


Article

A Framework for Analysis and Expansion of Public Charging Infrastructure under Fast Penetration of Electric Vehicles

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Abstract: The improvement commercial competitiveness of private electric vehicles supported by the European policy for the decarbonisation of transport and with the consumers awareness-raising about CO₂ emissions and climate change, are driving the increase of electric vehicles on the roads. Therefore, public charging networks are facing the challenge of supply electricity to a fast increasing number of electric cars. The objective of this paper is to establish an assessment framework for analysis and monitor of existing charging networks. The developed methodology comprises modelling the charging infrastructure electricity profile, analysing the data by using machine learning models such as functional k-means clustering and defining a novel congestion metric. The described framework has been tested against Irish public charging network historical datasets. The analyses reveal a lack of reliability of the communication network infrastructure, frequent congestion events for commercial and shopping areas in specific clusters of charge points and the presence of power peaks caused by the high number of simultaneous charging events. Several recommendations for future network expansion have been highlighted.

Keywords: electric vehicles (EV); charging point; public charging network; congestion; machine learning; plug-in hybrids (PHEV); functional data analysis (FDA); functional clustering; demand side management; data analytics

1. Introduction

In December 2019 the EU has proposed the European Green Deal where the majority of the member states commit to zero net emissions of greenhouse gases by 2050 and where economic growth is decoupled from resource use. One of the pillars of the green deal is the decarbonisation of the society. Among the various sectors, transport accounts for 18% of CO₂ emissions (5.85 Gt CO₂) [1]. The progressive mass electrification of the vehicle fleet has been widely seen as a key policy goal to reduce emissions and pollutants produced from the transport sector's long-lasting dependence on fossil fuels, which has been seen to create huge impacts at a range of scales, from raising global atmospheric CO₂ levels through to local build-ups of air-borne particulates damaging to human health [2]. Thus, electric vehicles have risen in popularity holding from more than 1% market share of new vehicles

in China and six European countries in 2015 [3] to a more than 2% in seven European countries in 2018. Three of these countries had more outstanding numbers than others: Sweden was recorded at 5.3%, Iceland 14% and Norway 39.2% [4]. In Ireland private vehicles are the most used mode of transport because of a widespread population living in rural areas which prevents the development of an efficient public infrastructure. Although, concerning electrification of private vehicles Ireland has lagged behind its European neighbours with less than 4000 registered EVs accounted for by the end of 2017 (from a total vehicle fleet of more than 1.98 million registered passenger cars) and a plug-in market share of just 0.7% of new car sales [5]. By the end of February 2019, the number of EVs in Ireland reached more than 9500, equivalent to +137% with respect to 2017.

Regulations have been set at EU level that are aimed at reshaping the general EU vehicle fleet, primarily focusing on minimising emission specifications for conventional vehicles (EC, 1999; EC, 2014a). In Regulation (EU) No 333/2014 (EC, 2014b) compulsory targets of national charging infrastructure provision have been set for 2020 associated with the promotion of more EV registrations. The EU's target for renewable energy sources in transport (RES-T) established a minimum 10% contribution of renewable to transport energy in each member state, primarily emphasising biofuels, with EVs able to play an ancillary role [6]. Thus, individual member states have retained full control over their targets and policy mix in pursuing the deployment of EVs in their national fleets [7]. Whilst some EU countries were slow to develop policy, Ireland was not amongst them, indeed measures intended to support the adoption of significant numbers of EVs were announced in 2008 and implemented to coincide with the de facto launch of the technology into the country in 2011 [8].

As charging EVs usually requires more time than refuelling conventional vehicles, the increasing usage of EVs also requires to face some challenges on the design of an efficient infrastructure to avoid malfunctions and network strains including highly concentrated demand, grid congestion, power loss and voltage fluctuations [9]. Moreover, once the state of charge (SOC) is low, EV users expect that they can charge their vehicles at any time and location at available charging stations, avoiding any waiting times due to charging queues [10]. As well as causing an additional load demand, the widespread of EVs charging points can provide power system flexibility and promotes grid and building integration of variable renewable energy [11]. EV charging flexibility potential could be realised by public awareness promotion [12] and by implementing more advanced tariff structures such as Time Of Use Tariffs. Many recent works focused their attention on how to appropriately distribute charging stations across the country in order to minimise the congestion effect [13,14]. Additionally, high concentration of charging requests is often needed in a restricted time period, causing overload conditions in local nodes of the grid. This may lead to a degrade in the quality of service, increasing line losses and damaging utilities and customer equipment [15–17]. Identifying eventual issues and most critical nodes in the power grid it is crucial to correctly manage and upgrade the public charging infrastructure.

In the literature, Micari et al. [18] describe a planning strategy for positioning EV charging points for calculating the number and position of EV charging points in a road network is outlined. The methodology is taking into account EV features, charging times and vehicles flow. The proposed strategy does not result validated with actual charging profile data. Similarly, Deb et al. [19] describe different approaches adopted for the planning of charging infrastructures identifying optimal placement of charging stations, and charge scheduling in the charging stations as the major concerns for the large-scale deployment of EVs. Objective functions taking into account cost, transportation and grid perspectives have been evaluated in the work, and future trends for the expansion of the infrastructure have been highlighted. The authors suggest the formulation of a multi objectives approach, including adding constraints for the installation, operating and maintenance cost, voltage stability indices, and waiting time as part of the optimisation problem while the expansion methodology does not rely on actual usage profile.. Other researchers, such as Davidov and Pantoš [20] present a stochastic optimisation model for the long-term expansion planning of the electric vehicle charging infrastructure based on the minimisation of the charging station overall costs subjected to the charging reliability and

waiting time in the event of congestions. Indeed, the methodology presented has not been validated with actual charging profile data.

The objective of the current paper is to assess a framework for the analysis and the expansion of a public charging infrastructure under the fast increase of electric vehicles. The assessment is based on the Irish case study, analysing metered data from the public network website. The work takes into account the registrations of new and imported (mainly from UK) electric vehicles in the whole country and offers a cluster based perspective of the metered data. The employed methodology is explained in Section 3 while the results have been reported in Section 4, in particular three different analyses have been carried investigating the daily charging profile, the energy consumption and the congestion effect. Discussion and final conclusion are discussed in Section 5.

2. Data Analysis on the Irish Public Charging Infrastructure and EVs

In the early 2000s the Irish government started to install and manage public charging infrastructure. The first wave of these points is currently seeing upgrades from 3.7 kW and 22 kW chargers to 50 kW DC fast chargers. This upgrade has been further reinforced by the announcement by the government of a €20 million investment in a further 50 kW DC fast chargers. There has been a steady increase in EVs registrations in the Ireland, as shown in Figure 1. In the past 5 years EV registrations have been increasing steadily, with a year-over-year growth of approximately 200%.

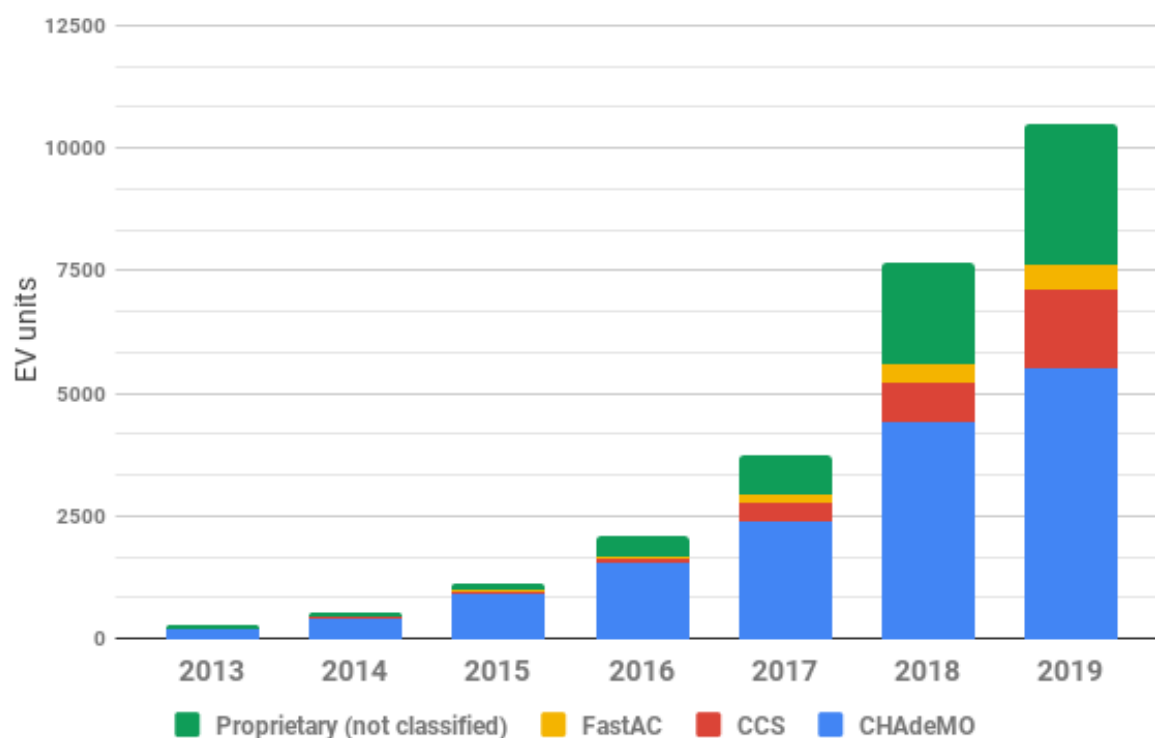


Figure 1. Number of EVs equipped with charging category.

