

Data analysis on the public charging infrastructure in the city of Amsterdam

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Abstract

In recent years electric mobility has gained a great deal of attention, leading to electric vehicles on the market and development of necessary charging infrastructure. Charging infrastructure is mostly enabled through subsidies by local or national governments to overcome the chicken and egg problem, while the business case for charge stations in this early stage of development is not yet sufficient. The municipality of Amsterdam is a forerunner in the development of charging infrastructure, with over 950 public charge points available. The municipality and service providers struggle how to optimize the roll out of further charge points and how to optimize the use of the charge points. This paper gives a descriptive analysis of a number of usage patterns of the public charging infrastructure in the city of Amsterdam, and as such provides an update on earlier monitoring studies [1]. This research is based on more than 405.000 charge sessions collected at existing local charge points from March 2012 until August 2014. We study some coefficients which could be used to gain insight in the actual usage patterns of public charging infrastructure and may lead to recommendations concerning further roll out of charge stations, increasing effectiveness and improving the business case for charge points. The conclusions and recommendations may have implications for, and may support municipalities in the effective development of charging infrastructure.

Keywords: EV (electric vehicle), charging behaviour, infrastructure planning

1 Introduction

The Amsterdam region is one of the frontrunners worldwide in stimulating the use of electric vehicles [2] [3]. Urged by air quality problems the municipality of Amsterdam has had an active role in facilitating e-mobility within the region of Amsterdam. In recent years its policy has consisted of a combination of (amongst others) infrastructure development (e.g. subsidizing

placement of hundreds of public charge stations), market measures (e.g. purchase subsidies and incentive systems such as priority in obtaining parking permits as free parking for electric vehicles) and demonstration and awareness programs. It has made the municipality of Amsterdam one of the frontrunners in electric mobility in Europe with close to 1000 public charge points, more than 10.000 electric vehicles including around 300 electric “Smart For Two’s” using the charge stations, demonstration of innovative

charging solutions (fast charging), and large vehicle demonstration programs for amongst others the Nissan Leaf, 167 electric taxis as well as electric car sharing schemes [4, 5, 6] .

1.1 Public charging infrastructure database

In an assignment for the municipality of Amsterdam the University of Applied Sciences Amsterdam, has conducted a study to analyse usage patterns of the current charging infrastructure starting in February 2012. The study utilizes the data collected in two large datasets provided by the utilities responsible for rolling out 1000 charge points by 2014. Part of the conditions set by the municipality to the utilities was to log a range of relevant variables that may allow the municipality (but also third parties) to analyse the utilization of the charging infrastructure and come to recommendations regarding its optimization. By mid 2014 a dataset of approximately 405.000 charge sessions were logged, a unique dataset that allows to establish deeper insight in actual usage of charge points.

1.2 Literature on charging infrastructure for electric vehicles

A great deal of research has been carried out on the topic of charging infrastructure. However, limited research was found on real world user data of charging infrastructure in the scale as available in the dataset of Amsterdam. Mostly real world data is confined to European projects in which on limited scale (battery) electric vehicles [7] have been demonstrated in a more or less controlled environment, e.g. in use by public transportation companies, or in small consumer demonstration projects [8]. European projects such as CIVITAS [9] and ELCIDIS [10] have delivered a wealth of information regarding amongst others consumer behaviour, performance characteristics of electric vehicles tested, and charging characteristics. However, these projects were mostly limited to tens of electric vehicles and in which the vehicles and charging infrastructure was tested by selected end users (mostly public transportation companies). The demonstration projects are limited both in sheer numbers (amount of electric vehicles) as in terms of realistic nature (less controlled environment). No literature was found on data, on a scale like Amsterdam can provide. More extensive is a dataset for charge stations available in the Netherlands [7] [11], providing room for analysis of more than 2000 charge points

in the Netherlands. The dataset available for the region of Amsterdam distinguishes itself in enabling to evaluate actual characteristics and load patterns of a more mature and representative charging infrastructure within a particular city region.

