:

v – defuzzification value

$t(x)$ – degree of truth in the point x

From the historical database (Big Data), we filtered the parameter of consumption that corresponded to the use of the available energy in the battery for each period of the day. When the vehicle is charging, the consumption have a null value. To apply the fuzzy logic it was necessary to make a calculation of the average energy consumption from the filtered data. For the implementation of FL we defined an upper bound value, a

lower bound value and number of degrees of truth. To the results of the fuzzy function is given the value of centroid, which indicates the average value of the figure, or in other words, the point in the center of the figure which is the shortest distance for the all points of the figure. Fuzzification was applied to average and standard deviation values.

The distribution that best represents the consumption of EVs is the normal distribution [19]. The normal distribution can be obtained using (2):

$$fp(P) = \frac{1}{\sqrt{2\pi} \times \sigma^2} \times e^{\frac{-(P-\mu)^2}{2 \times \sigma^2}} Z \quad (2)$$

Where:

μ – average value of consumption;

σ – standard deviation of consumption;

P - values resulting from the fuzzy function;

With the fuzzified values previously calculated the normal distribution functions were derived. In this distribution the average value and the standard deviation are the respective FL values. As a final result is obtained the interval of probability (pessimistic and optimistic) of a given EV have one specific consumption in a period of time. This can be used to the driver make a more accurate planning of his journey and for the power system know the period of the EV need to load.

In Fig. 2 is possible to see the flowchart of the algorithm to implement the FL and the normal distribution in this specific case.

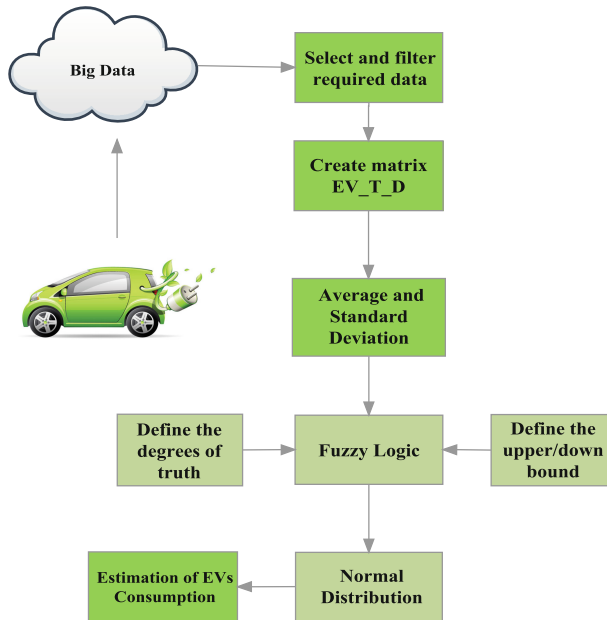


Fig. 2. Flowchart of the proposed FL

3 Numerical Example

Currently there is no enough historical data related with the operation of EVs, e.g. location, charged energy and time of charging. Hence, a scenario was generated considering a realistic study, for the city of Vila Real in Portugal, for a fleet of 30 Electric Vehicles (EV). The historical data was divided in two groups, due to the difference in behavior between weekdays and weekends. The weekdays had a total of 254 days, while the weekends and holidays corresponded to a total of 111 days. Several possibilities are taken into account. The EVs may leave earlier, breakdown can occur or the EV owner may change the charging station. The program considers possible changes in the planned route, i.e. breakdowns or failures in the EV fleet, therefore it simulates a realistic behavior. The script stores the data in Excel format, being the starting point for the FL.

To execute the FL it was necessary to prepare data and calculate the average and standard deviation of the EV's consumptions for each hour and day. To achieve this, the Excel data were loaded using MATLAB, where each excel sheet represent one day. Each sheet stored the information of the entire trip. For each EV, the information stored over a period of 24 h with a resolution of 1 h was: energy consumption, connection status ("1" in the case the EV was connected and "0" if it was not), bus connected in the grid, battery status and battery capacity. The data was properly filtered corresponding to the consumptions, i.e., for each EV and for each period of the day, the consumption of the EV's had. As a result a matrix that contained the data to be used to calculate the average and standard deviation was obtained (*EV_T_D*). The dimensions of this matrix was $30 \times 24 \times 254$ with 30 EVs (lines of the matrix), 24 periods (columns of the matrix), and 254 days (weekdays). The next step in the methodology was to calculate the average and standard deviation of each EV for each hour. This results are in two matrices with 30×24 dimensions indicating the average and standard deviation of a given EV. The same procedure for the weekend's scenario.