CHAdeMO continues to be the dominant technology in Ireland, due to the popularity of the Nissan Leaf and its dominance in the early stages. The segment with the highest growth is the none fast charging, which is composed mostly by PHEVs. Combined Charging System (CCS) vehicles have also gained some market share with sales mainly from Hyundai and BMW. As there is only one model in the FastAC segment (Renault Zoe) the growth as been very limited, representing 4.58% of the total registrations.

As more models enter the market and gain more participation in the market, the demand for a fast charging stations will change as well. To increase the effectiveness of public charging

stations investment, the mix of fast charging stations must correlate the amount of vehicles that are able to connect to them. Table 1 shows the amount of registered vehicles grouped by the type of charging point connection they are compatible with and the amount of EVs per connection in the island. When calculating the ratio between vehicles and connections the results show a non uniform distribution. In one side of the spectrum, there are 64.74 vehicles per CHAdeMO connection; on the other hand there are only 6.76 vehicles per FastAC connection.

Table 1. EV registrations per charging point in 2019.

Charging Mode	EV Registrations	Charging Points	Vehicles per Charging Point
Standard Type 2	10,477	964	10.87
CHAdeMO	5503	85	64.74
CCS	1620	71	22.82
FastAC	480	71	6.76

The Irish public charging infrastructure is equipped with a telecommunications system to support operation of the public Electric Vehicle (EV) charge points, including a Supervisory Control And Data Acquisition (SCADA) system for Electric Vehicle (EV) owners and facility for payment management. The Supervisory Control And Data Acquisition (SCADA) system provides status information such as: type of charger, availability connections and whether the charger is out of order. This interconnectivity provides scope for analysing the charging infrastructure to highlight eventual issues and most critical nodes in the power grid.

The dataset employed in this work consists in metered data from the public network website containing the status of the public charge point network in Ireland, taken at five-minute intervals, from November 2016 to February 2019. Two different types of charge points have been considered: standard charge points, slow charge points of up to 22 kw Alternate Current (AC), and three different types of DC and AC rapid charge points, CHAdeMO, Combined Charging System (CCS) and FastAC. In standard type charge points typically two connections are available and they can be used simultaneously, while a rapid charge point can have either one, two or three connections, each with a different connection type (CHAdeMO, Combined Charging System (CCS) or FastAC).

Information contained in the dataset includes the recording date and time, the charge point Id, the charge point type, latitudinal and longitudinal coordinates, the address of the charge point and the status. Five different status have been reported: Out Of Service (OOS), Out Of Contact (OOC), partially occupied (Part), fully occupied (Occ) and Unknown. An unknown status exists where the status data was either not available or otherwise not polled due to connection issues at the time interval in question. The available status has been omitted and it can be deduced by the absence of a record. Starting from charge points coordinates additional information can be manually derived to enrich the data at hand. In particular, the following information have been added regarding the position of a charge point: the county and the town, the area (city, town or country side) and the position details (commercial, residential and motorway).

The data cleaning process and the manual classification of charging points have provided a clear baseline representation of the network usage which evolution has been observed for more than three years.

3. Methodology

In this section the methodology employed to obtain explained results in Section 4 is presented in details.

3.1. Modelling the Electricity Profile

Majority of EVs charge at a level of 400 V–800 V or 100 V–200 V for Plug-in Hybrids. The onboard Battery Management System (BMS) communicates this voltage, coupled with the current flow and sometimes battery temperature, to the charge point if it is DC. When using the AC charge socket on an EV, the EV takes the voltage at distribution level; 230 V single phase or 400 V three phase and utilises the lower powered onboard charger. Usually, a DC charger will contain a rectifier and a DC-DC converter in order to convert three phase 400 V to a DC level required by the EV's BMS. At high power charging points the basic operation is that the charger forces as much current up to the rated power into the battery without raising its temperature until 80% is reached, thereafter the charger switches to a much lower power charge as the battery charge characteristic becomes constant voltage as illustrated in Figure 2.

We assume that there are $M \geq 1$ number of charging events for a charging point in the dataset, denoted by index $n, n \in N = \{1, \dots, M\}$, where $t > 0$ is the date time of the timestamp data, $T_n > 0$ is the duration of the charging event ($t_n = 0$ at the start of a charging event), I_n is the initial State Of Charge (SOC) at $t_n = 0$, X_{In} is the probability of selection and $B \geq 1$ number of EV models able to connect the station, denoted by index $a, a \in A = \{1, \dots, B\}$, where Y_a is the probability of selection, $R_a > 0$ is the rated charging power, $C_a > 0$ is the time in which power $P(t_n) = R_a$ and $F_a > 0$ is the time it takes to fully charge the battery of the EV. In order to include the initial SOC in the model, $t_s = t_n + F_a(1 - I_n)$ is the time considering the effect of the initial energy stored in the battery. The power consumption of the charging stations for each charging event is defined as

$$P_{n,t} = \begin{cases} R_a & \text{if } t_s < C_a \text{ and } t_n < T_n \\ R_a - \frac{t_s R_a}{(F_a - C_a)} & \text{if } C_a \leq t_s \leq F_a \text{ and } t_n < T_n \\ 0 & \text{if } t_s > F_a \text{ or } t_n > T_n \end{cases} \quad (1)$$

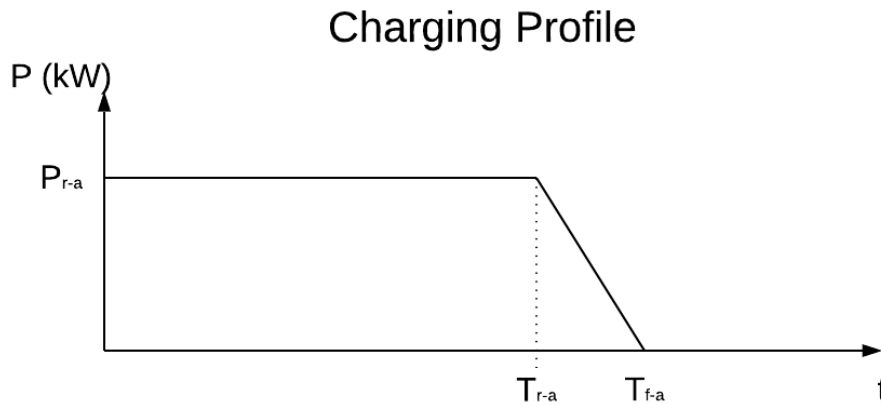


Figure 2. Generic EV charging profile.

At the start of each charging event, an Electric Vehicle (EV) model was assigned to a charging event using a random function in which the probability of occurrence was based on the market share of the vehicles that were able to connect to a station. A limitation of this approach is that the model assumes of the model is that all cars are used in the same way and the distribution Electric Vehicle (EV)s charged in public stations is proportional to the market distribution. I_n was determined by a stochastic function following the recorded distribution of Weldon et al. [21], showed in Figure 3.

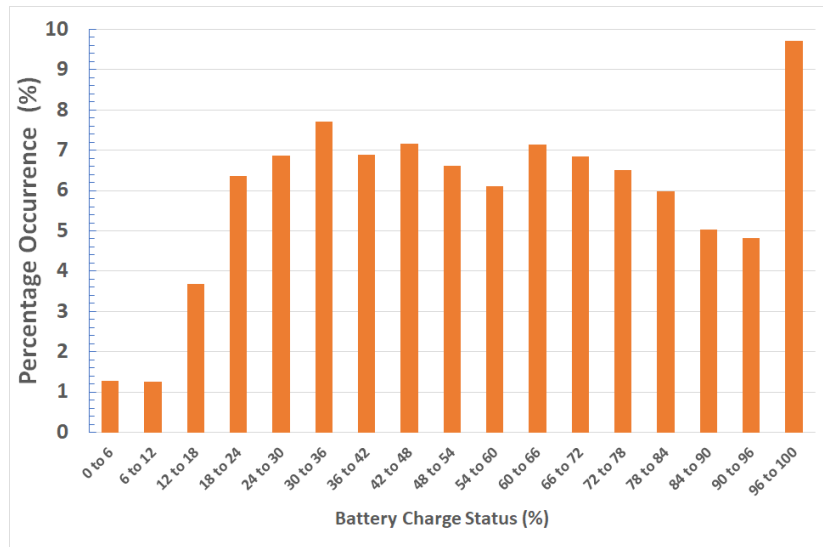


Figure 3. State of Charge distribution for EV in Ireland [21].

The initial State Of Charge (SOC) value was used to reduce the maximum charging time of the vehicle (if a battery is fully charged when connected to a station then the maximum charging time will be zero and will not consume power), emulating the hysteresis effect of the energy inside the battery. The maximum capacity of the vehicle's battery was also taken into account, limiting the maximum allowed time of a charging event for a particular car. Once the maximum time is reached, considering the vehicles characteristics and the initial SOC, the power consumption will be forced to zero.

One of the assumptions of the model is that the power consumption remains constant at R_a until the battery reaches 80–90% of charge at time C_a . Then the power will reduce at a constant rate until the power is dropped to zero.