2 Characteristics of charge station dataset

2.1 Background for data logging

In the past years the municipality of Amsterdam has had a stimulating policy regarding the development of a charging infrastructure in the region in order to facilitate purchase and use of electric vehicles. A programme called “Amsterdam Electric” was set up by the municipality in 2008 to set goals and implement policies to create an extensive charging infrastructure. The first ambition was to develop a public charging infrastructure of 1000 charge points by 2014. By August 2014 475 charge stations had been achieved, accumulating to 950 charge points (every charge station has 2 charge points or sockets).

The contract for development of the charging infrastructure was awarded to two consortia: Essent (infra provider) and Nuon/Heijmans (infra provider/engineering company responsible for installation). One of the contractual requirements set by the municipality for the infra providers was to monitor the actual utilization of the charge points by monitoring and logging information of the most relevant usage variables of the charge points. With the growing infrastructure this has accumulated to a dataset of more than 405.000 charge session measurements (including datalogs of a range of different variables per charge session) over the course of two and a half year (March 2012 to August 2014). This provides a unique dataset for establishing utilization and optimization of electric charge points in a municipality on a more representative scale.

Until recently the datasets of both infrastructure providers were only used to evaluate progress in *charged energy* and the *amount of charge sessions* on a monthly basis. Recently the “University of Applied Sciences Amsterdam” was asked to combine the two datasets and analyse which other variables could be used to show the progress of the use of public charging infrastructure in Amsterdam. In this paper we give an update of earlier analysis of usage characteristics of the charge infrastructure [1] to include a more thorough analysis of relevant

coefficients that can support classifying usage profiles of a city or neighbourhood.

For a precise description of the data preparation and filtering we refer to [1].

3 Results

In this section we plot the time evolution of certain variables. These time series show the growth of EV usage in the city of Amsterdam. We present the cumulative growth and the evolution of the usage on a monthly and on a daily basis (Figure 1, Figure 2 and Figure 3 respectively).

3.1 Cumulative data

The following figures show the growth of usage of public charge stations during the last two years in Amsterdam. During the analysis period a growth in the *number of charge stations* can be observed from around 100 (May 2012) to 475 (August 2014). We see an approximate growth of 0.44 new charge stations a day.

The number of *unique users* grows from around 600 (May 2012) to over 10.000 (August 2014). This translates to an approximate growth of 10.4 new users a day. We emphasize here that the growth of 10.4 users a day counts every new user that has charged its EV in Amsterdam at least once. This thus includes users that never return. Hence, this growth does not necessarily mean that the population of *active* users grows with this number. A better estimation of the number of active users, could be the active users per month. This variable will be discussed in the next section.

Note that the number of unique users, presented here, is actually the number of unique charging cards. Charge point operators claim that people often lose their card. This would mean that the number of unique users is likely to be an overestimation.

During the last two and a half years the total *number of charge sessions* has grown from zero to over 400.000. This gives an approximate number of 450 sessions a day. During the same period, the total *amount of charged kWh* has grown from zero to more than 3.000.000 kWh, translating to an average of 3500 charged kWh a day.

In the plot of the number of users we see a sudden jump. This jump is most likely caused by new regulations at the end of 2013, where favourable

