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Statistical characterisation of the real transaction data gathered from electric vehicle charging stations

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ABSTRACT

Despite the many environmental benefits that a massive diffusion of electric vehicles (EVs) could bring to the urban mobility and to society as a whole, numerous are the challenges that this could pose to the electricity distribution grid, particularly to its operation and development. While uncoordinated management of EVs can lead to load imbalances, current or voltage variation excess and steep power requests, properly designed and well-coordinated integration approaches can in contrast provide flexibility, hence value, to the whole electrical system. Such step can be achieved only if real data are available and real drivers' behaviours are identified. This paper is based on a real dataset of 400,000 EV charging transactions. It shows and analyses an important set of key figures (charge time, idle time, connected time, power, and energy) depending on driver's behaviour in the Netherlands. From these figures, it emerges a key role of the uncertainty of the relevant variables due to the drivers' behaviour. This requires a statistical characterisation of these variables, which generally leads to multi-modal probability distributions. Thereby, this paper develops a Beta Mixture Model to represent these multi-modal probability distributions. Based on the emerged statistical facts, a number of results and suggestions are provided, in order to contribute to the important debate on the role of EVs to move to a fully decarbonised society.

1. Introduction

Electric vehicles (EVs) are small distributed sources that can alternatively store or deliver electricity upon request. The classical EV operation is in grid-to-vehicle (G2V) mode, in which the EVs are charged in appropriate charging stations. EVs operating in vehicle-to-grid (V2G) mode are a further option that can be deployed [1,2], discharging EVs' battery in order to source electricity to the grid when needed, provided that the technical aspects for the grid connection are solved and a specific regulatory framework is in place in the relevant jurisdiction.

The increasing development of EVs can help societies to live in more sustainable and less polluted cities. However, numerous challenges are arising for the electricity distribution grid, its operation and design from both technical and economic perspectives [3]. In particular, the uncoordinated management of EVs can lead to load imbalances, excessive currents or voltage deviations, and steep power requests (steep ramp-up of generation) [4]. Properly designed and well-coordinated EV integration approaches can in contrast provide benefits to the whole system. The added storage capacity, together with the fast ramping-up and ramping-down capabilities, makes the EVs an excellent asset for the electrical grid. For these features, EVs have been already highlighted as future participants in the electricity market, particularly to offer ancillary services to the grid, such as frequency and voltage regulation, and load balancing [5]. In this context, ad-hoc incentives and tariffs need to be studied to engage users into these services while ensuring their mileage needs and constraints are satisfied.

In particular, EVs may contribute to enhance the *flexibility* of the overall demand. In particular, the point of interest is the operational flexibility that can be defined as "the technical ability of a power system unit to modulate electrical power feed-in to the grid and/or power outfeed from the grid over time" [6]. EV flexibility has been addressed in the literature in different ways:

a) Considering G2V only, the key aspect is the flexibility referring to variable EV charging load.
b) In V2G applications, the number of grid services that EVs can

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provide increases, adding more options to modify the demand patterns, as well as the provision of reserves [7].

The EV aggregations (in both G2V and V2G paradigms) are considered as possible source of operational flexibility. Another option is Vehicle-to-building (V2B), in which the EV batteries can be used also as electrical energy storage units for the local building (e.g., offices and in general workplaces), without sending power to the external grid. Workplace EV charging is addressed in Ref. [8] by taking into account the uncertain EV charging demand, also considering different options of G2V for general users and possible V2B only for the local employees.

An interesting classification of the flexibility sources is presented in Ref. [6], by dividing them into different categories based on whether they are used (actual flexibility) or not (potential flexibility) and how they can be obtained (for example, within an ancillary service market). Flexibility has also been defined in Ref. [9] for the collective EV charging demand, adapting the model introduced in Ref. [10] for aggregate residential users, based on the statistical properties of the demand variations in time.

The most common option to provide EV charging flexibility is to use automated charging management systems [11], also considering the specific standards for limiting the EV charging rate [12]. The effect of the EV charging is more important at the distribution system level, due to the fact that the "dumb" charging strategy can lead the operation of the system to be out of the acceptable range [13]. However, an intelligent management of the EV charging process would allow the exploitation of the potential EV flexibility [14]. In this framework, optimisation of the EV charging schedule is addressed in Ref. [15] by adding a conditional value-at-risk term to the objective function. Furthermore, the optimisation model presented in Ref. [16] handles both the renewable energy sources (RES) curtailment and the EV charging in such a way that the overall strategy becomes economically convenient; one limitation in this contribution is the description of the departure and arrival times by means of Gaussian distributions, not obtained directly from an analysis of EV information, but starting from data regarding Internal Combustion Engine (ICE) cars.

The Gaussian distribution is used in other contributions (e.g., [17]), but is generally not suitable to model the statistical properties of the relevant variables that characterise the EV mobility. The scarcity of available real data regarding EVs and their charging stations has pushed researchers to define ad-hoc probability distributions for a number of variables used in the study of EV integration in the electrical networks, in some cases starting from travel survey data on sets of individual vehicles (not only EVs). Finding out suitable probability distributions for these variables is an open challenge, and has to be driven by real data. The lognormal distribution is adopted in Ref. [22] to represent EV-related random variables (arrival time, departure time, and initial state of charge).

Other approaches consider EV-related patterns taken from specific databases without performing a detailed statistical characterisation. The contribution presented in Ref. [18] studies 255 charging stations in the UK, considering weather data, and the EV charging demand patterns are clustered with a k-means algorithm. The work of Kara et al. [19] identifies the benefits, for load aggregators and the distribution grid, of applying smart charging driven by time-of-use pricing to 2000 non-residential EV charging stations. The ElaadNL database has been analysed also in Ref. [20] to quantify the demand response potential of consumers coordinated with EV charging, and in Ref. [21] by developing eight indicators to allow a comparison among EV public charging infrastructures.

Concerning ancillary services, the EV contribution to the frequency control (in particular to the inertial control) has been analysed in Ref. [23], with the implementation of a proper EV battery control; however, it is necessary to determine the "availability" of this flexibility, by investigating real data linked with the real behaviour of the drivers. The paper [24] tries to cover this gap, by analysing 390k transactions, and, thanks to clustering techniques, offers a categorisation of the arrival time, departure time, idle time, by quantifying the available flexibility obtained from the EVs.

From the literature, it emerges that some of the present basic issues to be further addressed refer to the uncertain nature of the variables used in the study of the EV mobility, including the charging modes, the behaviour of the drivers, the number of charges during the day, and the dependence on time of the moving EVs. For these variables the study of their specific characteristics in a given context can provide valuable conceptual inputs. This paper aims at following this line, by analysing a large dataset of real charging transactions of EVs in the Netherlands during one year.

The main contributions of this paper address the following aspects:

- The provision of real figures about drivers' behaviour and EV presence in a charging station (in terms of connected, charge and idle times);
- The identification of the probability distributions of a number of relevant variables, with specific focus on the multi-modal nature of these distributions – an issue that has not been consistently addressed yet in the literature on EVs;
- The development of a Beta Mixture Model (BMM) to represent the multi-modal probability distributions of the relevant variables; and,
- The provision of hints/facts on the potential of EVs to provide V2G services.

The next sections of this paper are organised as follows. Section 2 describes the structure of the database used, and provides an overview on the electricity demand in the Netherlands and illustrates the EV profile demand, plug-in and plug-out characteristics during working days and weekends. Section 3 describes how to represent the multi-modal probability distribution by developing a BMM approach customised to the analysis of the EV-related variables. Section 4 presents the results for the charge, idle and connected times, and applies the BMM approach to provide the statistical representation of these variables. Section 5 illustrates a spatial analysis of the charging stations based on their geographical coordinates. Section 6 focuses on the electrical power and energy required at the charging stations under observation. Section 7 presents a discussion on the usage of the information presented in the prospect of the interaction with the electrical grid, with the possible deployment of V2G solutions. Section 8 summarises the conclusions and provides a list of current and future research activities.

2. Electric vehicle database overview

The EV dataset has been obtained from ElaadNL, a Dutch research centre, specialised in the field of smart charging infrastructure and interoperability [25]. The ElaadNL database contains the records of the charging stations' utilisation. It includes historic transactions data, from January 2012 until March 2016, of 1750 publicly accessible charging stations (2900 charging points) installed over the entire geographical area of the Netherlands. The charging stations are all 3-phase with a maximum output power of 12 kW. The database represents around 16% of all the publicly accessible charging stations available in 2015 in the Netherlands [26], which were widely spread in the whole country. The database has recorded approximately 1 million recharges over the 4 years, and for each transaction the parameters are updated every 15 s (the database has around 32 million rows). From the transactions identifier it has been possible to estimate that around 30,000 EV drivers have used the ElaadNL charging stations during the 4 years of observation. At each recharge, in addition to the transaction identifier, the parameters measured and recorded are:

1. *Charge time*: it represents the time, measured in seconds, during which the EV has been actively supplied with power.
2. *Idle time*: it counts the time, measured in seconds, that occurs

between the end of the recharge and the moment at which the EV has been plugged-out from a user (note that no effective energy transfer takes place in this period).
3. *Connected time*: it is the time difference, measured in seconds, between the start and the end of a transaction. It corresponds to the sum of the charge and idle time.
4. *Energy meter*: it is the energy, measured in Wh, charged from the beginning to the end of the transaction.
5. *Power meter*: it is the average power value, represented in W every 15 s while the EV is being recharged.
6. *Geographical coordinates*: they refer to the latitude and longitude of each charging station.

This study focuses on the year 2015, being the most recent and populated year available in the dataset. The total number of transactions is about 400,000. The year 2015 alone contains 38.5% of the total number of transactions in the whole dataset. Transactions with duration of less than 10 min have been neglected because they have been considered not relevant (they refer to occasional partial charging of the EV and represent only 0.5% of the database). For the analyses carried out in this paper, the time resolution of the data used is 1 min.

Geographical information systems (GIS) can be a very powerful tool when combined with real databases. The combined use of spatially referenced data, databases, and possibly other information on the territory and on the main activities carried out in different zones, can for instance help understanding where to install future charging stations across the Netherlands and to enhance the usage of the installed or planned infrastructure. From the geographical coordinates of each charging station, it is also possible to gain more information on their position with respect to the road classification used in the OpenStreetMap project (Openstreetmap.org).