In the case of FastAC chargers, it was found that in Ireland, only the Renault Zoe was designed to use this type of stations. The behaviour of the FastAC charging algorithm has never been disclosed by the manufacturer, therefore the authors have developed a step wise approximation model comparing the limited literature [22] and online resources [23]. The step wise approximation is a limit of the current study and further refinement it will be object of future work. The power consumption of the FastAC43 stations for each charging event has been approximated with the following step wise function:

$$P_{n,t} = \begin{cases} 42 & \text{if } t_s < 20 \text{ and } t_n < T_n \\ 32 & \text{if } 20 \leq t_s \leq 27 \text{ and } t_n < T_n \\ 16 & \text{if } 27 < t_s \leq 62 \text{ and } t_n < T_n \\ 0 & \text{if } t_s > 62 \text{ or } t_n > T_n \end{cases} \quad (2)$$

In this case the charging profile is different than a CHADEMO. To reduce the temperature of the battery when fully charged, the FastAC charges at 42 kW for the first 20 min, then the power is reduced to 32 kw for 7 min and the final 35 min it is charged at 16 kW. The total aggregated power $P(t)$ is defined by

$$P(t) = \sum_{n=1}^M P_n(t) \quad (3)$$

3.2. Functional Data Analysis and Clustering

In order to analyse the usage patters of the public charging stations, the data have been studied focusing on the within day variability. The aim is to highlight the hours of the day with the higher consumption to improve the stability of the Irish power grid. For this reason, the data have been

treated as time dependent looking at the daily percentage of usage per hour. To this end, we make use of tools from Functional Data Analysis (FDA), the branch of statistics dealing with curves, surfaces or anything else varying over a continuum [24]. For each charge station and for each day, a curve representing the daily percentage usage per hour has been defined through a kernel density estimation smoothing method [25]. Due to the big amount of data, 344 charge points per 365 days, each station has been represented by its average profile and stations with common behaviours have been identified. The purpose is to detect what distinguishes the daily average charge points usage to upgrade the Electric Vehicle (EV) charging network. To this end, a functional k-means clustering algorithm [26] has been applied as explained below.

Given a set of curves $f_i(t)$ with $i \in \{1, \dots, n\}$, s.t $f_i(t) \in L^2[a, b]$, the functional k-means clustering aims to partition the n observations into k sets as to minimize the within-cluster dissimilarity, i.e., the distance between observations of the same set. The algorithm works as a standard k-means algorithm but redefining an appropriate distance in the functional data framework. More exactly, given two functional curves $c_1(t)$ and $c_2(t)$, the squared L^2 distance $d_{L^2}(c_1, c_2) = \int_a^b [c_1(t) - c_2(t)]^2$ is used. In the first step, an initial set of k -centroids, i.e., k -curves $s_j(t)$ with $j \in \{1, \dots, k\}$, is fixed. Then, the algorithm proceeds by alternating between two steps:

1. Assignment step : assign each curve $f_i(t)$ to the cluster whose centroid $s_j(t)$ has the least distance.
2. Update step: calculate the new centroids $s_j(t)$, i.e., the mean curves, of the observations in the new clusters.

The algorithm stops if the total within-cluster dissimilarity decreases less than a given tolerance or after a maximum number of iterations.

3.3. Congestion Metric

In the literature, researchers have analysed the idea of congestion applied to various research areas. The definition of congestion could differ for two different research areas and could depend from local dynamics and cultural perspectives.

For instance, Ye et al. have quantified the concept of traffic congestion using a traveller scoring mechanism integrated into three original developed metrics [27]. Other works, mainly on traffic congestion, define it as the amount of travel time in excess compared to free-flow travel conditions [28]. One of the most used techniques for ranking processes or entities is principal component analysis (PCA). PCA techniques have been used for ranking countries based on their readiness for e-commerce adoption or [29] or for text analysis in the legal sector [30].

In the Internet architecture, congestion events occur when one of more services continuously require bandwidth causing delays in transmission. The protocol detects congestion when it does not receive the acknowledgement of transmission within the established time window. [31]. Lee et al. approached the traffic congestion metrics proposing a different index for different time of the day or road branch category. In their study, they compared the metric results with typical free-flow condition [32]. Such as a hybrid model was also compared with a proprietary single index model providing a more detailed classification of congestion in metropolitan areas.

Other works include the analysis of congestion using bus mobility data [10,33] that calculated the waiting time for EV charging in the future, and they performed a cost-benefit analysis. As described in Section 1, in the past five years, Ireland has shown a growing acceleration rate in the number of Electric Vehicle (EV) registrations. Utilising the data from 2016 to 2019 and taking into account the increased number of electric vehicles, a congestion metric has been defined as:

$$c = 1..M \text{ where } M = \text{number of charging points} \quad (4a)$$

$$x_t(c) = \{0, 1\} \forall t \quad (4b)$$

$$x_{t+l-1}(c) + x_{t-1}(c) = 0 \quad (4c)$$

$$\text{Let } F_{t,t+l}(c) = \begin{cases} 1 & \sum_{i=t}^{t+l} x_i(c) = l - 1 \wedge x_{t+l-1}(c) = 0 \wedge x_{t-1}(c) = 0 \\ 0 & \text{otherwise} \end{cases} \quad (4d)$$

$$\text{Let } G_{t,t+l}(c) = \begin{cases} 1 & \sum_{i=t}^{t+l} x_i(c) = l - 1 \wedge x_{t+l-1}(c) = 0 \wedge x_{t-1}(c) = 0 \wedge \sum_{s=t}^{t-P} x_s(c) > 1 \\ 0 & \text{otherwise} \end{cases} \quad (4e)$$

where M is the total number charging points and c is the index of the charging station. $x_t(c)$ is a binary variable that assumes the value 1 if station i has an occupied status at reading t and 0 if it is not in use. A charging event is considered a congested event $G_{t,t+l}(c)$ if a different charging events occur previously or if the time between two charging events is smaller than a threshold P . In the current research the value of P is 2 min. The congestion index proposed in this paper is defined as the ratio of congested versus charging events and it can be defined as:

$$\text{Cong}(c) = \sum_{t=1}^T \sum_{l=1}^T \frac{G_{t,t+l}(c)}{F_{t,t+l}(c)} \quad (5a)$$

where c is the charging station id and K is the number of the event occurred during the time interval considered. The variable F is the number of charging events for the time interval while the G is the number of congested charging events.

4. Results

A statistical analysis has been carried on the data set, evaluating the network with a time resolution of 5 min and assessing the following four operational parameters: the occupancy profile and the reliability of the network, a power model of the public charging infrastructure, a functional clustering analysis to group charging stations with similar profiles, an evaluation on the congestion events on the basis of the associated cluster and the position detail.

4.1. Occupancy Profile Analysis

Figure 4 shows an increase in the total public charging network connected hours from 2017 to 2018. The monthly data reported in Figure 5 shows a positive trend with a reduced usage for November 2018, probably because of some network communication failure. As illustrated in Figure 6, the trend is continuing during the 2019. In January and February 2019 the Electric Vehicle (EV) registrations had an additional peak of 1124, which was almost the total number of Electric Vehicle (EV) registrations for 2018 which is equivalent to 1224. The occupancy of the network shows an additional positive trend. It should be noted, despite the usage increase, that the percentage of network communication errors has kept the 30% of the total highlighting a severe technical problem of the infrastructure.

Total connection hours

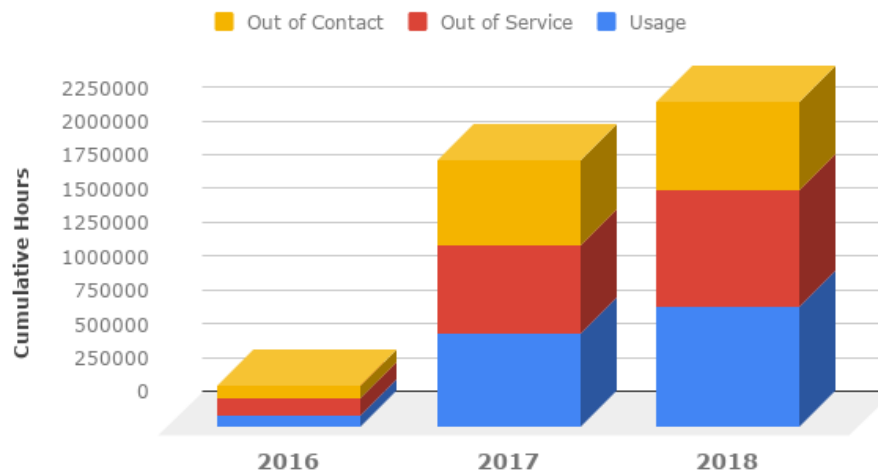


Figure 4. Annual usage/data from the public network in hours.

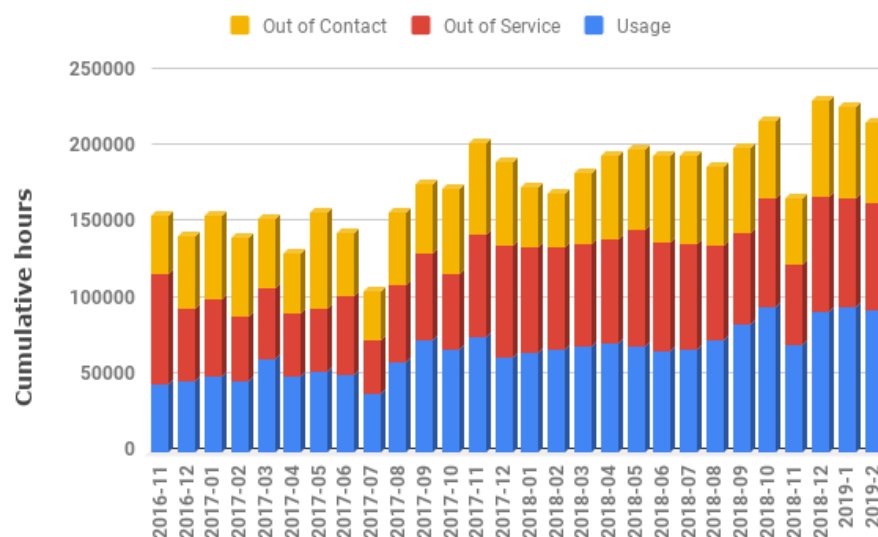


Figure 5. Monthly usage/data from the public network in hours.