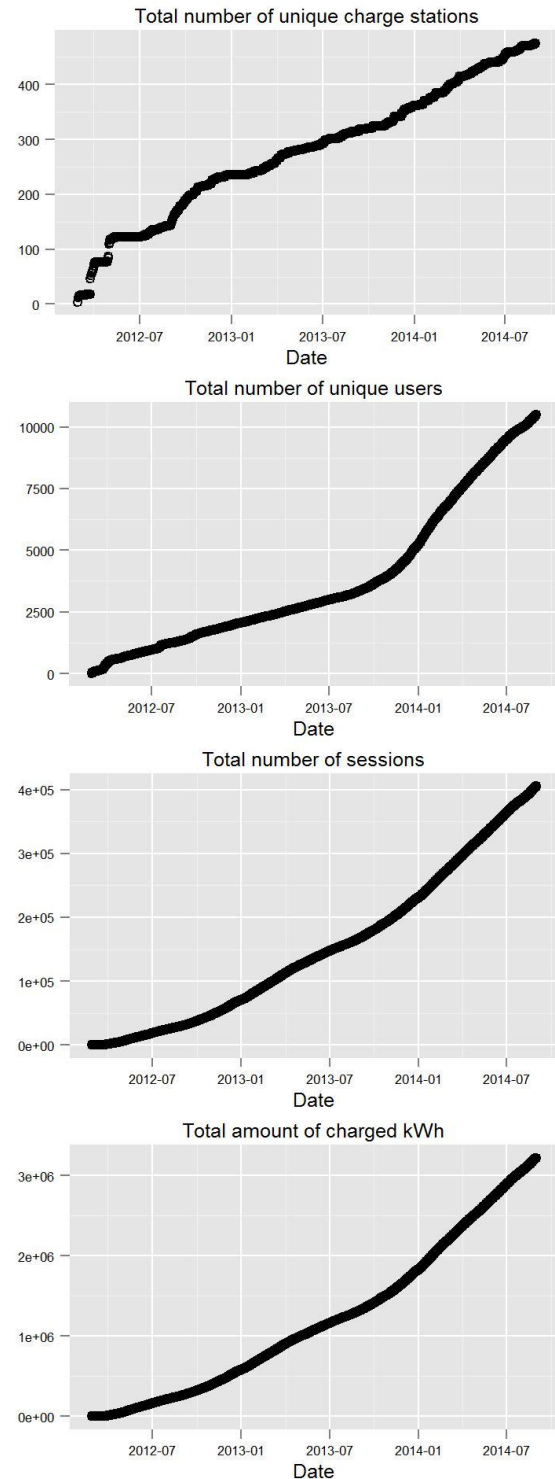


Figure 1: Daily cumulative data

tax benefits for purchasing (plugin) electric vehicles in the Netherlands were terminated. This led to a tremendous increase (doubled) in sales of (plugin) hybrid vehicles in the last quarter of 2013. Plug in electric vehicles were responsible for the majority of this increase (e.g. Mitsubishi Outlander) [12].

It may not be surprising that the number of sessions and the amount of used kWh are highly (significantly, $p < 0.001$) correlated with the number of users (both correlations well above 0.9). This means that the usage of the charge stations is driven by the number of active users. We do, however, notice that the number of sessions and the amount of charged kWh has not experienced the same drastic jump as the number of active users. Possibly this is due to the large number of plugin electric vehicles sold in this period, which do not necessarily need to be charged. The data suggest that these PHEVs are not using the charging infrastructure as heavily as regular full electric vehicles.

One of our goals is to be able to predict the number of users and sessions and the amount of charged kWh for every new charge station placed in whichever city in whichever neighbourhood. In this paper we will make a first step in predicting these variables for the city of Amsterdam. Later study will focus on the generalisation of these predictions in other cities.

As emphasized before, the plots in Figure 1 show cumulative graphs. To predict the usage of new charge stations it is more valuable to look at time series of the monthly, weekly or daily usage. Given that usually only monthly usage assessment are made, this study takes the opportunity to evaluate the differences and value of looking at weekly and daily level.

3.2 Monthly data

In Figure 2 the monthly usage of the stations is presented. If we compare the number of used stations per month with the total number of stations (see Figure 1), we see that almost all stations are used on a monthly basis. The percentage of stations that is used drops from 100% (early 2012) to 89% (August 2014).

From July 2013 we see that the number of monthly active users increases faster. This is not the same jump we observed in the user plot of Figure 1. While the cumulative plot detects new users (including day trippers and lost cards), the user plot from Figure 2 counts the monthly user load on the stations.