Many studies on location and operation of the EV charging infrastructures have been presented in the literature. In order to understand the nature of these studies, it is important to contextualise the solution used for EV charging. The main differences depend on the following aspects:

- The presence of G2V and/or V2G (depending on the regulatory framework in place in the jurisdiction).
- The solutions available for EV charging (and, in case, V2G), namely, the location of the charging points at home, or in public spaces outside home, or in charging stations close to the streets, or in specific (public or private) parking lots.
- The entity that manages the charging points for each solution indicated above, e.g., the network operator, or one or more aggregators, or the single user (for home charging). A practical scheme to represent the various possibilities is reported in Ref. [27].
- In case V2G is available, the way to manage the interactions between the EV user and the charging point/station, e.g., with a transaction-based system at known prices (also with possible incentives), or with market-based solutions.

In this paper, the solution analysed depends on the existing framework in the country where the data are available. In particular, V2G is not allowed, and the charging points are located in public spaces close to the roads. The road classification used in this paper is the standard one, which divides the roads into five types, in descending order of their importance (e.g., in terms of vehicle capacity) in the road network [28]:

1. Motorway;
2. Primary road (often linking large cities);
3. Secondary road (often linking towns);
4. Tertiary road (linking villages); and
5. Road in a residential area, that serves as an access to housing.

The majority of the studied charging stations, up to 72%, is located in a residential area.

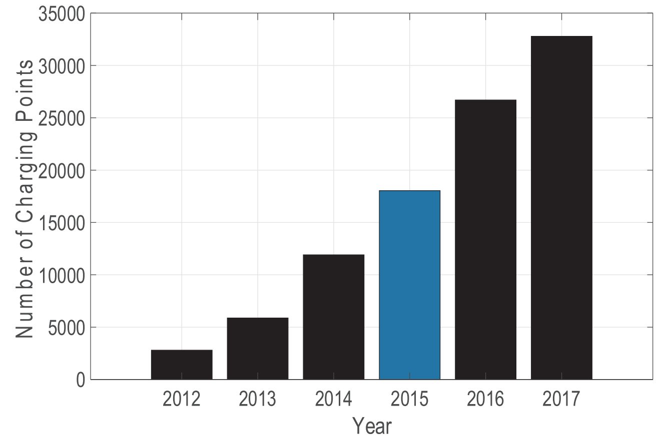

Fig. 1. Publicly accessible charging points in the Netherlands.

2.1. The Netherlands: electric vehicles and energy demand

The Netherlands is among the leading countries in terms of policies aimed at building a more sustainable mobility sector. It has recently been announced that by 2030 no ICE vehicle will be sold anymore on the market [29]. In these years, the number of EVs, both Plug-in Hybrid Electric Vehicles (PHEV) and Full Electric Vehicles (FEV), increased from 2549 in 2012 to almost 110,000 in mid-2017 [26]. The same trend can be observed from our dataset in terms of publicly accessible charging points installation in the country (Fig. 1, in which the analysed year 2015 is highlighted).

In 2012, the number of publicly accessible charging points in the Netherlands was 2803 and reached 32,785 in 2017 [26]. Focusing on the year 2015, 18,139 publicly accessible charging points were available and an interesting trend is reflected in our database (Fig. 2) in the number of recharges for each week. By looking at the chart, it is evident the increase in the number of transactions across the year. This fact depends on the higher penetration of EVs in the country, and also to the increasing number of installed charging stations.

It is particularly interesting to observe that the few drops identified during the year correspond to national holidays such as King's Day, Christmas and the summer break. The energy demand supplied to all the EVs per week during this year corresponds on average to 62 MWh, with a maximum value of 80 MWh. The two most stable seasons are winter and spring with no remarkable peaks and valleys, except for a few cases. On the other hand, summer months have a remarkable

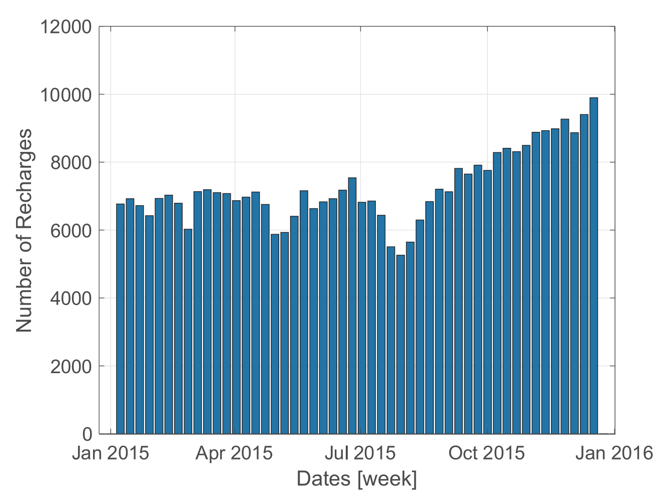

Fig. 2. Number of recharges per week in 2015.

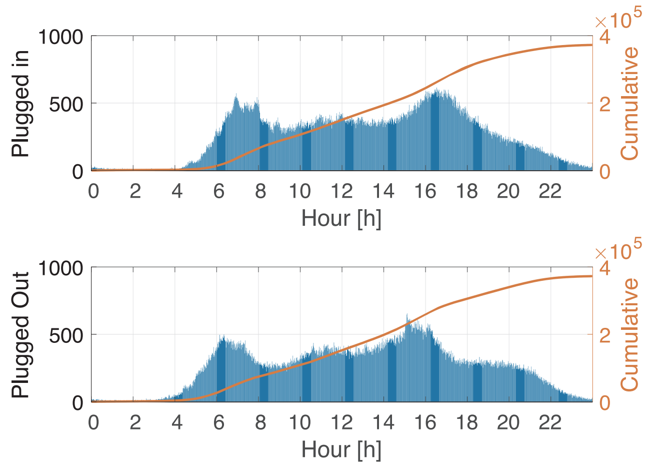

Fig. 3. Average weekday plug-in and plug-out of EVs in 2015.

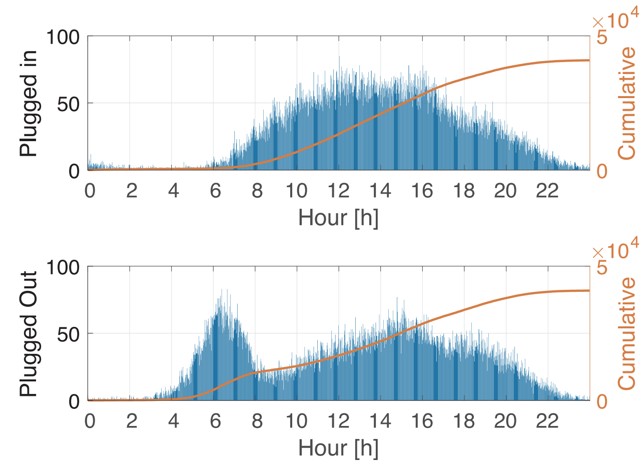

Fig. 5. Average Sunday plug-in and plug-out.of EVs in 2015.

declining profile especially in August's central weeks: around 20% of the energy demand in fact drops up to a reduction of 10 MWh. Then, there is an almost constant increase of number of recharges, reaching 100,000 per week at the end of the year.

2.2. Electric vehicles profile: plug-in and plug-out

This section focuses on drivers' behaviours, and particularly on when EV users plug-in and out their vehicles. This information can be extremely valuable for different actors. From a different perspective, we can use it to check for instance whether the assumptions and distribution profiles taken from the literature can be validated through the real users' behaviour identified through the database. Only publicly accessible charging stations are addressed in this paper. Home charging is not considered. The charging points used are located in public charging stations that could also be close to the households, but in any case lie outside the private properties. Fig. 3 shows an example of average time distribution (with a time step of 1 min) of plug-in and plug-out events during a weekday. Figs. 4 and 5 show the same distributions for a Saturday and a Sunday, respectively.

From Fig. 3, two main peaks appear during weekdays. No activity occurs during the early morning until 4:30 am, while considerable plug-in and plug-out events are registered in the morning between 6:00 am and 8:00 am, when Dutch drivers reach their working place. The peak number of vehicles plugged in (slightly above 500) is reached at 7:30 am, when 30% of the whole charging stations are in use (the highest percentage along the day). This early plug-in can potentially be explained by the fact that the EV owners have an available charging station close to their workplace. A secondary peak of plug-in and out is noticeable between 4:00 pm and 6:00 pm. Giving a look at the cumulative vertical axis on the right-hand side of Figs. 3–5 it can be seen that 85% of the activities occur before 7:00 pm during the week. This information can already help us discussing the validity of certain assumptions, such as the reduced, or almost negligible, night impact of EV charging.

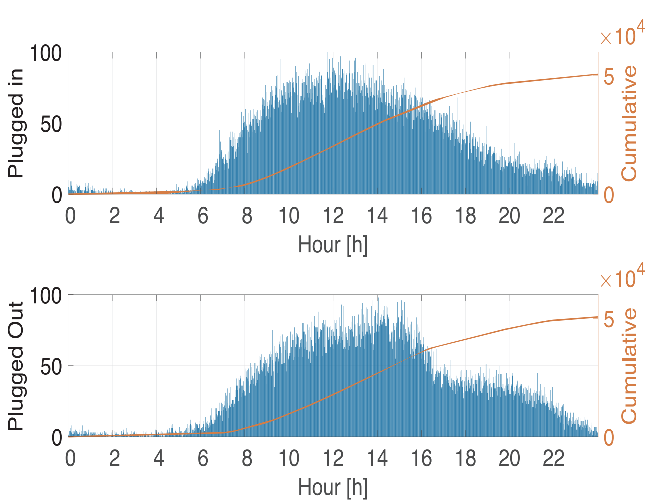

Fig. 4. Average Saturday plug-in and plug-out of EVs in 2015.