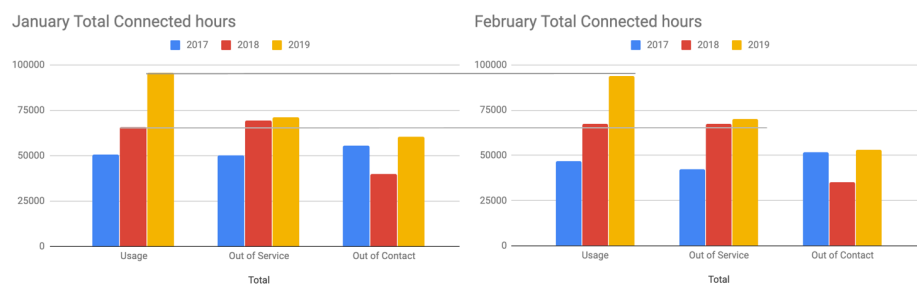


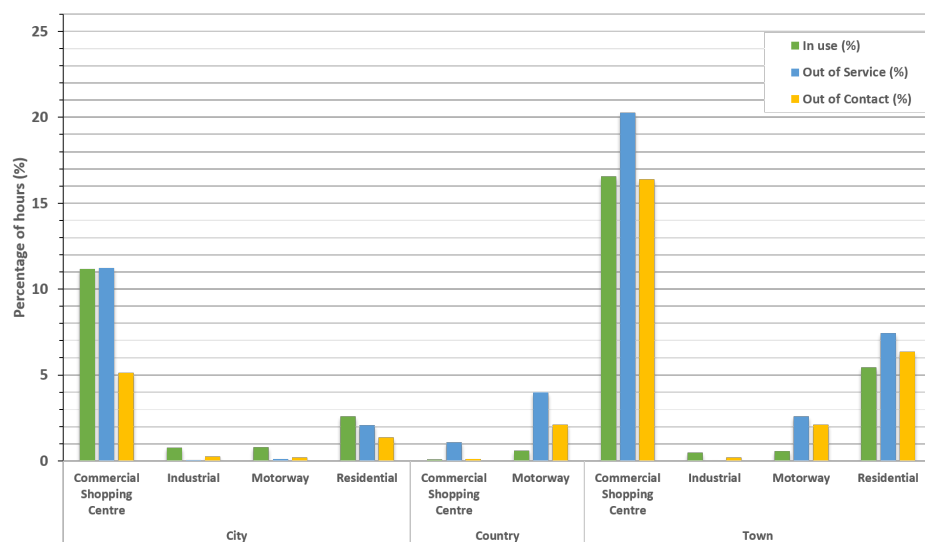
Figure 6. January/February comparison between three different years 2017–2019.

In Table 2 the number of charge points is reported considering in detail their position, in particular if the charge point is located in a country, town or a city. In addition, it has also been considered if the charge point is closed to a commercial area, a motorway or if it is in an industrial or in a residential area.

Table 2. Number of charging point by category and position.

	Position	Commercial	Industrial	Residential	Motorway
CHAdeMO – CSS – FastAC	City	7	0	4	0
	Country	0	0	0	20
	Town	16	2	1	5
Standard Type 2 Charge stations	City	50	2	3	16
	Country	0	0	0	11
	Town	131	5	15	54

For each of these subgroups of charge points the percentage of usage hours during the monitored period is reported in Figures 7 and 8. It should be noted the percentage of use of the standard charging points in Figure 7 is generally higher than the fast charging point because of different power ratio and, consequently, different time length of charging events. Standard Charging point power ratio span from 3 kW to 7.7 kW while fast charging reach peak power up to 50 kW.

**Figure 7.** Total percentage of usage hours during monitored period for Standard Charging (Standard Type 2).

The total number of usage daily hours on the network have been evaluated. From Figure 9 an increasing trend in the total usage of the network can be observed over the considered period of time. In addition during Saturdays, holidays and Sundays the usage seems to be lower than in the working days. In addition, some issues in the data can be identified, in particular we observe some days where total usage hours on the network are equal to zero, for example from 12 to 24 November 2018, these could have been due to some connection problems occurred in the network.

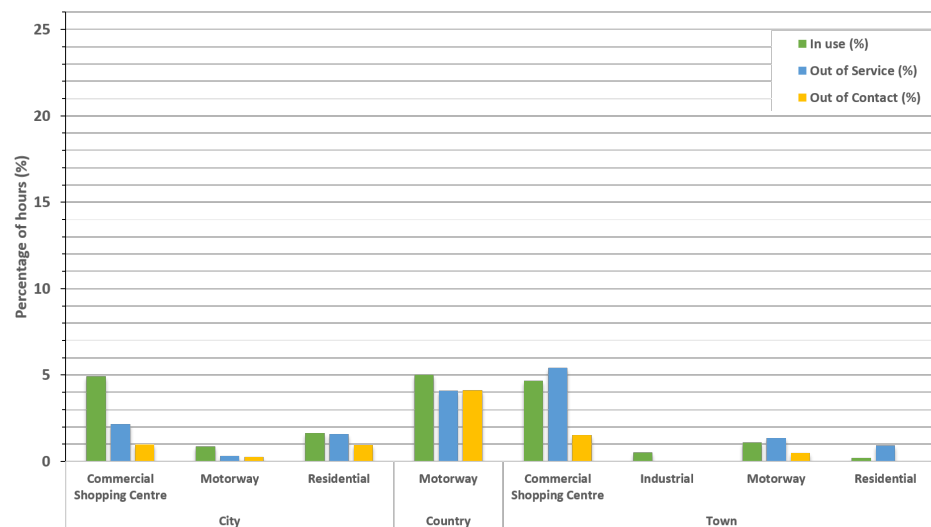


Figure 8. Total percentage of usage hours during monitored period for fast charging (CHAdemo, CCS and FastAC) grouped by location.

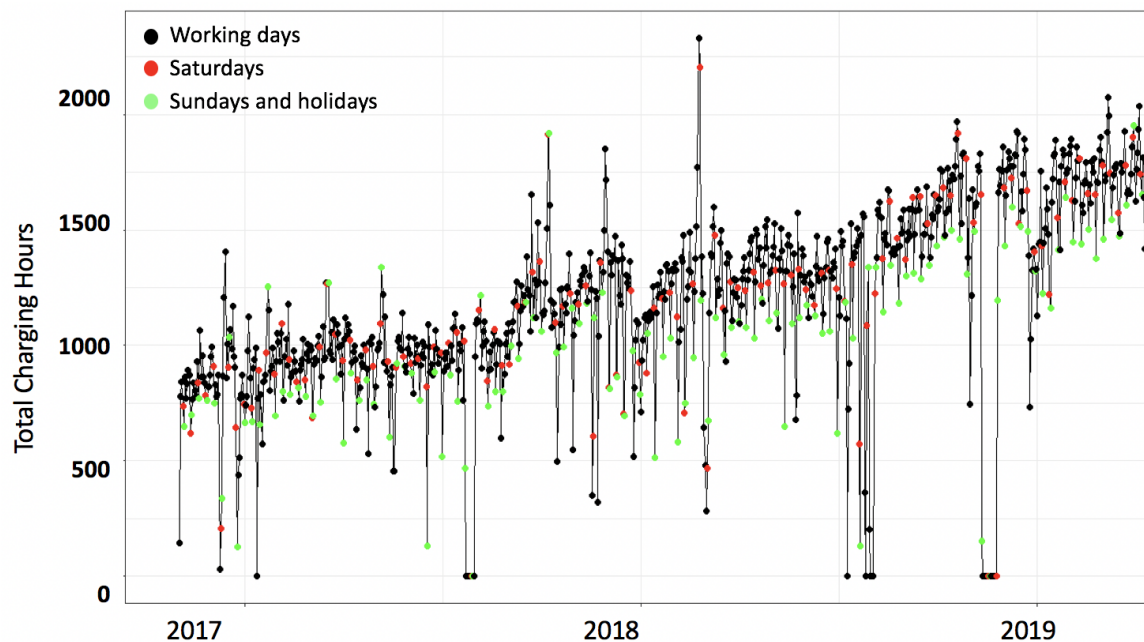


Figure 9. Total daily usage hours during monitored period.

4.2. Electricity Profile

Based on the energy consumption model described in Section 3 it has been possible to assess the impact of the public charging network on the power system and provide further observations on the utilisation of the infrastructure for demand response. Based on the electric vehicle model registration data and the static State Of Charge (SOC) distribution of Weldon et al. [21], the numerical model described in Section 3.1 has been applied to the available data from November 2016 to February 2019. The output of the model is an estimation of the average power ratio for each charging station with five minutes time resolution. For each charging station type, the cumulative average power ratio is calculated and the evaluated from the power system perspective.

Figure 10 depicts the average power ratio for the Irish public charging network, from 2016 to 2019. The top bar shows the average power ratio for the fast-charging infrastructure. As described in the previous section, CHAdemo is the most used charging connector for Ireland because of

the compatibility with the majority of the Electric Vehicle (EV)s registered. Despite being only 85 CHAdeMO charging points present on the dataset, the average power ratio consumption at any time step is between 200 kW–500 kW with a steadily increasing slope. It should also be noted that simulation includes only the data station connected during the time interval. If the communication system was disconnected or the station was out of contact or out of service electricity profile model returns an empty value. The plot shows these missing data as gaps in the time series. However, when the communication system is disconnected, or the status is Out Of Contact (OOC), the charging station could be operational. Major data missing events occurred between the 27 July 2017 to the 1 August 2017 and more recently from 12 November 2018 to 26 November 2018.