Comparing the number of unique active users per month with the total number of unique users, one sees that a large percentage of identified users do not use the charging infrastructure on a monthly

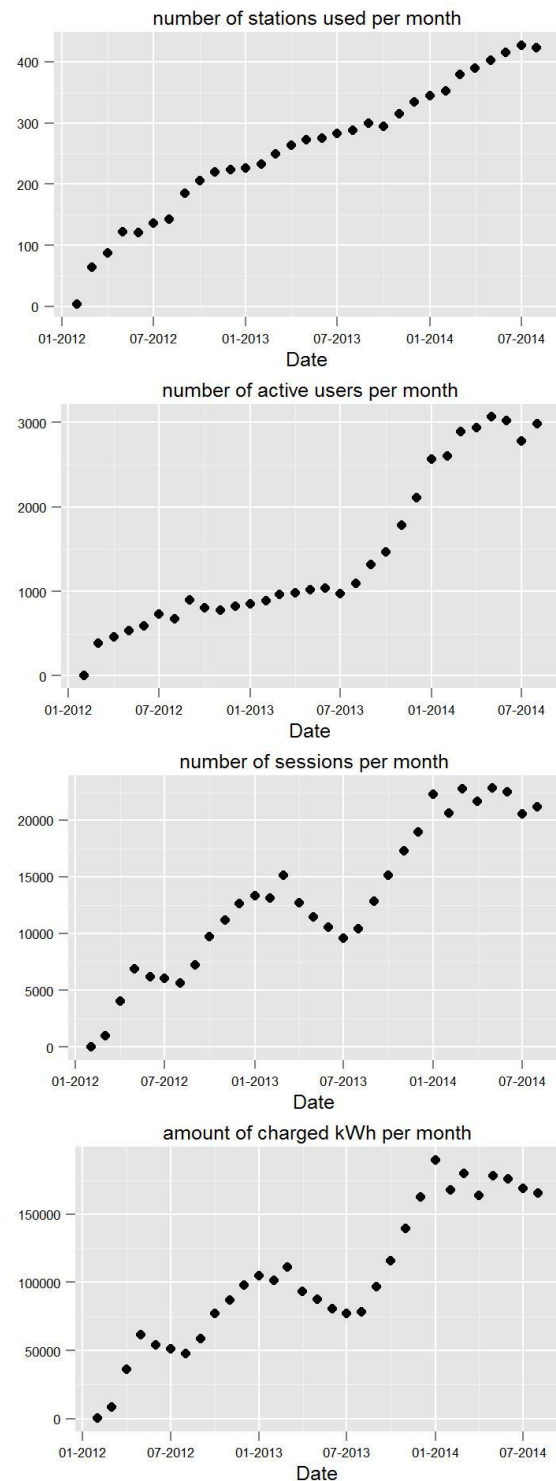


Figure 2: Monthly data

basis. This percentage increases from 0% (early 2012) to 72% (August 2014). This could be due to day trippers. Another factor could be the overcounting of unique users due to, for instance, lost charging cards. In that sense, we expect the

number of monthly active users to be a better estimator for the size of our population.

The two plots, showing the sessions per month and the charged kWh per month, display seasonal behaviour. The seasonal fluctuation seems to grow as the trend of the time series grows. Because of the small amount of data points (and periods) we refrain from using forecasting techniques, for now. In both plots we see a growing (approximate) linear trend with a season. In the winter the charge stations are used more heavily than in the summer. We can explain this behaviour by noticing that a large part of the EV's is used for commuting to and from work. Hence, the stations will be used less during the holidays in the summer.

Comparing the plots in Figure 2 we see a clear seasonal pattern in the number of sessions and amount of charged kWh, which seems to be lacking in the active users per month. This is probably explained by the choice of time units. If a person takes a holiday of three weeks (not using his car), he still will be counted as soon as he uses that car only once during that same month. For this reason, it could be interesting to look at the daily usage of the stations. This is done in the next subsection.

3.3 Daily data

In Figure 3 one sees the daily usage of the stations. In all four plots we see an approximate linear growth. This means that the average use of the charge stations is increasing (as expected and already demonstrated in the monthly data). We further see a growing variance, which means that the more people use the stations, the more distinct behaviour we see. This is reflected by the difference in usage of the stations during weekdays and weekends (in weekends there are less users, less energy charged, a smaller amount charge sessions compared to weekdays).