The co-optimisation aimed at maximising the profits from energy arbitrage and minimising the transformer aging provided by Sarker et al. [30] has shown that, if EVs are mainly recharged during the night, the transformer deterioration is considerably accelerated. By looking at ElaadNL database, the low EV night charging indicates that the transformer ageing would not be relevant during the night because of the low utilisation rate. Uncontrolled charging events during weekdays show that users mainly recharge when they reach the charging points located either close to their workplace or close to their homes. If compared with weekends, several differences appear. For Saturday and Sunday, from Figs. 4 and 5 the number of charging stations effectively in use never reaches 100, which corresponds to only 6% of the whole considered stations. It is worth mentioning the important number of plugged-out EVs on Sunday morning, which reduces from 80 to 20. Saturday and Sunday have a saddle shape with a peak of plug-in's around noon. As seen for weekdays, 85% of the activities occur before 7:00 pm.

In order to construct the probabilistic representations of the plugged in and plugged out EVs, the data indicated in Figs. 3–5 are considered as histograms to be used for determining the probability density functions (PDFs) of the relevant variables. Each histogram refers to one-minute data and thus contains 1440 points. Since the number of occurrences is relatively high, the empirical PDF (EPDF) is formed with 1440 classes, avoiding the further merging of these data into a lower number of classes. Looking at the shape of the histograms, it is evident that standard single-mode probability distributions would be poorly representatives of the actual situation. Thereby, a multi-modal representation is formulated as shown in the next section.

3. Handling multi-modal probability distributions with the Beta Mixture Model

The posterior PDFs found for many relevant variables are multi-modal, and as such cannot directly fit into a standard (single-mode) probability distribution. In order to deal with multi-modal PDFs, it is possible to follow specific procedures. Let us assume to know the number M of modes existing in the posterior PDF. One possibility would be to approximate the posterior PDF by using a mixture of M multivariate normal distributions, each one characterised by its mode, variance matrix and relative mass [31]. The relative mass is the weighting factor used to combine the distributions, and appropriate weighting schemes have to be defined to determine the most suitable combination. For example, comparisons among weighting schemes have been addressed in Ref. [32] by using a weighted combination of multiple Laplace approximations obtained from significant modes. The normal-mixture approximation is suitable if the modes are relatively well separated and for each mode the normal approximation is appropriate. For the real transaction data considered in this paper, these hypotheses are not generally satisfied. In fact, the PDFs for the data analysed are not symmetric, nor defined on an unbounded support $(-\infty, +\infty)$. In this case, the analysis has to be extended to identify the probability distributions of interest to create the mixture, and to formulate suitable weighting schemes to establish the proportions of each probability distribution in the mixture.

The possibility of formulating an algorithm to approximate the multimodal probability density functions by mixtures of standard distributions is discussed in Ref. [33]. Among the various possibilities, the BMM [34] is indicated to be appropriate to represent the probability distributions found in the analysis of EV-related data [31].

Let us consider the Beta probability distribution, defined in the following way, by considering the two shape parameters $a > 0, b > 0$ and the variable $x \in [0,1]$:

$$\mathrm{Beta}(x|a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1} \tag{1}$$

where $\Gamma(.)$ is the Gamma function. The Beta probability distribution is appropriate to represent variables defined between a minimum value $x_{\min}$ and a maximum value $x_{\max}$, by rescaling the horizontal axis from the support [0,1] to $[x_{\min}, x_{\max}]$. Moreover, by changing its parameters it is possible to represent different PDF shapes, from left-skewed to symmetric to right-skewed PDFs.

An interesting aspect is that the mode ξ of the Beta probability distribution is calculated analytically starting from the parameters $a > 0$ and $b > 0$:

$$\xi = \frac{a-1}{a+b-2} \tag{2}$$

Considering a multi-modal EPDF with M modes, it is possible to construct its approximation based on the BMM, in which M Beta probability distributions are combined together to form the final PDF. In particular, starting from $m = 1, \ldots, M$ Beta probability distributions $\mathrm{Beta}(x|a_m, b_m)$, the BMM is constructed by considering the weighted sum:

$$\mathrm{BMM}(x) = \sum_{m=1}^{M} (w_m \mathrm{Beta}(x|a_m, b_m)) \tag{3}$$

in which the weights are defined in such a way that

$$\sum_{m=1}^{M} w_m = 1 \tag{4}$$

If the empirical PDF is composed of N points, and by definition $x_1 = x_{\min}$ and $x_N = x_{\max}$, it is possible to calculate the distance between a given BMM and the EPDF as

$$d(\mathrm{BMM}, \mathrm{EPDF}) = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (\mathrm{BMM}(x_n) - \mathrm{EPDF}(x_n))^2} \tag{5}$$

In this paper, the identification of the BMM is carried out by minimizing the distance $d(\mathrm{BMM}, \mathrm{EPDF})$. The unknowns considered are included in the vector $\boldsymbol{y} = [w_1, \ldots, w_{M-1}, b_1, \ldots, b_M, \xi_1, \ldots, \xi_M]^T$, where the superscript T denotes vector transposition. In particular, the last weight w_M is not included among the unknowns because it is directly implemented in (3) as $w_M = 1 - \sum_{m=1}^{M-1} w_m$, thus reducing one unknown and taking automatically into account the equality constraint (4). In addition, the modes $\xi_1, \ldots, \xi_M$ are preferred to the shape parameters $a_1, \ldots, a_M$ as the problem unknowns, because in the initialisation phase of the optimisation problem it is easier to set up an initial value of the mode with respect to the initial value of the shape parameter. At the end of the optimisation, the shape parameters a_m, for $m = 1, \ldots, M$, will be calculated from (2) as

$$a = \frac{1-2\xi}{1-\xi} + \frac{\xi}{1-\xi} b \tag{6}$$

On the basis of the above indications, the optimisation problem is set up as follows:

$$\min_{\mathbf{y}}\{d(\mathrm{BMM}, \mathrm{EPDF})\} \tag{7}$$

subject to
$b_m > 1$, for $m = 1, \ldots, M$
$0 \le w_m \le 1$, for $m = 1, \ldots, M-1$
$0 \le \xi_m \le 1$, for $m = 1, \ldots, M$.

The vector $\mathbf{y}$ is initialised in such a way that its entries satisfy the inequality constraints. In particular, extensive testing carried out by the authors suggests initialising the modes of the Beta probability distributions to values close to the modes of the EPDF; however, there is no need to try and calculate these modes, also because the modes of the EPDF do not correspond with the modes of the individual Beta probability distributions used in the BMM. Likewise, the parameters b_m, for $m = 1, \ldots, M$, can be initialised to higher values if there are sharper peaks around the corresponding modes, and to lower values otherwise. Finally, the weights can be initialised in a uniform way, that is, $w_m = 1/M$, for $m = 1, \ldots, M-1$.

Different tools can be used to solve the optimisation problem. However, when using the Beta distributions, a classical tool such as the *maximum likelihood* parameter estimation is limited by possible singularities in the log-likelihood function when the observations are close to 0 or 1 [36]. In this paper, the solver fmincon from Matlab® with the interior point algorithm has been used. Due to the nature of the problem, the initial conditions affect the solution, and it cannot be guaranteed that the global optimum is found. However, it is possible to carry out a goodness-of-fit test in order to check whether the BMM fits the empirical data in a satisfactory way. In this paper, the Kolmogorov–Smirnov (KS) test is used as the goodness-of-fit test. In the KS test, the cumulative distribution function (CDF) is constructed for the BMM, and the empirical cumulative distribution function (ECDF) is constructed for the empirical data (in this case, it is a stepwise curve with N steps). Then, the KS test error $\varepsilon_{\mathrm{KS}}$ is calculated as the maximum vertical difference between the CDF and the ECDF. The goodness-of-fit test is successful if the error $\varepsilon_{\mathrm{KS}}$ is lower than the critical value $\varepsilon_{\mathrm{KS}}^{\mathrm{crit}}$ that defines the limit value for the KS test error. For a generic probability distribution, the value $\varepsilon_{\mathrm{KS}}^{\mathrm{crit}}$ is found in a specific table provided in Ref. [37], depending on the sample size N and on the level of significance. By considering 5% as the level of significance, the resulting expression of the critical value is $\varepsilon_{\mathrm{KS}}^{\mathrm{crit}} = \frac{1.36}{\sqrt{N}}$.

An example of application of the proposed procedure is shown here with reference to the EVs plugged in and plugged out presented in Figs. 3–5. Table 1 shows the number of modes resulting in the various probability distributions, as well as the initial unknowns of the BMM, the corresponding final values, and the outcomes of the KS test. Fig. 6 shows the graphical representation of the EPDFs and of the BMM. The BMM support for the PDFs is defined in the interval (0, 1). Because of the 1-min time resolution, this range corresponds to the time interval (0, 1440) in minutes.

In the examples shown in Table 1, without loss of generality the initial weights applied to the Beta probability distributions that form the BMM are assumed to be the same, equal to $1/M$. The initial values of

Table 1
Calculation of the BMM components for the number of plugged in and plugged out EVs in the various day types.