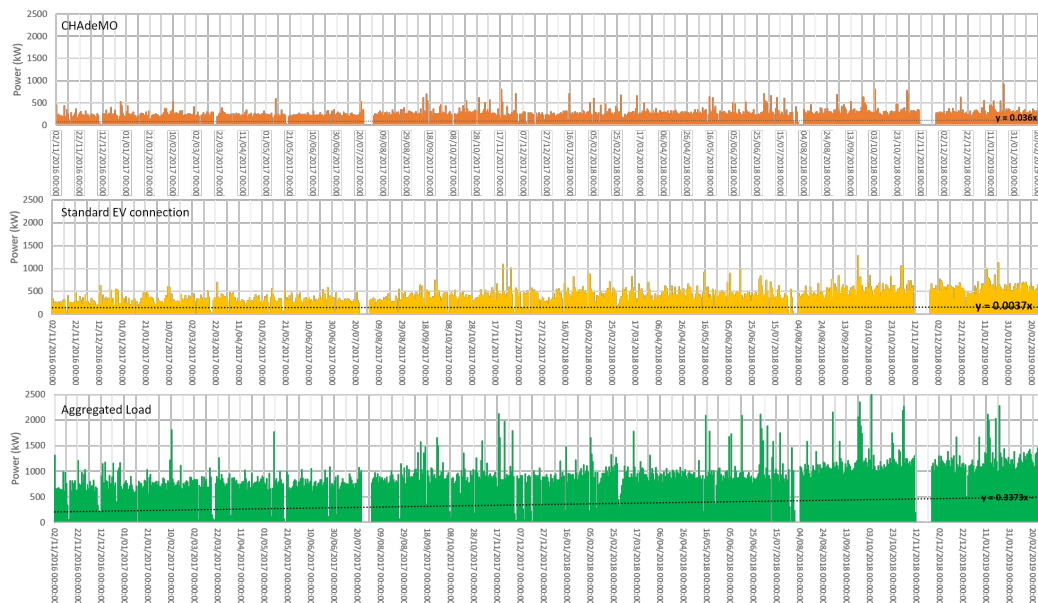


Figure 10. Irish public charging infrastructure power consumption model.

The second plot illustrates the average power ratio of the 964 Standard Type 2 Electric Vehicle (EV) charging points. In the last few years, there was a growing registration of Electric Vehicle (EV)s, which caused an increasing average power ratio as can be illustrated. From the electricity profile perspective, it should be noted that the average power ratio crossed the threshold of 500 kW in 2018. The figure also shows a higher slope compared to the fast charging infrastructure.

The third plot presents the aggregated overall average power ratio of the public charging infrastructure. The plot displays a steady increase of ratio on the network, which positively correlated to the Electric Vehicle (EV)s registrations. The aggregated load shows frequent power peaks that could exceed the 2.5 MW, and they are becoming more prevalent with the increased usage of the charging network during peak hours. In terms of energy consumption, the Irish public charging infrastructure confirms the increasing trend. As depicted in Figure 11, the largest amount of energy consumed was from the standard type 2 stations (43%), followed by CCS (31%), CHAdeMO (20%) and FastAC (6%). Despite having a lower power capacity, they represent the majority of charging points installed in the country. As illustrated in Figure 12, Combined Charging System (CCS) and CHAdeMO energy consumption are in the same order of magnitude, while FastAC is marginally lower than the rest. The distribution of energy consumption is fairly constant throughout the dataset. Despite having practically the same amount of charging points, FastAC chargers are barely used compared to the rest because of the limited amount of vehicles able to use them (only 280 Renault Zoe). Therefore, the amount of FastAC (43) charging stations don't seem to be proportionate to the number of vehicles capable of charging.

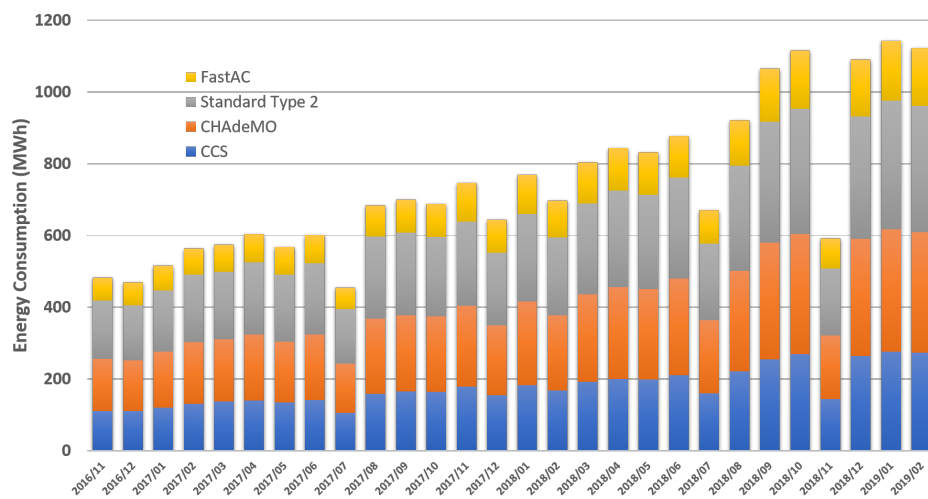


Figure 11. Monthly energy consumption for the EV infrastructure, divided by type of charging station.

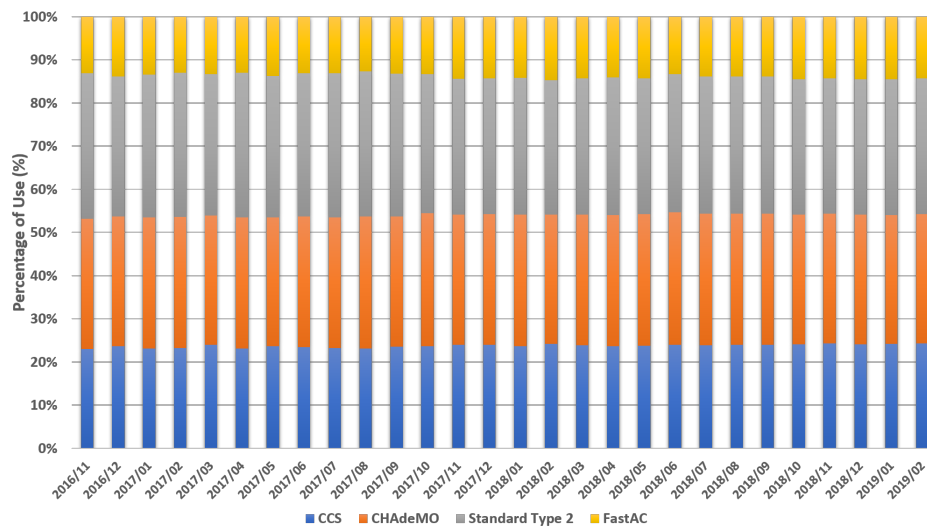


Figure 12. Monthly share of use of the the EV infrastructure, divided by type of charging station.

4.3. Functional Clustering Analysis

A functional clustering analysis has been used for segmentation of the charging point network, as explained in Section 3.2, providing a metric for the identification of standard occupancy profiles of the charging stations. For each hour the usage percentage of each charge point has been evaluated and data are then treated as functional, applying a smoothing technique, obtaining a daily charging profile. Each charge point is then evaluated observing its average daily charging profile, and the clustering algorithm has been applied on different subsets of charge points. First the functional k-means algorithm has been applied separately on Fast and standard charge points, as they have different usage characteristics (charging time, number of connections, number of simultaneous available connections). Then, also apriori information about position details have been included in the analysis to obtain more homogeneous subgroups to which the clustering analysis has been applied. This two steps approach has allowed us to identify more informative daily charging profiles. In details, the clustering analysis has been applied to the following seven subgroups: Fast (e.g., CHAdeMO – CSS – FastAC), Fast-Commercial, Fast-Motorway, Standard, Standard-Commercial, Standard-Motorway and Standard-Residential. Number of charge stations per type are reported in Table 2. The Fast-Residential subgroup has not been considered in the analysis due to the low number of charge points included in

this group. In all cases, the optimal number of clusters k has been chosen observing the percentage of explained variance when varying the value of k and applying the elbow method.

The obtained results for Fast and Standard type charge points are reported in Figures 13 and 14 respectively. From Figure 13, it can be observed that three different daily usage profiles have been identified. The first one, the green cluster, reveals a fast increasing percentage of usage from 8 a.m. to 12 a.m., a slow decrease from 12 a.m. to 8 p.m. and a fast decrease after 8 p.m. Overall this cluster is the one with the highest percentage of usage during the whole day. The charge points belonging to this cluster are almost all located in the city of Dublin. The remaining two clusters, the blue and orange ones, instead, have a smoother morning increasing and night decreasing usage. While the blue cluster represents the usual profile in the urban areas, the orange cluster is the one with the lowest percentage of usage during the day and this profile is typically in the rural areas.

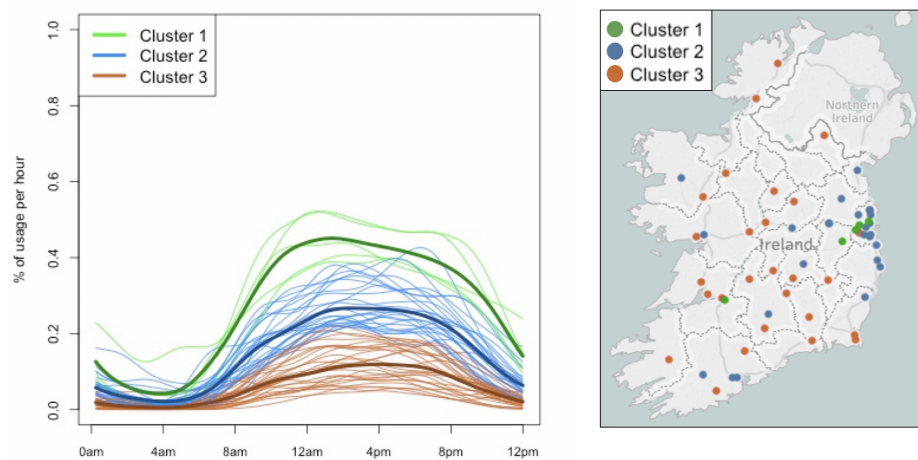


Figure 13. Functional clustering for Fast charging points (CHAdeMO – CSS – FastAC) and relative position on the map.