One of our goals will be to forecast such time series as in Figure 3 do so we need to study the growth and behaviour of the users. To best describe this behaviour we have to identify some outliers, such as the holidays. As a large percentage of the charge behaviour is work-based, this behaviour will tend to be very different on holidays. To be able to forecast we need to implement these holidays in our forecasting model. We will analyse this in the near future

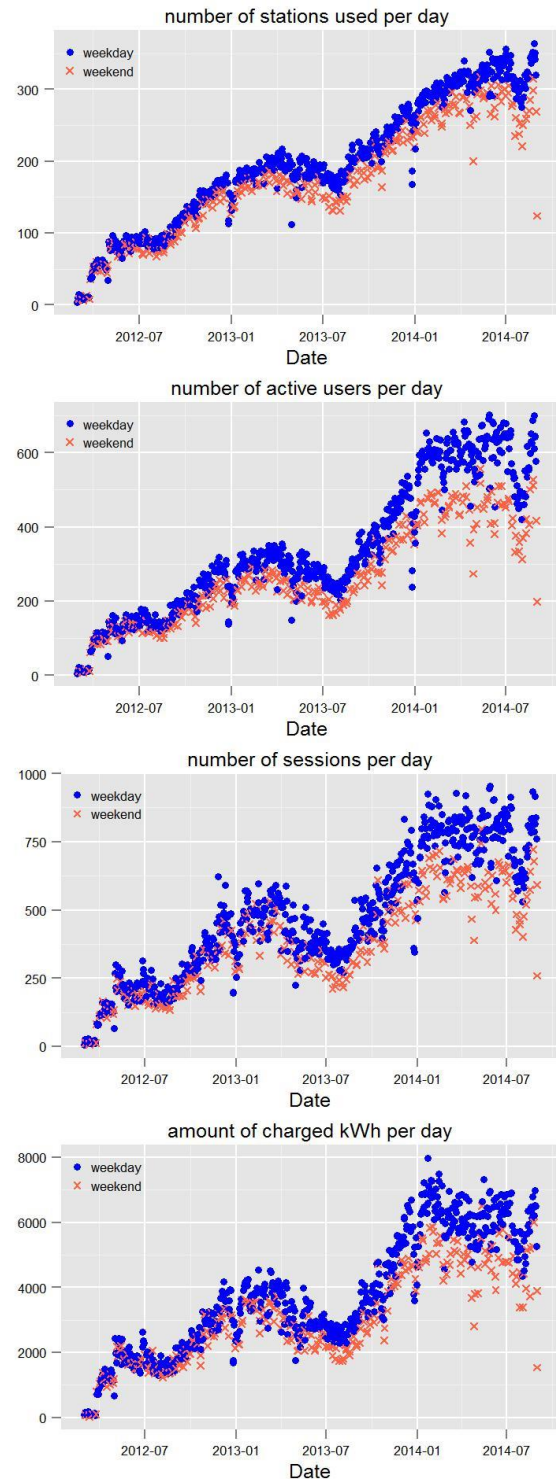


Figure 3: Daily data

using forecasting methods for time series with complex seasonal patterns.

As discussed earlier, the pattern of these time series is mainly driven by the number of users, which is in turn partially explained by regulations concerning placement of charge stations and purchase of EVs:

due to placement of charge stations the number of charge sessions and load charged has increased; the growing number of EVs in the market has a similar effect.

This means that the patterns of the time series are driven by the fact that charge stations are relatively new in the city of Amsterdam and that the (local) government accommodates placement of new charge stations and the purchase of electric vehicles. As we cannot assume that the governmental regulations will always be the same (in time or geographically), we will need another way to look at the data to be able to predict some future behaviour of EV-users in Amsterdam or other city. For this reason we suggest to study some coefficients that are more robust. That is, coefficients that are independent of the number of charge stations or the user load. In the remainder of this section we will discuss possible coefficients that could be useful for further research.