	Weekday plugged in (Fig. 3)	Weekday plugged out (Fig. 3)	Saturday plugged in (Fig. 4)	Saturday plugged out (Fig. 4)	Sunday plugged in (Fig. 5)	Sunday plugged out (Fig. 5)
Number of points	1440	1440	1440	1440	1440	1440
Number of modes	4	4	3	3	3	3
Modes (initial) (example)	0.28	0.28	0.45	0.50	0.27	0.25
	0.50	0.45	0.60	0.60	0.65	0.60
	0.70	0.65	0.90	0.80	0.78	0.80
	0.95	0.85				
Modes (final)	0.30	0.27	0.39	0.45	0.67	0.26
	0.70	0.47	0.56	0.62	0.49	0.61
	0.70	0.65	0.85	0.77	0.72	0.84
	0.46	0.81				
Weights (initial) (example)	1/4	1/4	1/3	1/3	1/3	1/3
	1/4	1/4	1/3	1/3	1/3	1/3
	1/4	1/4	1/3	1/3	1/3	1/3
	1/4	1/4				
Weights (final)	0.23	0.22	0.17	0.43	0.02	0.24
	0.14	0.31	0.62	0.14	0.48	0.63
	0.56	0.18	0.20	0.43	0.50	0.13
	0.08	0.29				
Parameter *b* (initial) (example)	100	80	50	50	150	150
	30	50	20	70	10	10
	100	50	40	50	20	20
	40	30				
Parameter *b* (final)	76.76	62.36	24.80	12.95	150.08	71.85
	33.40	17.21	6.39	30.26	9.12	5.33
	2.34	38.11	1.61	2.19	3.05	5.09
	42.65	3.47				
Parameter *a* (final)	32.80	23.60	16.05	10.69	300.71	26.47
	76.42	15.44	7.81	47.81	8.69	7.65
	4.13	69.92	4.49	5.05	6.22	21.84
	36.12	11.66				
KS test error	0.0041	0.0090	0.0083	0.0092	0.0100	0.0109
KS test limit	0.0358	0.0358	0.0358	0.0358	0.0358	0.0358

the coefficients b_m and modes ξ_m, for each mode $m = 1, \ldots, M$, are considered in a number of exemplificative cases. In general, the final result of the optimisation depends on the initial values. However, from the cases analysed it can be shown that it is not strictly necessary to use initial values close to the final values. For example, in the Weekday Plugged In case, the initial modes are 0.28, 0.50, 0.70 and 0.95, while the final modes are 0.30, 0.70, 0.70, and 0.46. It can be noticed that the repeated value of the mode 0.70 actually corresponds to the coexistence in the BMM of two Beta probability distributions with the same mode, but with different parameters (i.e., coefficients *b* equal to 33.40 and 2.34, and the corresponding coefficients *a*) and different weights (0.14 and 0.56). Concerning the weights, the initial values again can be largely changed in the final solution. An example is the Sunday Plugged In case in which, starting from three equal weights (1/3 each), the final weights are 0.02, 0.48, and 0.50. Large variations from the initial values to the final ones are generally found as well for the parameters *b* of the individual distributions that form the BMM. Fig. 6 also shows the ECDF and the CDFs used for the KS test; in all cases, the KS test error is significantly lower than the limit value of the KS test. The zoom shown in Fig. 7 represents the details containing the shape of the ECDF and the entries used for the KS test.

4. Idle, charge and connected times

To provide a more comprehensive view, three variables deserve due attention: the charge, idle and connected times. They can in fact provide more valuable facts as the average duration of recharges, and on the ranges of time in which the vehicles are fully recharged but still connected to the stations, thus potentially 'on' to offer V2G services to the grid.

Table 2 reports the mean values and standard deviations for the charge, idle and connected times for the year 2015. The connected time is the sum of the charge and idle times, and is higher for the roads in residential areas. In fact, if the EVs remain parked close to the houses, for the EV owners it could be not so urgent to disconnect them. This is a relevant point, and is due to the fact that currently there is no shortage of locations to plug in the EVs, and there is no specific penalty for the occupation of the charging stations without charging the EV. Furthermore, as it may be expected, there is a poor correlation between the charge time and the idle time. This can be seen in the joint distribution of the charge and idle times reported in Fig. 8, also showing the dispersion of the idle time, with standard deviation increasing when the type of road passes from the primary to the residential.

In more detail, the transactions have a similar average charge time independently of the position. Different outcomes emerge when we look at the idle times. In this case, the position of the charging stations has a clear impact on them. The smallest idle time, as expected, is recognisable in the primary roads, where drivers do not stop for long time. Longest times are instead registered for charging stations installed at the residential level, with an average connected time of about 7 h. This can be explained as follows. In many cases the charging has started in the evening (e.g., after 6 pm) and has already been completed before or just after midnight. After the charging is complete, the EV remains plugged in during the rest of the night. However, in these conditions the EV charging has little or no impact on the consumption during the night hours and early morning.

By analysing the idle and connected times, it is possible to extrapolate some interesting behaviour patterns. On the average, 75% of the EVs connected at any time to the charging stations are already completely recharged. This trend could indicate that consumers are still not aware about the required time to charge their vehicles. This information can also be used to foresee some aspects of the EV availability to V2G (Section 7).

The ElaadNL database shows that there are high values of charge

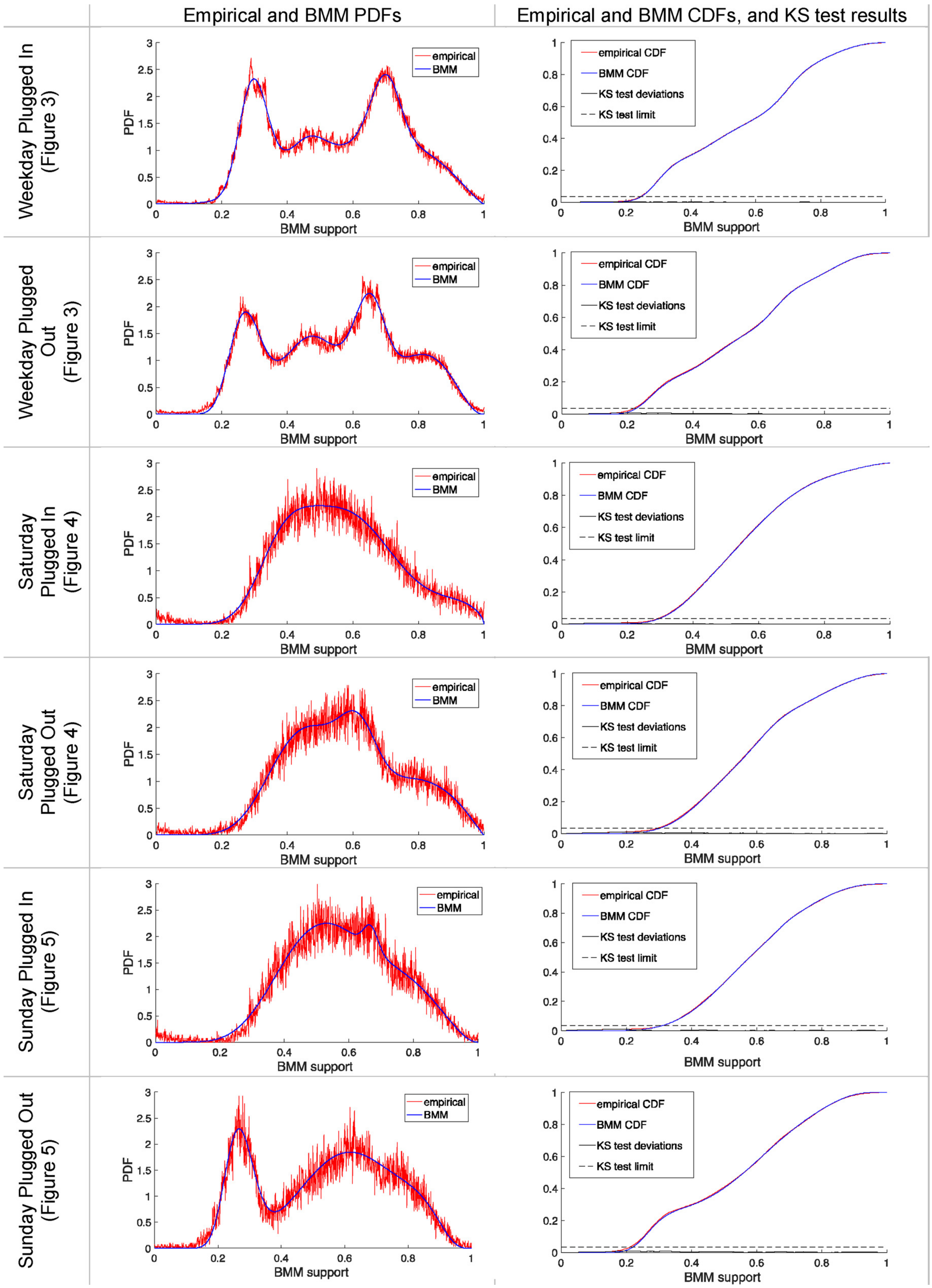

Fig. 6. Results of the PDFs of the plugged in and plugged out EVs with the Beta Mixture Model.

time, which reaches almost 22 h in a row. In the Netherlands, 5.44% of the electric vehicles were Model Tesla S in 2015 [26], which is equipped with a lithium-ion battery of up to 80–100 kWh. This explains the 22 h charging at a power rate of 3.3 kW [38]. It is worth mentioning that all the information ‘distilled' from the dataset can become very useful to provide a sound base for programming and managing the drivers' recharging behaviour according to the system operator needs.

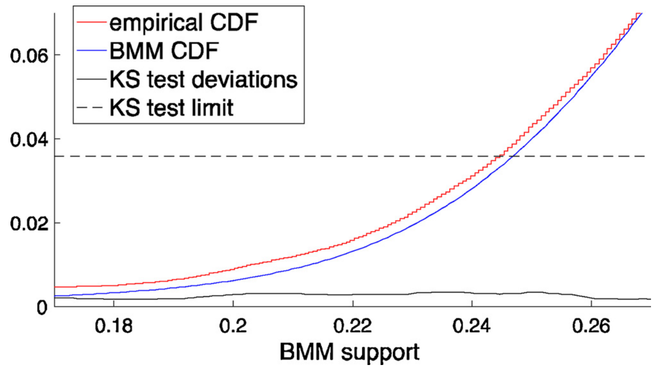

Fig. 7. Zoom of the results for the weekday plugged in case.

Table 2
Charge and idle time statistics for the charging stations based on road classification (mean value μ and standard deviation σ).

Road type	Charge time $\mu \pm \sigma$ [h:min]	Idle time $\mu \pm \sigma$ [h:min]	Connected time $\mu \pm \sigma$ [h:min]	Correlation between charge time and idle time
Primary	2:06 ± 1:32	2.07 ± 4:10	4.13 ± 4:51	0.2955
Secondary	2:14 ± 1:27	2:27 ± 4:28	4:41 ± 5:12	0.3771
Tertiary	2:14 ± 1:32	2:40 ± 4:47	4:54 ± 5:26	0.2883
Residential	2:13 ± 1:30	3:19 ± 5:21	5:33 ± 6:00	0.3047

4.1. BMM results for the charge time

Tables 3a and 3b reports the values obtained by applying the proposed BMM approach to the charge time data synthesised by using a specified number of points to represent the corresponding PDFs. Fig. 9 shows the empirical data and the BMM outcomes. The situation changes from the primary and secondary roads, in which 4 modes are used to provide better representations, to the tertiary and residential roads, where a two-mode model is sufficient to identify the main charge time behaviours.