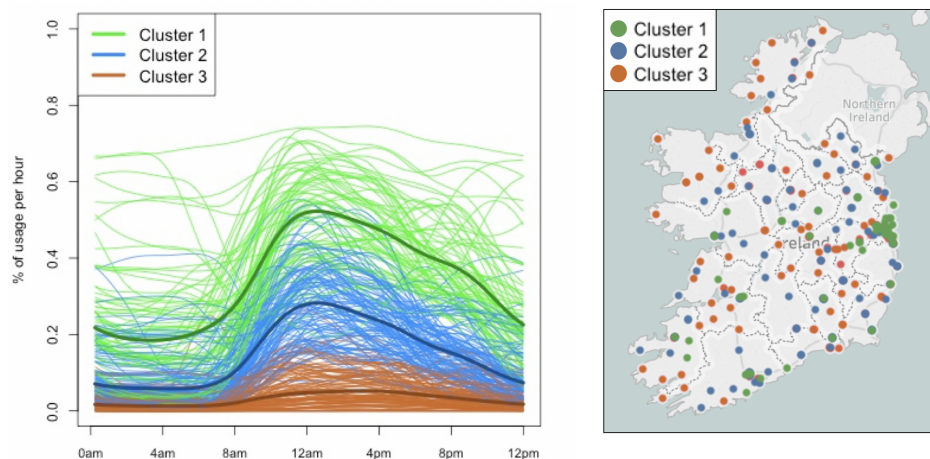


Figure 14. Functional clustering for Standard Type 2 charging points and relative position on the map.

Results concerning the standard type are reported in Figure 14. As in the fast charge points scenario, we observe three different clusters with an increasing percentage of usage during the day. The cluster with the highest usage profile is located in the center of Dublin while the one with the lowest usage is more located in the rural areas. With respect to the results obtained in the previous group, in this case the clusters have the same shape, namely a fast morning increasing usage and a subsequent slow decreasing during the day, but with the difference that the Standard Type charge points seem to be also used at night.

Clustering results on the subgroups obtained adding apriori information on position details are reported in Figures 15 and 16 for Fast and Standard charge points respectively. In Figure 15, it is possible to observe that in both cases two clusters are characterised by an increasing usage with the same shapes. In Figure 16 it is interesting to notice that for Residential charging points the cluster with the highest usage, the green curve, has almost a flat shape during the whole day, indicating that charge points in this cluster are used also during the night. This cluster is almost located in the city of Dublin. These results will be further analysed in the next paragraph when the concept of congestion will be introduced.

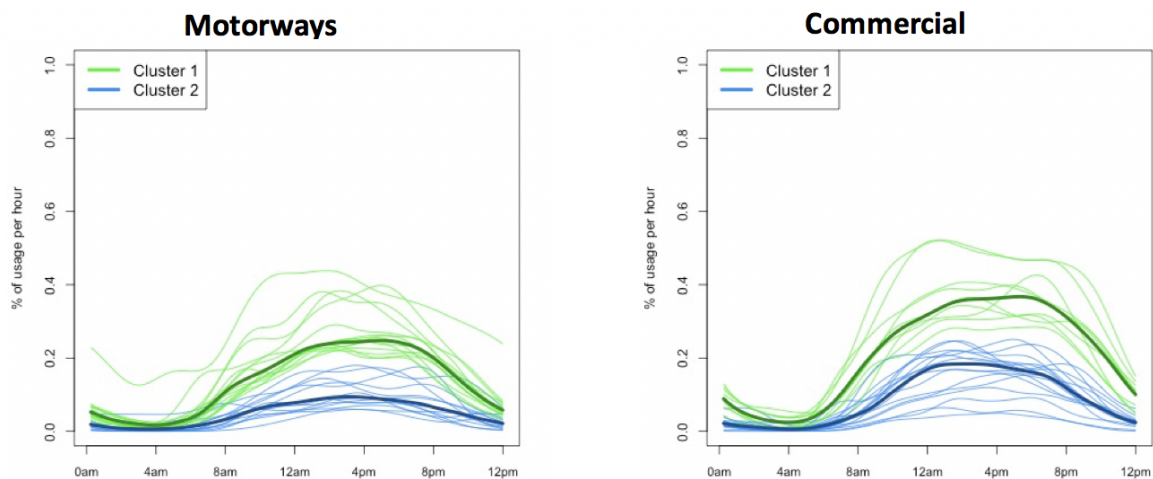


Figure 15. Clustering results for Fast-Chmercial and Fast-Motorway subgroups.

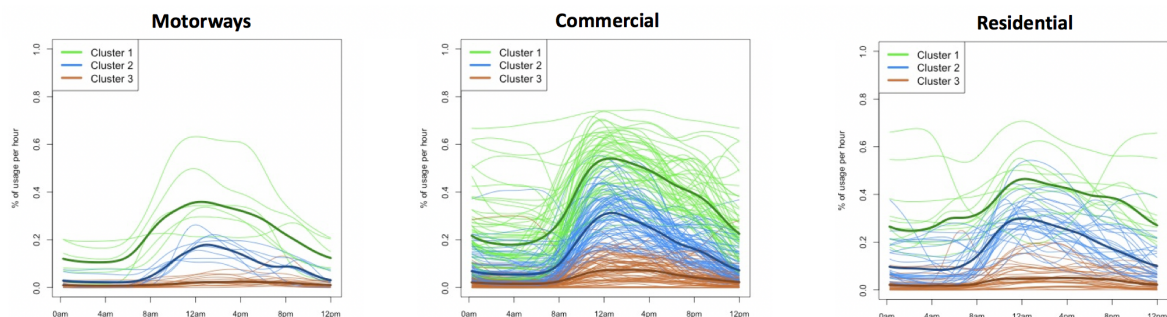


Figure 16. Clustering results for Standard-Commercial, Standard-Motorway and Standard-Residential subgroups.

4.4. Congestion Event Metric

The congestion metric is a data-driven model for the identification of the expansion needs of the current infrastructure, and its evaluation is explained in details in Section 3.3. The positive trend of Electric Vehicle (EV)s registrations poses some challenges in terms of national charging infrastructure. The data shows a rapid saturation of the availability of Electric Vehicle (EV) charging stations leading to an increasing number of congestion events

The metric has been calculated for each functional cluster group that showed similar charging profile and classified category. The usage of the charging stations and the congestion are illustrated in Figures 17–19. The figures present both the congestion metric and the usage of the charging stations category divided by functional clusters. The functional clustering analysis section shows three clusters grouped by occupancy profile pattern similarity. In the analysis, cluster 1 has the highest usage and it also shows the highest congestion event percentage. Figures 17–19 show high congestion in cluster 1 for the charging point positioned on the motorway. The charging points on the motorway are usually

positioned in rural area, therefore high congestion on one of these charging points requires a more detailed analysis. It has been found that the motorway group in cluster 1 is composed of a single charging point located close to a motorway junction in the capital (Dublin). The charging point is just few hundreds of meters to the main Irish airport terminal, Dublin airport. Such a finding is an additional validation of the effectiveness of the methodology applied in the current research.

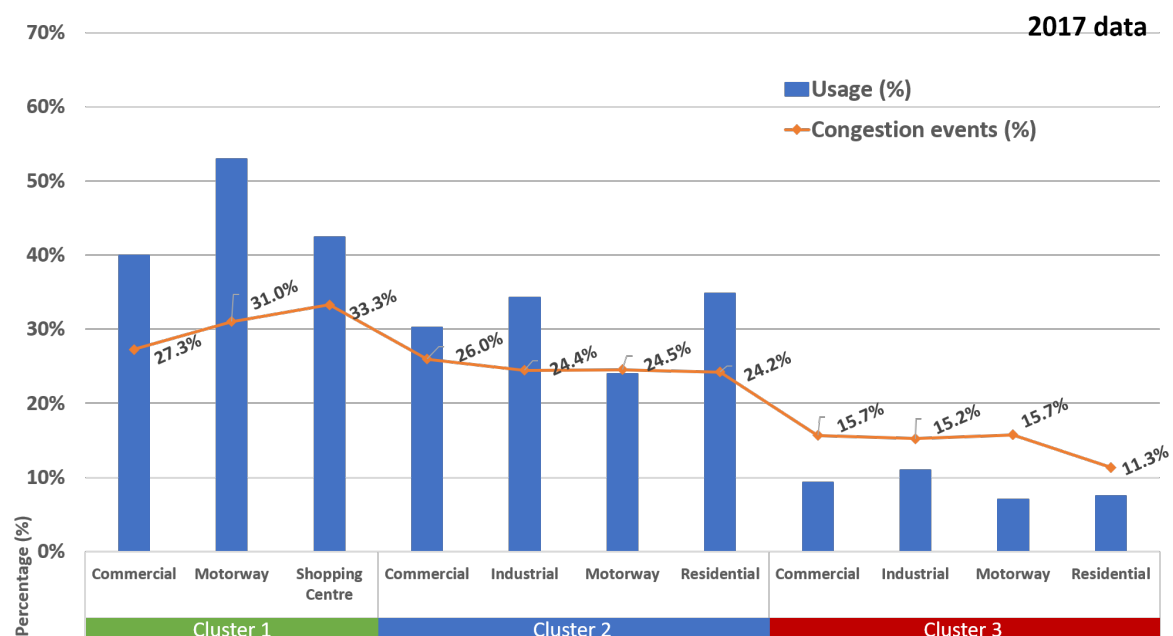


Figure 17. Network infrastructure usage and congestion events in percentage for year 2017.