Turning now to an analysis will uncertainty associated with consumption, considering a specific case where we choose the EV-1, this for the weekdays. Initially, we calculate the average fuel consumption per trip to a period of 24 h a day (the average value for each hour along of 254 days), getting the graph in Fig. 3 where we observe the variations of these consumption for each hour.

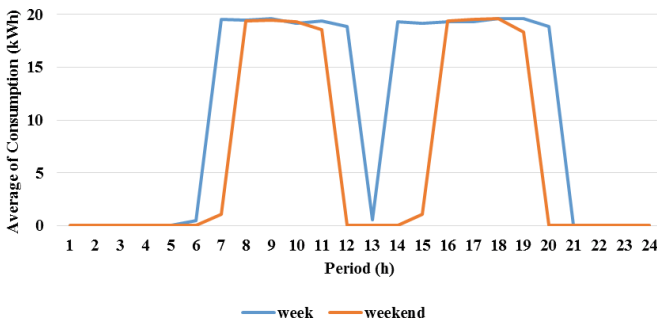


Fig. 3. Average of consumption for the EV-1

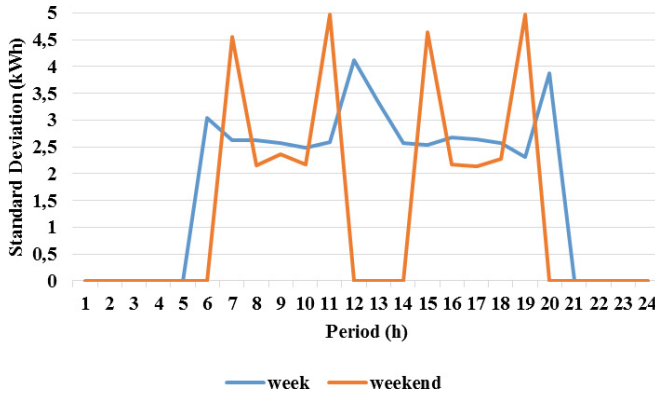


Fig. 4. Standard deviation of consumption for the EV-1

The next step is the calculation of the standard deviation of the value of consumption, as shown in Fig. 4.

After performing the calculation of the average and the standard deviation is already possible to apply the fuzzy function for the average and standard deviation values. To proceed to the implement the FL we need to define the lower bound, the upper bound, and the degrees of truth. In this study we have considered 100 degrees of truth. In order to present a better result, we considered two distinct cases, one case more pessimistic and other more optimistic. For the first case, the pessimistic, the lower bound was -10% and the upper bound was 30% . To the second case, the more optimistic, we utilized a value of -30% for the lower bound and 10% to the upper bound. The results of fuzzy method obtained in the EV-1, in the hour 7, are shown in the following Tables 2 and 3. Both tables are related with the implementation of the FL method, the first one was applied to the average value, while the second one characterizes the implementation to the standard deviation values.

The representation of the FL for the average can be seen in the Fig. 5 (Pessimistic Case) and Fig. 6 (Optimistic Case). In each figure it is possible to see the triangular fuzzy function and the centroid value for each case regarding the EV-1 in the hour 7. As it is referred in Table 2, it was obtained a fuzzy average consumption that can for

Table 2. Average Fuzzy values (kWh) for EV-1 in the hour 7

Case	Average	Lower bound	Fuzzy value	Upper bound
Pessimistic	19.52	18.15	20.17	26.22
Optimistic		13.21	18.87	20.76

Table 3. Standard deviation fuzzy values (kWh) for EV-1 in the hour 7

Case	Standard deviation	Lower bound	Fuzzy Value	Upper bound
Pessimistic	2.62	2.43	2.70	3.51
Optimistic		1.77	2.53	2.78

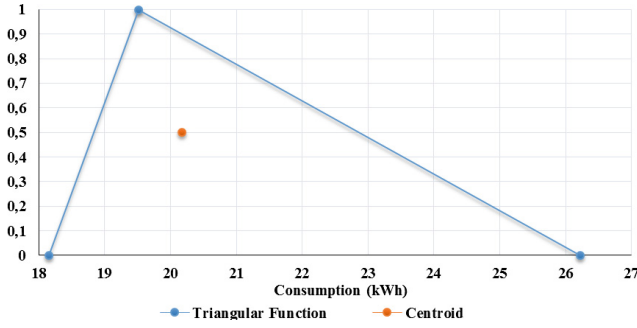


Fig. 5. Representation of fuzzy for the average in EV-1 (Pessimistic Case)

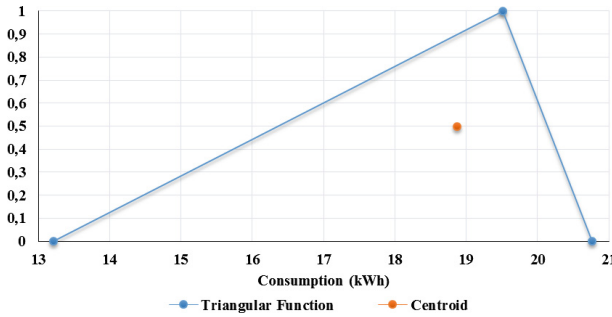


Fig. 6. Representation of fuzzy for the average in EV-1 (Optimistic Case)

the pessimistic and optimistic case, varying between 18.87 and 20.17 kWh, depending on the considered deviations.