Fig. 10 counts the occurrences, hour by hour, of the recharges having a given duration for the different roads classified. As mentioned in Section 2, the transactions lasting less than 10 min have been neglected. The cumulative line in red indicates that for 80% of the time the EVs are charging to a charging station for less than 8 h independently of the road classification. The remaining 20% can stay charging for even longer time periods (up to 24 h). It is remarkable that 50% of the occurrences falls within the first 4 h. This does not mean that the EVs are fully recharged in only 4 h, but that they have been charging up to 4 h to satisfy users' needs in that circumstance. The highest number of recharges lasts for 4, 6 or 8 h depending on the road type. The second peak observable at 8 h clearly suggests that these EVs could have been charged very likely at work, or at home (with a smaller probability). Based on this analysis, in the presence of local electrical energy storage one could store part of the electricity coming from photovoltaic systems to cover the EV demand during the night hours, thus mitigating the possible curtailment of part of the production from PV systems in clear sky conditions.

Table 3a
BMM components of the charge time PDFs for the various road types.

Road type	Primary	Secondary	Tertiary	Residential
No. points	60	50	50	50
No. modes	4	4	2	2
Modes	0.11	0.09	0.07	0.06
	0.05	0.14	0.17	0.17
	0.18	0.22		
	0.25	0.04		
Weights	0.24	0.29	0.88	0.86
	0.57	0.18	0.12	0.14
	0.12	0.36		
	0.08	0.17		
Parameter b	149.76	145.30	25.52	24.62
	42.78	571.90	999.79	999.89
	999.88	124.42		
	59.37	120.06		
Parameter a	20.04	14.46	2.71	2.55
	3.17	92.44	203.13	202.97
	221.57	34.82		
	20.75	5.74		
KS test error	0.1179	0.1331	0.1509	0.1410
KS test limit	0.1756	0.1923	0.1923	0.1923

Table 3b
Percentage of null idle time values.

Type of road	Primary	Secondary	Tertiary	Residential
Percentage of null idle time values	45.1%	36.8%	32.3%	35.9%

4.2. Characterisation and relevance of the idle time

From Fig. 8, it is easy to see that the idle time data contain a

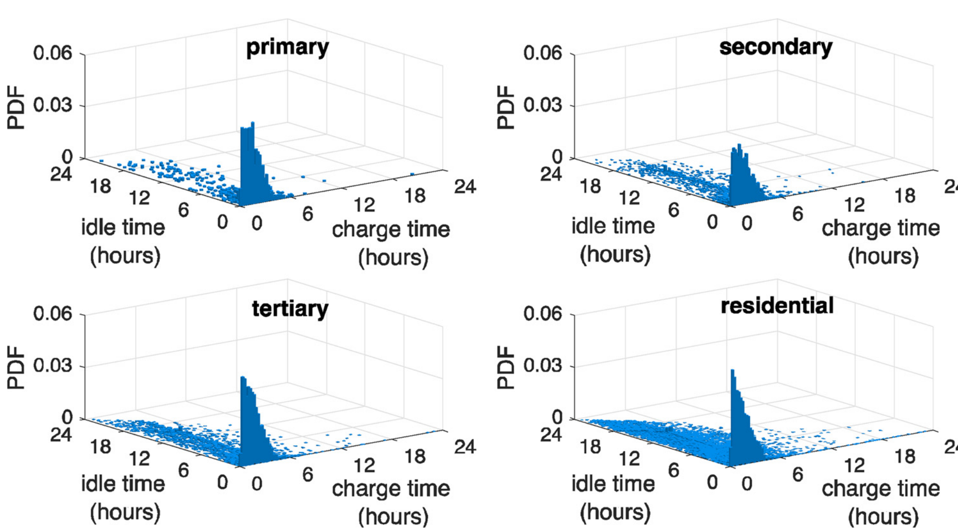

Fig. 8. Joint probability distribution of the charge and idle times.

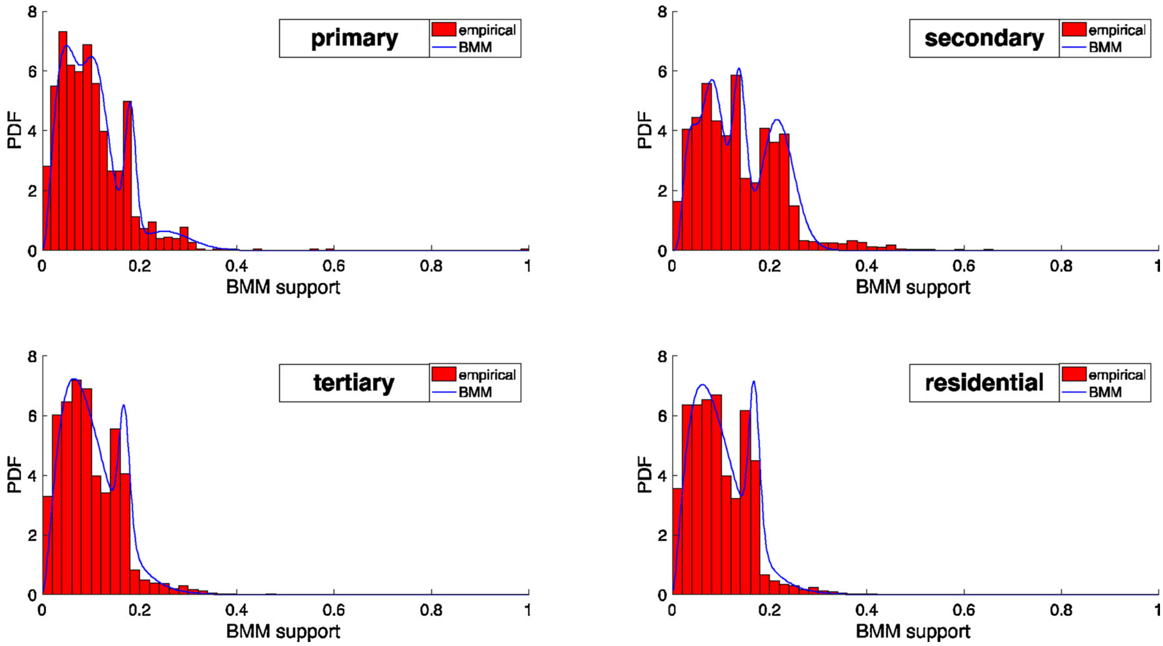

Fig. 9. BMM applied to the multi-modal probability distributions of the charge time.

significant number of null values, as well as a high dispersion of the other values. Thereby, the idle time is not addressed by calculating the BMM with the whole set of data. The null idle times are extracted and associated with a Dirac pulse in the origin of the PDF, whose amplitude is equal to the posterior probability of the null idle time. Tables 3a and 3b indicates the percentage of null idle time values that contribute to the Dirac pulse in the corresponding PDF. The remaining part of the data exhibits an initial decreasing evolution when the idle time increases, then there are some intermediate values for which the decreasing evolution does not appear any longer, and for the higher idle times the values indicatively tend again to decrease. This evolution is then addressed by a special version of the BMM, chosen after extensive testing. Three Beta probability distributions are considered, two of which have the mode equal to zero (the presence of two distributions

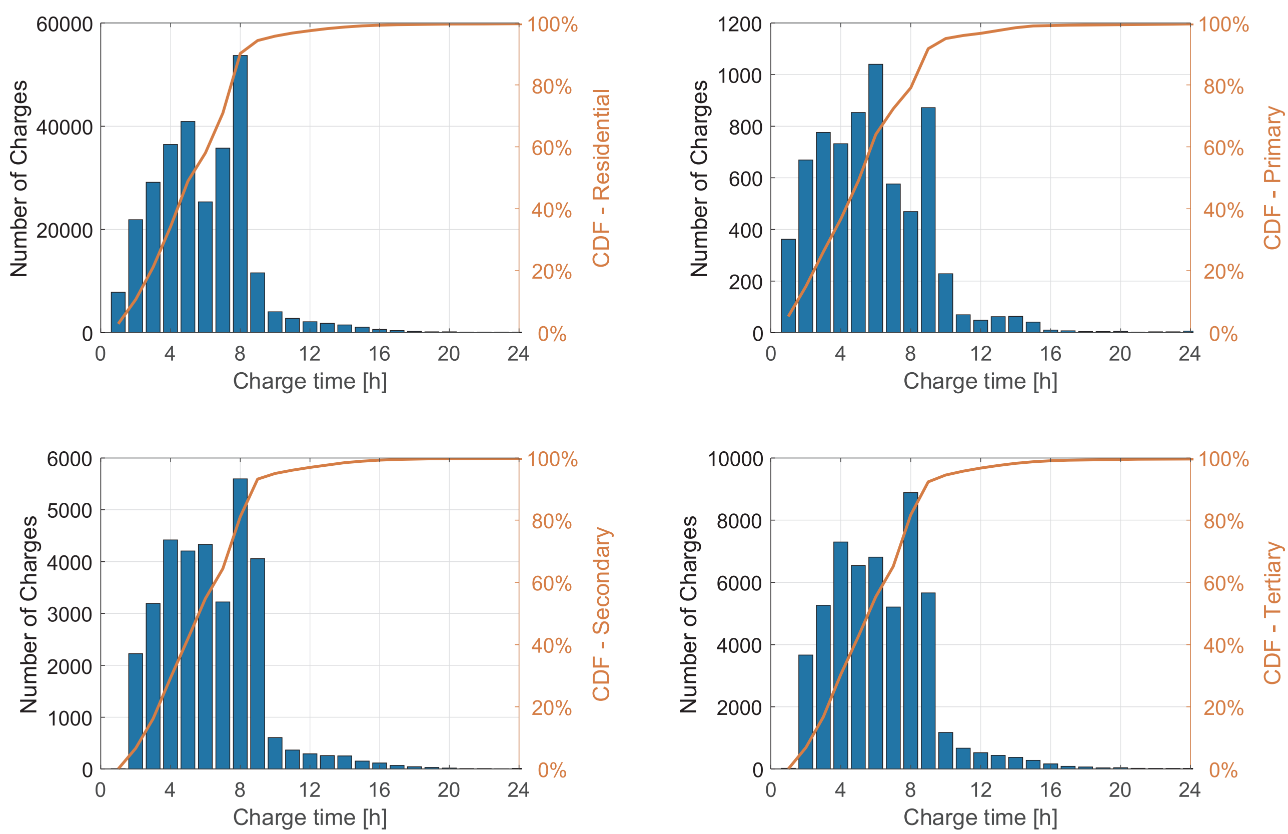

Fig. 10. Time distribution during the day (cumulative values are indicated on the right-hand side of the vertical axis). (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Table 4
Dirac pulse amplitudes and BMM components of the idle time PDFs for the various road types.