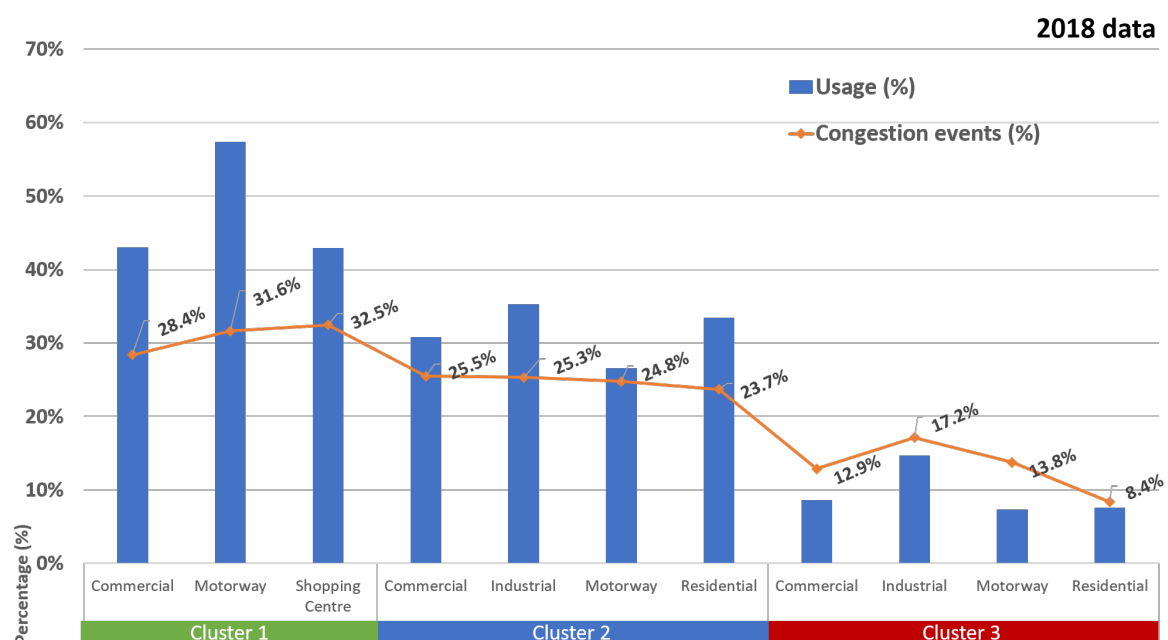


Figure 18. Network infrastructure usage and congestion events in percentage for year 2018.

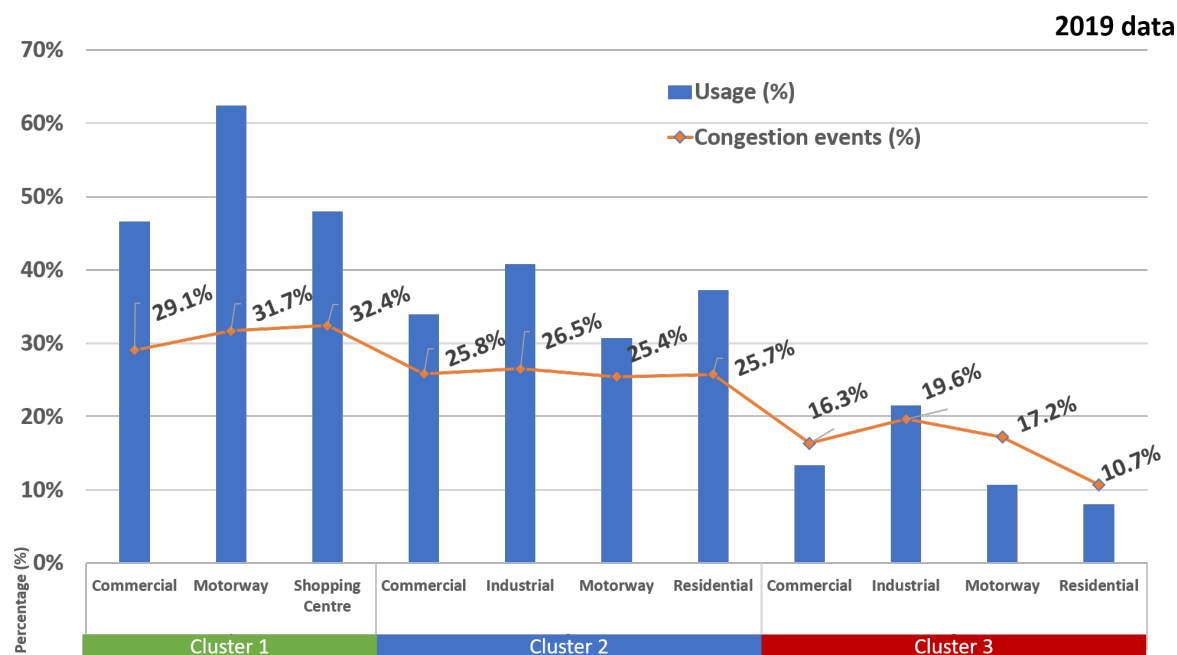


Figure 19. Network infrastructure usage and congestion events in percentage for year 2019 (Jan–Feb).

Figure 20, shows a comparison of the congestion metric events for the identified clusters, comparing the three reference case years (2017–2019). It should be noted a consistent higher congestion percentage of cluster 1 compared to cluster 2 and cluster 2 compared to cluster 3 respectively. Additionally, year 2019 shows an overall higher increase of the congestion events on cluster 2 and 3 compared than cluster 1 that probably reached a saturation point.

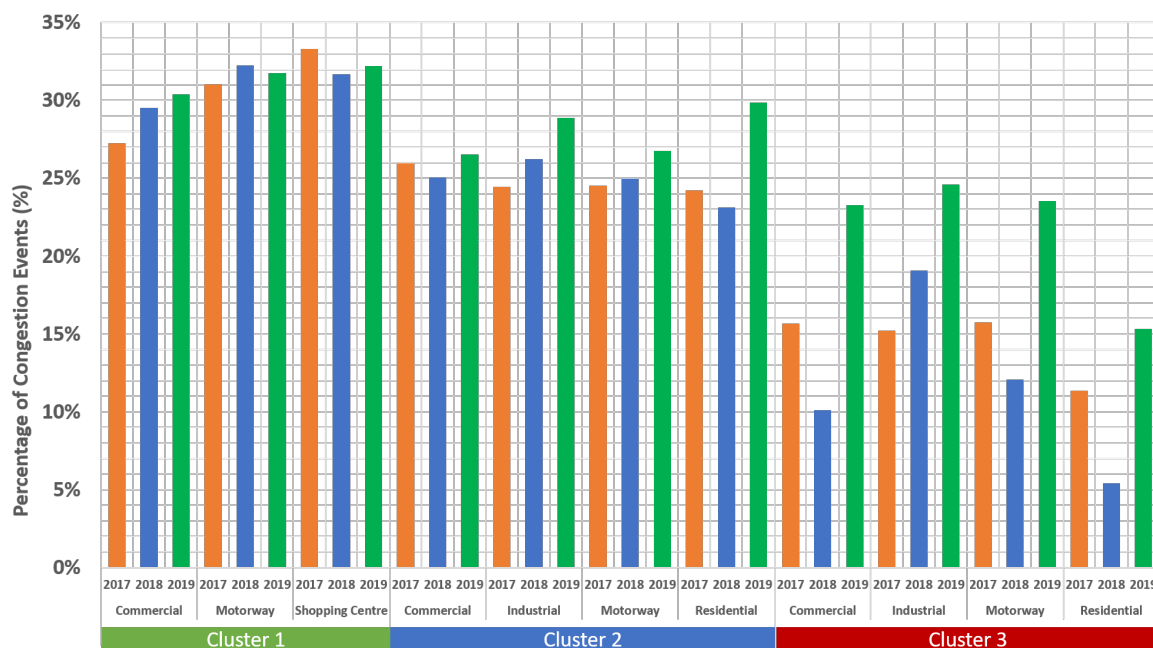


Figure 20. Summary graph of congestion event over 2017–2019.

5. Discussion and Conclusions

The current work appraises the implications of a fast-growing penetration of EVs on the Irish public charging network using occupancy data to evaluate the adequacy of the infrastructure to the

charging requirements. It provides insights from different perspectives such as the reliability of the charging point network, communication perspective, occupancy profile, charging point saturation and power system implications.

The data analysis takes into account the number of EVs registered in Ireland on a monthly basis and the supported capabilities of the single EV to be connected to one or more charging standards. Such as data analysis workflow outline a framework for the analysis and the expansion of a public charging infrastructure under the fast increase of electric vehicles. The framework is validated against metered data from the public network website of the Irish charging network. The analysis provides a cluster-based perspective of the metered data. The data cleaning process and the manual classification of charging points have provided a clear baseline representation of the network usage which evolution is observed for more than three years. Initially, the research assessed the reliability of the data communication network. The data showed a high percentage (30%) of data network errors caused by the charging network hardware or the data network itself.

The first metric employed in the study has been the number of vehicles per charging modes, splitting by fast and slow charging modes and by charging point location. The statistical results of the occupancy profile identify the areas of significant occupancy, which in the current research, are the commercial/shopping areas for both charging modes. The data also shows high usage of residential locations followed by motorway fast charging points in countryside. Then, a congestion metric to identify subsequent charging events has been designed and calculated for each charging station. When occupancy data is cross-checked with the clustering and congestion metric, the need for intervening on selected motorway fast charging points is outstanding. The data shows that locations such as Dublin Airport and adjacent areas identified by the analysis as an area of high percentage usage and congestion require immediate expansion. In contrast, other areas such as residential zones, despite a high usage, belong to a lower congestion cluster and the extension can be postponed. Therefore, the data analysis methodology implemented in the current research could highlight hidden network expansion requirements not visible by merely statistical means.