The next stage was to implement the normal distribution with the values that were obtained with the FL (average fuzzy values and standard deviation fuzzy values) by using (2).

Figure 7 depicts the normal distributions for each case, namely the original normal distribution: Fuzzy Optimistic and Fuzzy Pessimistic. The Fuzzy Optimistic and Fuzzy Pessimistic, resulted in the calculation of the normal distribution with the fuzzy values.. The Normal Distribution, considered the original values for average and standard deviation. These values of average and standard deviation for the three cases can be seen in Table 2 and 3, respectively. The values presented regard the consumption probabilistic distribution for EV-1 in the hour 7.

With proposed fuzzy-probabilistic methodology it was possible to obtain the probabilities range that a given consumption might reach. For example, the probability of EV-1 to have a consumption higher than 20 kWh over 24 h can be verified in the Fig. 8 for the optimistic case and pessimistic case, respectively.

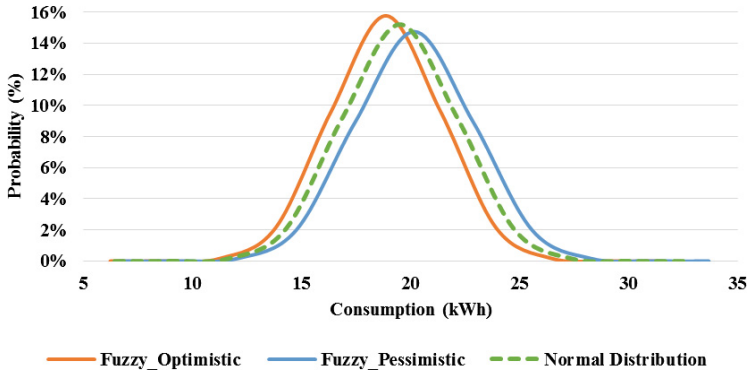


Fig. 7. Comparison with the 3 types of normal distribution

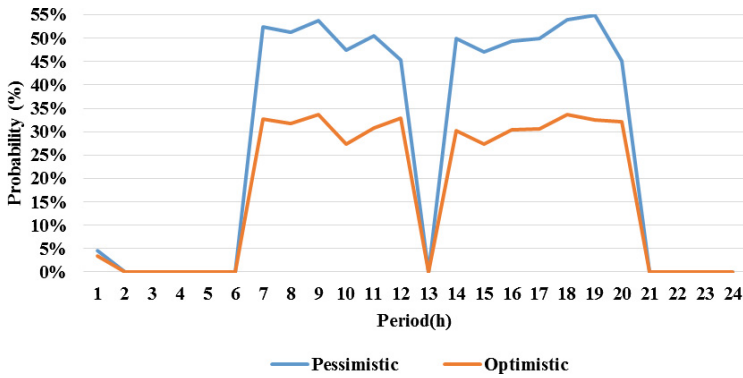


Fig. 8. Fuzzy probabilistic distribution of consumption for the EV-1

4 Conclusions

The paper presented a framework and methodology to estimate the uncertainty of the consumption of EVs. A Fuzzy Logic (FL) was implemented to estimate the probability of consumptions, but this methodology may also be applied to modulate the uncertainty of the charged energy. A case study was evaluated using a fleet of 30 Electric Vehicles (EV) and 2 different scenarios (weekdays and weekends). The methodology presented satisfactory results using low processing time that can be easily integrated with other applications. Authors aim to further develop the proposed idea as well as the data scheme necessary. This type of methodology could be used by automotive industry, network operators and electricity retailers to improve the user's experience and management of future smart grids in the presence of EVs.

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Advances in Artificial Intelligence and Its Applications
14th Mexican International Conference on Artificial
Intelligence, MICA 2015, Cuernavaca, Morelos, Mexico,
October 25-31, 2015, Proceedings, Part II
Pichardo Lagunas, O.; Herrera-Alcántara, O.; Arroyo
Figueroa, G. (Eds.)
2015, XXIX, 619 p. 197 illus. in color., Softcover
ISBN: 978-3-319-27100-2