Road type	Primary	Secondary	Tertiary	Residential
Dirac pulse amplitude	0.549	0.632	0.677	0.641
No. BMM points	30	30	30	30
No. BMM modes	3	3	3	3
Modes	0.	0.	0.	0.
	0.	0.	0.	0.
	0.67	0.53	0.53	0.55
Weights	0.39	0.49	0.58	0.39
	0.50	0.33	0.28	0.38
	0.11	0.18	0.14	0.23
Parameter *b*	39.61	38.43	62.26	60.75
	7.29	10.58	11.27	12.16
	3.52	3.03	2.98	3.03
Parameter *a*	1.	1.	1.	1.
	1.	1.	1.	1.
	6.14	3.32	3.20	3.44

with different parameters provides more flexibility in the determination of the first part of the distribution), and the third one has a mode initialised at values higher than 0.5. The null modes are excluded from the unknowns of the optimisation procedure (vector **y**), while the other variables (two weights, three coefficients *b*, and one mode) remain in the vector **y**.

Table 4 reports the results of the relevant coefficients and variables obtained from the application of the modified BMM procedure. Fig. 11 shows the graphical view of the empirical data and of the PDFs hence the overall area covered by the part of the PDF represented equals unity minus the Dirac pulse amplitude (i.e., the area represented for the primary roads is 1–0.549 = 0.451, while the area represented for the secondary roads is lower, being 1–0.632 = 0.368).

Fig. 12 illustrates the average number of charging stations that are really fuelling the EVs (in red) and the average number of EVs that are connected to the stations (in blue). The difference between the blue and the red curve gives the average number of connected vehicles already fully charged but still plugged-in. A repeating pattern for weekdays is easily identified for the active recharging which cannot be seen instead for the connected vehicles. The peak of connected vehicles is reached almost every day around 10:00 pm, which means that by the next early morning almost all vehicles are supposed to be fully recharged. The highest available capacity to be offered to the grid is thus reached in the early morning, which can be offered by EVs to the electrical grid operator if needed. From the dataset it is observed that, of the 1750 charging stations available at the EV peak time of use, only 250 are actively used at most, which corresponds to slightly less than 15%, and only about 400 charging stations (23%) are simultaneously connected. This seems to suggest two different contrasting things: either the charging infrastructure is more than adequate to cover the demand coming from EVs, or that a relatively small part of the charging stations is mostly used due to their location.

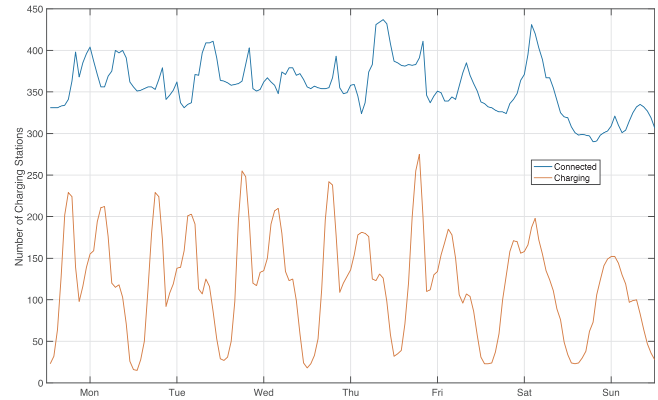

Fig. 12. Average EVs simultaneously plugged in (connected and charged). (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

de Hoog et al. [13] optimise the charging strategy by taking into account also the network constraints. The results of this research, considering also price-based optimisation, indicate that the EV demand is concentrated in the afternoon at 4:00 pm and during the night. This conclusion partially agrees with the real Dutch drivers, but it does not show the two-peaks shape that emerges from the ElaadNL dataset.

Fig. 13 reproduces three single days (Wednesday, Saturday, and Sunday) that can be helpful for a comparison with the weekly results shown in Fig. 12. Indeed, it is accentuated that the blue line can be modelled and assumed to be almost horizontal in certain time periods.

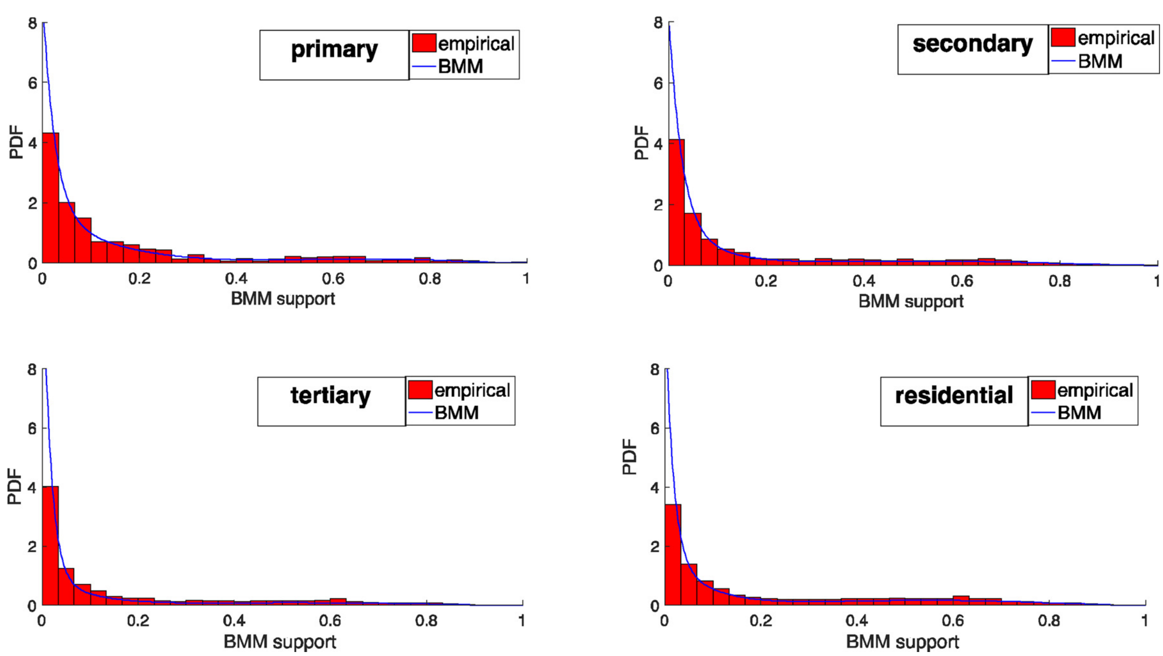

Fig. 11. BMM applied to the multi-modal probability distributions of the idle time (the Dirac pulse that completes each PDF is not represented).

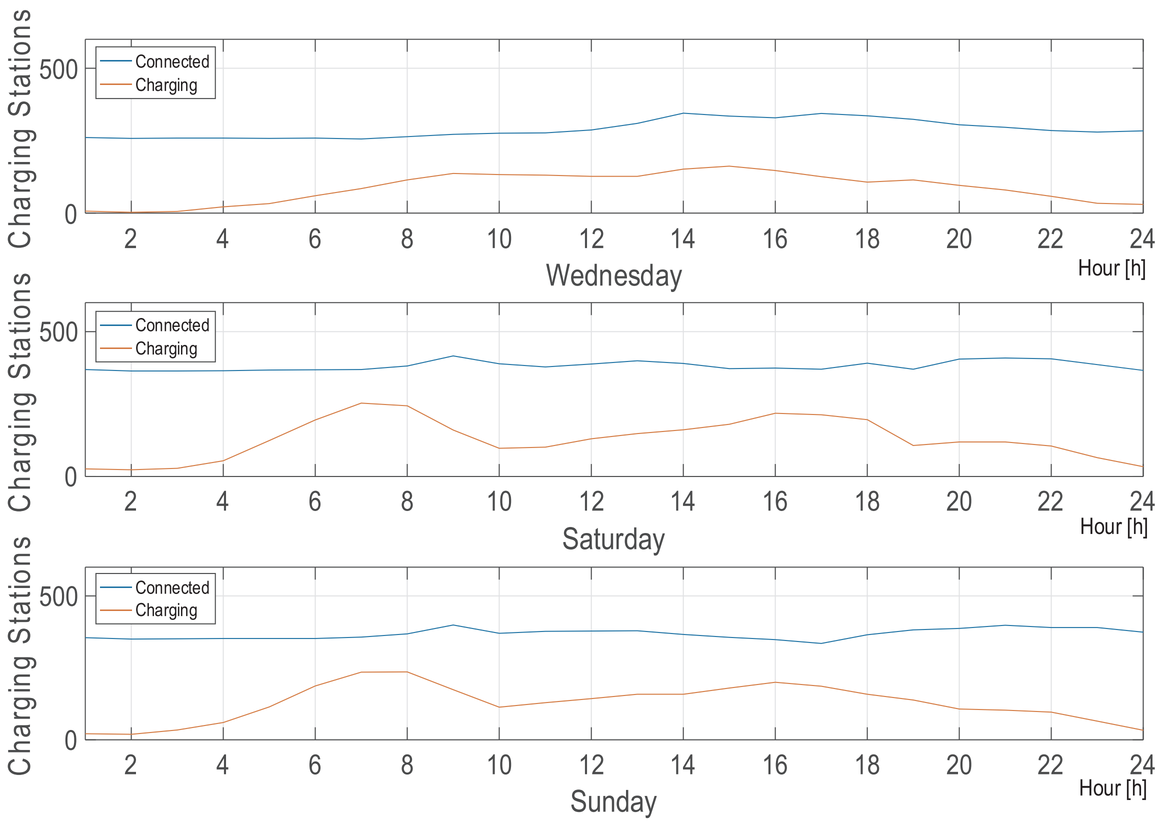

Fig. 13. Number of EVs connected or charging on Wednesday, Saturday, and Sunday. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

The average value on Wednesday, of EVs connected to charging stations, is 360 with only a negligible drop at 3:00 pm, and a peak at 9:00 am. On Saturday and Sunday the two lines, except for the early morning, seem to be shifted between each other. The average number of charging stations in use is higher than on Wednesday and slightly exceeds 400, and the number of charging stations used to recharge exceeds 200 during the weekend at hours 7 am and 8 am, as well as (slightly) at 4 pm.