3.4 Coefficients for charge point usage

In Figure 4 we see the variables of Figure 3 divided by the total number of charge stations. We immediately see that in these figures there is not a distinct growth. To test this hypothesis we have carried out ADF and KPSS (statistical) tests to establish to what extent these series can be characterized as (weakly) stationary. These tests suggest that three of these four time series (*number of used stations*, *number of sessions* and *amount of energy charged* – all per station) are indeed weakly stationary. This would mean that the trends of these time series have constant mean and variance. Hence, we were right to assume that these (three) series do not grow. Based on this analyses we can conclude that around three quarters of all stations are used per day, the daily number of sessions is about one and a half times the total amount of stations and daily there is a load of around 15 kWh per station.

Using the same tests it is suggested that the time series of the *daily users per station* is not stationary. This could be a result of the seemingly growing number of users per station or the growing distinct users per station. Especially the difference between weekday and weekend users per station seem to be high in comparison with the other figures.

In the near future we will study the precise seasonal patterns of these four coefficients using

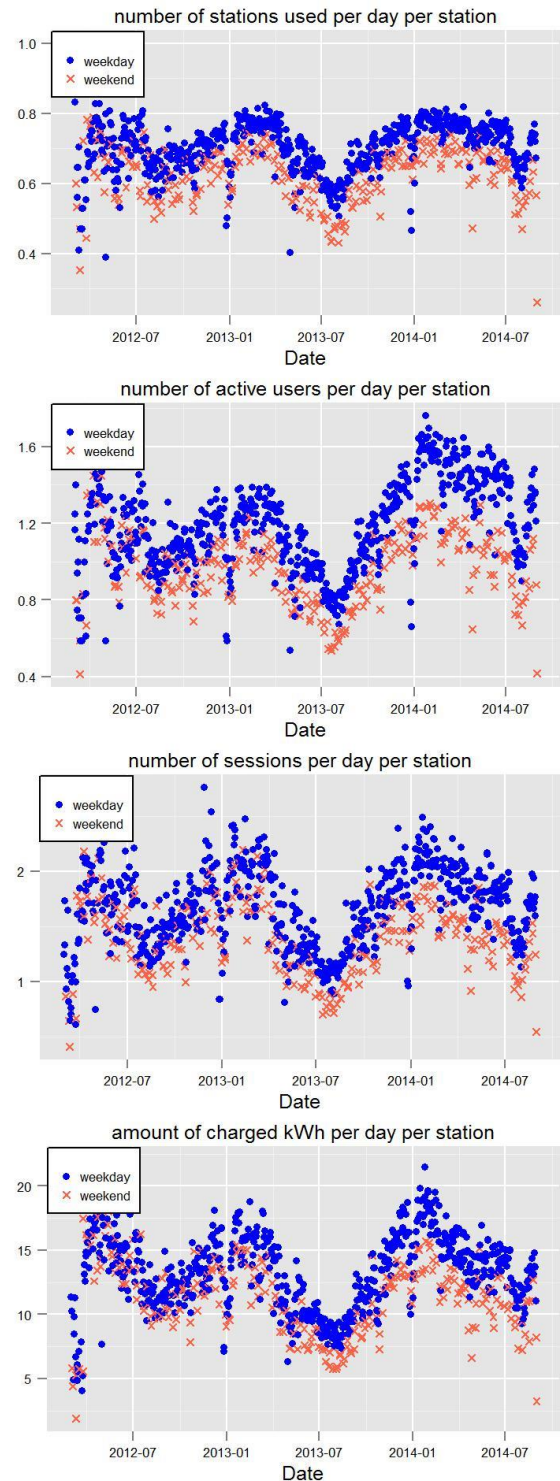


Figure 4: Ratio with number of total stations

techniques for time series with complex seasonality. For now, we will just conclude that these coefficients seem to drop in the weekends and in the summer; hence, whenever the stations are used less (compare with Figure 3).

One way to compensate for the number of active users is by dividing the variables by this number. This is done in Figure 5. In these plots one sees a completely different structure. In the data of the stations used per day per active user one sees a reversed picture: in the summer period and in weekends one sees a greater coefficient. Hence the typical weekend and summer user uses more (different) stations than the typical weekday and winter user. An explanation could be that the percentage of the car sharing program users is larger in the weekends and holidays. Another explanation could be that weekday trips are more routine-like than weekend or holiday trips.