Additionally, the energy profile of the whole network has been modelled. In the test case, the simultaneous use of fast charging points can cause power peaks of three times the magnitude of the average power consumption. An opportunity to use such capacity as demand response aggregation to reduce power peaks consumption has been identified in the analysed public network data.

In conclusion, four relevant points have been assessed by this research:

- From the communication perspective, the current communication network has been verified out of contact (OOC) or out of service (OOS) for more than the 30% of the total operation time, decreasing the overall system reliability and the user perception of the charging infrastructure reliability. The limited EV battery capacity requires more frequent access to the charging network. Consequently, users rely on the information provided by the network status applications. The continuous outage of communication infrastructure as analysed in the current work slows down the technology mass adoption.
- From the end-user perspective, the exponential trend in Electric Vehicle (EV)s registrations has dramatically increased the occupancy time of the charging points, which peak during weekdays from 1200 to 1400 h. Such a trend is amplified in an urban area with high population density and in commercial/shopping center areas characterised by sharing parking premises.
- From the network perspective, the current infrastructure is reaching a saturation point, with high congestion phenomena. Both the functional clustering analysis and congestion metric have registered significant bottlenecks in shopping malls and point of interest. These critical nodes require immediate expansion both at the specific node level and in the adjacent areas.
- From the power system perspective, the total power usage of the infrastructure does not have a relevant impact on the power grid. However, during occupancy peak hours, the estimated infrastructure power peak could reach three times the average power consumption causing grid network overloads. Therefore, the exponential growth of EV adoption and the consequent

charging infrastructure expansion can benefit from demand-side management strategies to provide effective ancillary service to balance the electricity demand and generation without needing additional peak capacity.

The clusters analysis and the congestion metric identified critical charging point areas that require expansion. Future works will include the control of the network as demand response aggregator and validating the assessment framework outlined against other datasets.

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References

1. Dyke, K.J.; Schofield, N.; Barnes, M. The impact of transport electrification on electrical networks. *IEEE Trans. Ind. Electron.* **2010**, *57*, 3917–3926. [CrossRef]
2. European Environment Agency. *Adaptation Challenges and Opportunities for the European Energy System*; European Environment Agency: Copenhagen, Denmark, 2019. Available online: <https://www.eea.europa.eu/publications/adaptation-in-energy-system> (accessed on 24 February 2020).
3. International Energy Agency. *World Energy Statistics 2016*; IEA: Paris, France, 2016. Available online: <https://doi.org/10.1787/9789264263079-en> (accessed on 24 February 2020).
4. O'Neill, E.; Moore, D.; Kelleher, L.; Brereton, F. Barriers to electric vehicle uptake in Ireland: Perspectives of car-dealers and policy-makers. *Case Stud. Transp. Policy* **2019**, *7*, 118–127. [CrossRef]
5. European Automobile Manufacturers Association. ACEA Report: Vehicles in use Europe 2017. *Consult. Febr.* **2017**, *22*, 2018.
6. Capros, P.; De Vita, A.; Tasios, N.; Siskos, P.; Kannavou, M.; Petropoulos, A.; Evangelopoulou, S.; Zampara, M.; Papadopoulos, D.; Nakos, C.; et al. *EU Reference Scenario 2016-Energy, Transport and GHG Emissions Trends to 2050*; European Commission: Brussels, Belgium, 2016. Available online: https://ec.europa.eu/energy/sites/ener/files/documents/20160713%20draft_publication_REF2016_v13.pdf (accessed on 24 February 2020).
7. Hervas-blasco, E.; Navarro-Peris, E.; Rosa, M.D.; Corberán, J.M. Potential fuel saving in a powertrain derived from the recovery of the main energy losses for a long haul European mission. *Energy Convers. Manag.* **2017**, *150*, 485–499. [CrossRef]
8. Santos, G. Road transport and CO2 emissions: What are the challenges? *Transp. Policy* **2017**, *59*, 71–74. [CrossRef]
9. Arias, N.B.; Franco, J.F.; Lavorato, M.; Romero, R. Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation. *Electr. Power Syst. Res.* **2017**, *142*, 351–361. [CrossRef]
10. Oda, T.; Aziz, M.; Mitani, T.; Watanabe, Y.; Kashiwagi, T. Mitigation of congestion related to quick charging of electric vehicles based on waiting time and cost-benefit analyses: A Japanese case study. *Sustain. Cities Soc.* **2018**, *36*, 99–106. [CrossRef]
11. Pallonetto, F.; Mangina, E.; Finn, D.; Wang, F.; Wang, A. A Restful API to Control a Energy Plus Smart Grid-ready Residential Building: Demo Abstract. In Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings (BuildSys '14), Memphis, TN, USA, 4–6 November 2014; ACM: New York, NY, USA, 2014; pp. 180–181. [CrossRef]
12. Will, C.; Schuller, A. Understanding user acceptance factors of electric vehicle smart charging. *Transp. Res. Part C: Emerg. Technol.* **2016**, *71*, 198–214. [CrossRef]

13. Namdeo, A.; Tiwary, A.; Dziurla, R. Spatial planning of public charging points using multi-dimensional analysis of early adopters of electric vehicles for a city region. *Technol. Forecast. Soc. Chang.* **2014**, *89*, 188–200. [CrossRef]
14. Petrou, K.; Quiros-Tortos, J.; Ochoa, L.F. Controlling electric vehicle charging points for congestion management of UK LV networks. In Proceedings of the 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 18–20 February 2015; pp. 1–5.
15. Kook, K.S.; Maitra, A. Impact Evaluation of Plug-in Electric Vehicle Loading on Distribution Systems in North America. *J. Korea Acad.-Ind. Coop. Soc.* **2009**, *10*, 2236–2245.
16. Clement-Nyns, K.; Haesen, E.; Driesen, J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Trans. Power Syst.* **2009**, *25*, 371–380. [CrossRef]
17. Pallonetto, F.; Mangina, E.; Milano, F.; Finn, D.P. SimApi, a smartgrid co-simulation software platform for benchmarking building control algorithms. *SoftwareX* **2019**, *9*, 271–281. [CrossRef]
18. Micari, S.; Polimeni, A.; Napoli, G.; Andaloro, L.; Antonucci, V. Electric vehicle charging infrastructure planning in a road network. *Renew. Sustain. Energy Rev.* **2017**, *80*, 98–108. [CrossRef]
19. Deb, S.; Tammi, K.; Kalita, K.; Mahanta, P. Review of recent trends in charging infrastructure planning for electric vehicles. *WIREs Energy Environ.* **2018**, *7*, e306. [CrossRef]
20. Davidov, S.; Pantoš, M. Planning of electric vehicle infrastructure based on charging reliability and quality of service. *Energy* **2017**, *118*, 1156–1167. [CrossRef]
21. Weldon, P.; Morrissey, P.; Brady, J.; O'Mahony, M. An investigation into usage patterns of electric vehicles in Ireland. *Transp. Res. Part D: Transp. Environ.* **2016**, *43*, 207–225. [CrossRef]
22. Newe, H.; Deters, S.; Saiju, R. Analysis of Electrical Charging Characteristics of Different Electric Vehicles Based on the Measurement of Vehicle-specific Load Profiles. In Proceedings of the NEIS 2019, Conference on Sustainable Energy Supply and Energy Storage Systems, Hamburg, Germany, 19–20 September 2019; pp. 1–6.
23. Charging with a Renault ZOE (CCS). Available online: <https://support.fastned.nl/hc/en-gb/articles/360035723373-Charging-with-a-Renault-ZOE-CCS-> (accessed on 24 February 2020).
24. Ramsay, J.O.; Silverman, B.W. *Functional Data Analysis*; Springer: New York, NY, USA, 2005.
25. Hastie, T.; Tibshirani, R.; Friedman, J. *The Elements of Statistical Learning*; Springer Series in Statistics; Springer New York Inc.: New York, NY, USA, 2001.
26. Tarpey, T.; Kinateder, K.K. Clustering functional data. *J. Classif.* **2003**, *20*, 93–114. [CrossRef]
27. Ye, L.; Hui, Y.; Yang, D. Road traffic congestion measurement considering impacts on travelers. *J. Mod. Transp.* **2013**, *21*, 28–39. [CrossRef]
28. Bertini, R.L. Congestion and its extent. In *Access to Destinations*; Emerald Group Publishing Limited: Bingley, UK, 2005; pp. 11–38.
29. Sharma, S. Principal component analysis (PCA) to rank countries on their readiness for e-tail. *J. Retail Leis. Prop.* **2008**, *7*, 87–94. [CrossRef]
30. Phahlamohlaka, M.; Coetzee, M. CaseRank: Ranking case law using precedent and principal component analysis. In Proceedings of the 2018 Conference on Information Communications Technology and Society (ICTAS), Durban, South Africa, 8–9 March 2018; pp. 1–6.
31. Courcoubetis, C.A.; Dimakis, A.; Kanakakis, M. Congestion Control for Background Data Transfers with Minimal Delay Impact. *IEEE/ACM Trans. Netw.* **2017**, *25*, 2743–2758. [CrossRef]
32. Lee, A.S.; Lin, W. Traffic Congestion Assessment of Metropolitan Areas Through Hybrid Model Ranking. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 772–777. [CrossRef]
33. Iyer, S.R.; Boxer, K.; Subramanian, L. Urban Traffic Congestion Mapping Using Bus Mobility Data. *CEUR Workshop Proc.* **2018**, *2227*, 7–13.