The EV charging scenario used in [39] assumes that the peak happens in the early morning until 7 am, which is aligned with the real data profile of ElaadNL database. Lopez et al. [36] assume different charging and idling time for the nine EVs used. The charge time is mainly concentrated during the early morning, which does not seem in line with Fig. 12. This difference might mainly be caused by the fact that many EVs are already fully charged around 11:00 pm.

4.3. Other probabilistic information

From the point of view of the EV driver, further inputs have to be provided, such as the probability distribution of percentage of EVs intended to reach a charging point at each time moment [41], or the synthetic information on need-for-charge and willingness-to-supply formulated in the approach that considers vehicle originating signals [42]. This information is not available in the ElaadNL database, as it depends on last minute intentions of the drivers, which would need an online information system to be collected in real time.

5. Latitude and longitude analysis

This section provides more information about the geographical analysis performed. Fig. 14 helps us understand where further charging stations could be installed by analysing the usage of those already installed.

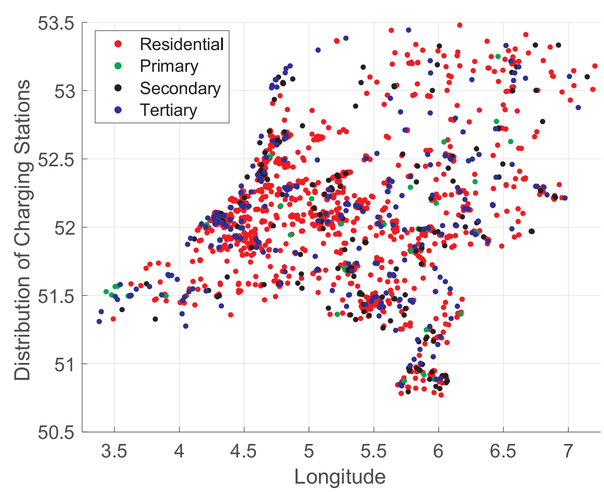

Fig. 14. Distribution of the charging stations based on the road categorisation.

The charging stations considered are distributed as follows (Fig. 14): 1213 are residential, 287 on tertiary roads, 187 on secondary roads, 57 on primary roads, and 2 on motorways (not visible in the figure, as there is not enough information). At the same time, from the ElaadNL database it is possible to see that the charging stations installed on the motorway have been utilised few times, which clearly highlights the fact that drivers prefer fast chargers in this specific location. In Fig. 15, the red line indicates the percentage of charging stations on each category of road compared to the total number of ElaadNL charging stations. The blue bars represent the frequency of utilisation of that category of charging station. It can be concluded that the charging stations at the residential level (that is, located close to households) are the most used, followed by the ones close to the working places.

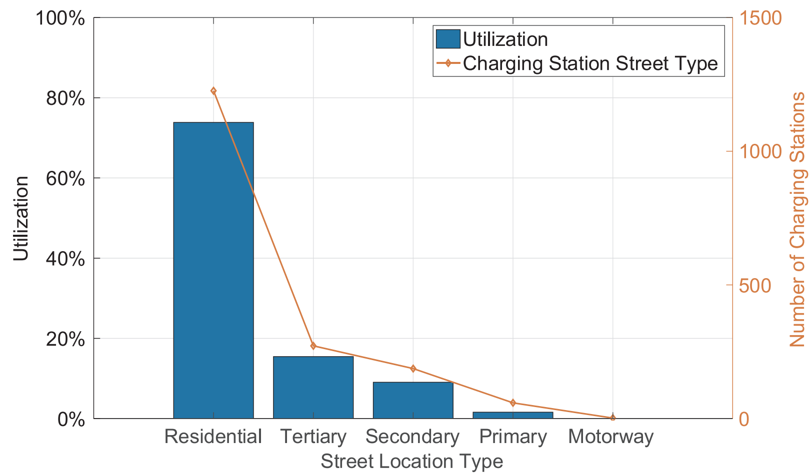

Fig. 15. Utilisation of the charging stations based on the road categorisation. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Moreover, apparently the charging stations installed on primary roads are not used as expected. Primary roads can be considered as a sort of motorways, which seems to explain why they have not been much utilised. This could suggest to companies installing charging stations that on motorways and primary roads it is necessary to install only stations with fast chargers. At the residential level the utilisation is higher, which means that the drivers prefer charging stations close to their homes.

6. Energy and power analysis

The ElaadNL database allows us also to extract useful information regarding the energy and power request from EVs and on how this curve is related to the traditional household consumption. Fig. 16 presents the average weekly EV energy demand and in the same plot highlights (below) the average profiles for Wednesday, Saturday and Sunday. In line with Figs. 5–7, the early demand is almost negligible, and relatively low in the late night (after 10:00 pm). The two-peaks shape is still present for weekdays and shows a peaks of above 150 kW per hour. The average daily energy demand is almost 950 kWh, with a yearly demand that reached 3.3 GWh for the year 2015.

From Fig. 16, it can be perceived that the weekly EV electricity demand profile during weekdays has some peaks anticipated with respect to the morning ramp (occurring after 6 am) and the evening peak (occurring around 6 pm) of the typical household demand in the Netherlands [43]. This lack of coincidence among the peaks is not the most critical case for the distribution network, however the non-negligible EV electricity demand occurring around 6 pm accentuates the grid stress especially in peak hours. The weekend request accounts for 24.7% (0.8 GWh) of the yearly electricity demand, which is mainly concentrated during the central part of the day, as it is visible in Fig. 16. Loisel et al. assume in Ref. [44] that the cars, due to longer travel activities in the weekend, consume more electricity than in the working days; from the results of Fig. 16, this fact is not confirmed for the set of

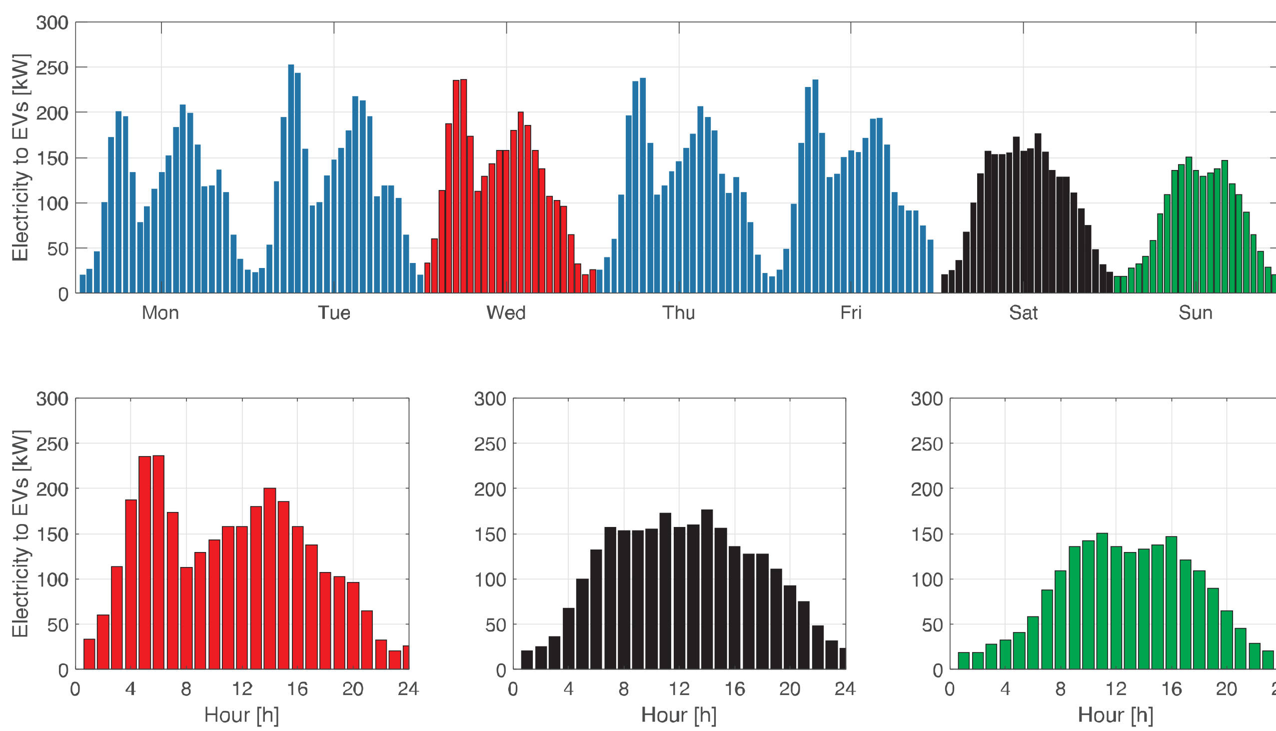

Fig. 16. Average EVs demand per week: weekly evolution (upper graph) and zoom for Wednesday, Saturday, and Sunday (lower graph).

Table 5
Energy statistics for the year 2015.

Charging station based on road classification	Energy $\mu \pm \sigma$ [kWh]	Max energy [kWh]	Correlation between energy and charge time
Primary	8.06 ± 9.61	66.7	0.6753
Secondary	8.34 ± 9.67	81.0	0.6938
Tertiary	8.50 ± 9.91	87.1	0.6743
Residential	7.85 ± 8.69	84.9	0.6616

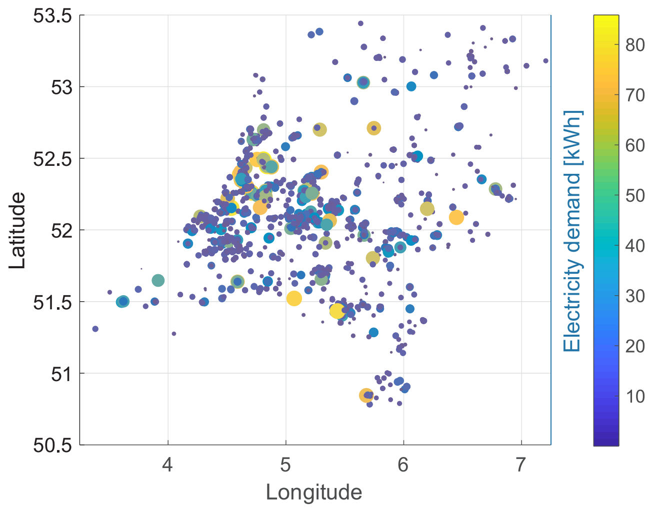

Fig. 17. Electricity demand across the Netherlands during a weekday.

transactions studied. In Ref. [45] the authors optimise the charging strategy by taking into account the battery degradation, as a result they obtain that the best strategy is to charge only once per day at 8:00 pm.

Table 5 lists the mean energy supplied for each transaction for the different street category. The primary road value is slightly lower if compared with the other roads. As expected, the maximum energy recharged corresponds to the full recharge of Tesla vehicles.

Fig. 17 helps understand the electricity demand from a geographical point of view. The figure represents, through the latitude and longitude coordinates, the 1750 charging stations on the horizontal and vertical axes, respectively.

In the representation shown in Fig. 17, the weekday demand is 990 kWh for the whole Netherlands. The demand is concentrated in the central-east area, and more precisely in Utrecht, Rotterdam and Den Haag. By analysing the chart, it becomes clear that the highest amount of charging stations is located mainly in these cities. These results can be extremely useful for the electrical network operators, because they provide useful information on how to expand or improve the grid system in this area. The costs of the infrastructure could be reduced by tailoring investments where EVs provide more value to the system. It is important to mention that 37.5% of these charging stations are equipped with two connectors, which mean that they can recharge at the same time two EVs with a maximum power rate of 12 kW each. By analysing the ElaadNL database it is still interesting to identify three main power output areas. Fig. 18 illustrates the partitioning into *high*, *medium* and *low* power regions. The smallest percentage covers the power supply around 2 kW. The majority of vehicles are instead charged at a power rate of 3.3 kW, and a smaller percentage of charging stations are using the maximum power rate (12 kW).

The partitioning into power regions is also helpful to interpret the results indicated in Fig. 19, in which the charge time is shown together with the energy for each transaction in the various types of road. From the figure it is clear that the charge occurs along two main directions, with a first direction having higher energy for the same charge time

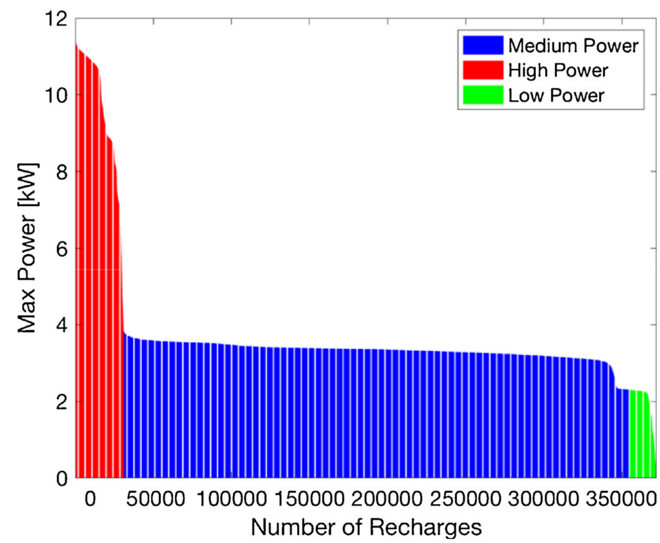

Fig. 18. Max power demand in 2015 across the Netherlands.

(corresponding to the high power region in Fig. 18), and the second direction, most frequently occurring, that indicatively corresponds to the medium power region in Fig. 18.

7. Relevance of the statistical results for implementing vehicle-to-grid

The results presented in this paper refer to G2V only. However, they may offer some indications on the potential of V2G application, provided that the data shown are carefully discussed. In general, if V2G is allowed, the charging behaviour changes depending on the grid connection options and on the revenues for V2G service provision. As such, there is no unique solution to handle V2G. The indications included here refer to the application of V2G to a small extent, starting from an initial situation in which V2G is not admitted. Massive deployment of V2G requires a comprehensive approach that is outside the scope of this paper.

In Ref. [46] a V2G concept is illustrated in which the EVs discharge occurs few hours during the early morning. This behaviour is in agreement with Figs. 3 and 5, where it is clear that the EVs are almost all connected and fully charged. Furthermore, as shown in Section 4, at any time of the day, 75% of the EVs connected to the charging stations are already completely recharged. Looking at Fig. 11, the tail probability corresponding to relatively high idle time (e.g., more than 6 h, corresponding to BMM support higher than 0.25) is relatively low, but not negligible. In the future, consumers not subscribed to the V2G service to the grid could be subject to penalties and fees to prevent unnecessary occupation of the charging stations. Penalties of this kind could be used to reduce the cost (and the number) of installed charging stations to foster a more effective use.

Singh et al. [47] developed a multi-charging station (V2G) optimisation for load management and grid support. The results show that at 9:00 am and 7:00 pm, EVs can provide support through discharging. Even though these results are not directly comparable with the outcomes of this paper, as in the presence of V2G the EV would be operated in a different way, from Fig. 13 it can be seen that at 9 am the difference between the connected and charged EV on Wednesday is the lowest one appearing throughout the day. This fact limits the potential of V2G in that time slot. From the same figure, the situation at 7 pm looks better.

The participation of EVs in energy and ancillary services has been studied in Ref. [48], where the maximisation of the aggregator's profit has been considered. The results indicate that V2G services should be provided in different time periods, e.g., at 5:00 am and from 8:00 am until 1:00 pm. In contrast, Karfopoulos and Hatziargyriou [17]

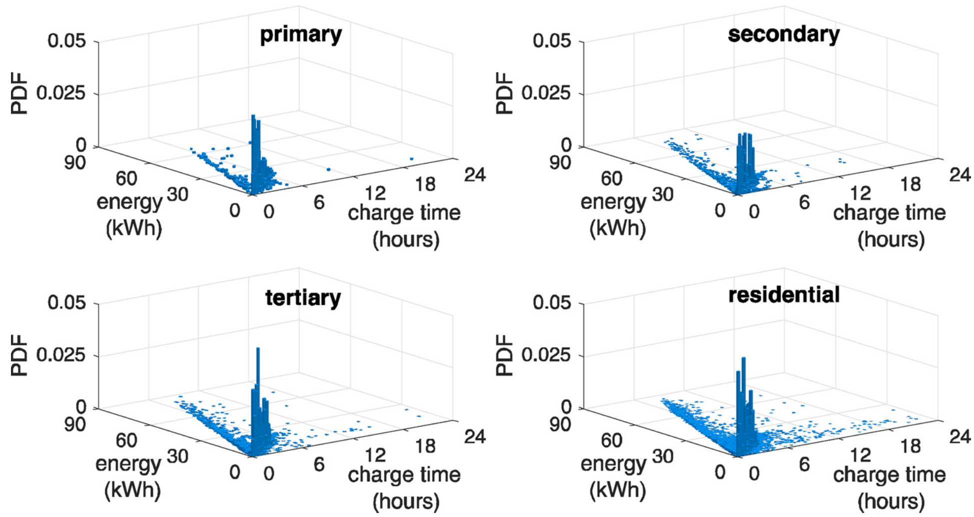

Fig. 19. Joint distribution of charge time and energy.

determined that, on a 24 h profile, EVs only support the grid through V2G for two hours per day (11:00 am–1:00 pm). From Fig. 13, the period 11:00 am–1:00 pm appears with the lowest difference between the connected and charged EV on Wednesday (thus leaving a relatively low margin to use the EVs for V2G), while during Saturday this margin is significantly higher.

8. Concluding remarks

In the changing electrification sector, the emerging role that fleets of EVs will play in offering their services to the electrical grid, also to balance the intermittent production of renewable energy sources, is still not fully exploited. This paper analysed valuable real data on EVs charging behaviour in the Netherlands for the year 2015 coming from 1750 three-phase charging stations with a maximum power output of 12 kW. The study analysed the current EV status in the Netherlands. System operators and EV aggregators should take the growing importance of EVs into account. The global EVs demand in 2015 reached 3.3 GWh with only a penetration of 3 EVs for every 1000 vehicles. By looking at the energy demand, the data reveals that 25% of the total energy is supplied in the weekend, and the mean energy supplied to each EV is 8.5 kWh per transaction. Daily plug-in and plug-out distribution profiles highlighted remarkable differences among weekdays and weekends. Multi-modal probability distributions were identified for a number of relevant variables, and were handled through a Beta Mixture Model approach. A statistical analysis of connected, idle and charge times provided the following results: 50% of the recharges last for less than 4 h; the idle time depends on the geographical location of the charging station, and on average it lasts also for 4 h. These results constitute a basis on which future research activities on EVs integration, ancillary services, grid infrastructure impact, and EVs charging management, can be built by relying upon validated assumptions. Based on these results, future activities will focus on the implications on ancillary services, thus, on novel electricity market models, and on costs and benefits of the EV integration into the electrical grid.

When the number of EVs will become higher, further issues will likely appear, such as the possible unavailability of charging locations in a charging station, taking into account the probability that the EV is charged or queued at its arrival. On the operation side, the possible queuing will have to be handled through appropriate communication before the EV arrival. On the planning side, the risk of being not served will be included in the planning problems aimed at determining the location and sizing of new EV charging infrastructure.

Results of this kind can help policy makers, companies and network operators devise better strategies, economic tariffs and ad-hoc incentives and penalties to enhance the value of tomorrow's EV fleet and to minimise its impact on the grid infrastructure.

Acknowledgements

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