In the number of daily sessions per active user and the amount of used kWh per active user we do not see a difference between the weekends and the weekdays. We do see small dips in the summer months, but these are considerably less than the dips in Figure 5. Hence, these coefficients seem to be less seasonal dependent. We do see, however, a very small (significant) decreasing trend.

3.5 Other factors

One of the goals of this research is to establish reliable coefficients such as the amount of kWh per user to be able to predict the use of newly placed charge stations beforehand. These coefficients can help to predict future usage of charge stations in other areas of Amsterdam or other cities. One thing to remember is that the data presented in Figure 4 and Figure 5 are all, in some way or another, means. In Figure 4, for example, we looked at the typical usage per station, which means we did not distinguish between the stations themselves. First analysis of the data have already shown that stations in residential areas are used differently compared to stations in business areas. Hence, there is a need to cluster the stations. For the same reasons we want to cluster the users. Identifying the clusters in the time series of the coefficients could explain part of the variance and could make the forecast more precise. An attempt to do this will be made in a subsequent paper.

4 Reflection of results

The EV-database provides a rich dataset that enables analyzing the use and effectiveness of a relatively mature public charging infrastructure for electric vehicles. The fast growing amount of charge stations in Amsterdam has spurred the actual use of this charging infrastructure, both in

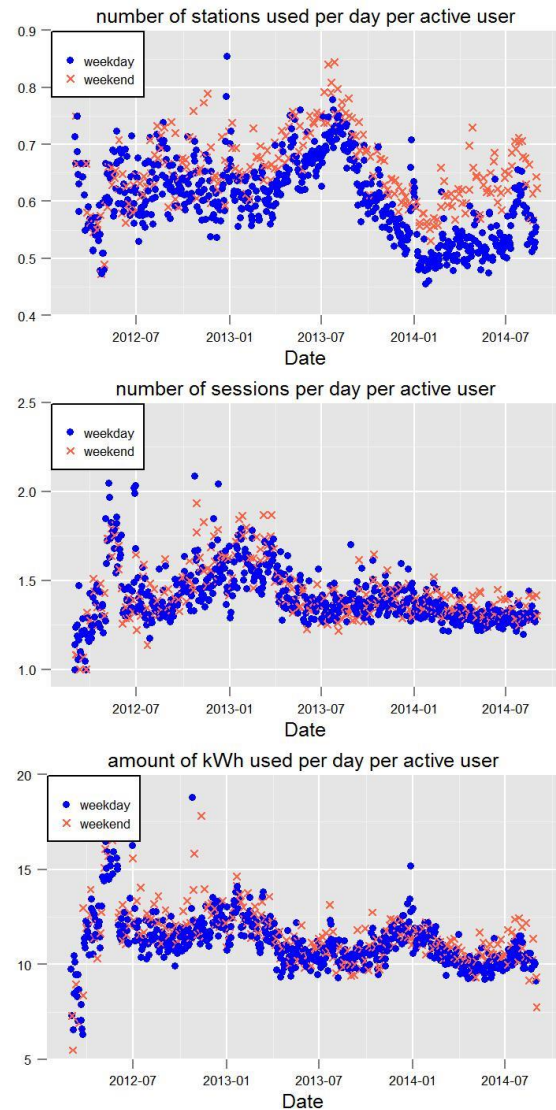


Figure 5: Ratio with number of active users

terms of amount of sessions as well as in the total amount of energy charged. The data provide some evidence that the facilitating role of the municipality in developing public charging infrastructure is successful for stimulating electric mobility and enables zero emission kilometres driven.

An important observation in this study relates to the large growth in unique users, which did not lead to significant growth in number of charge sessions and charged energy. As mentioned this may be explained by the fact that the growth in sales were largely PHEVs (not full electric vehicles) that are not dependent on charging infrastructure. Given the limited growth in charge sessions early 2014 the data suggests that these PHEVs do not use the charging infrastructure that heavily as regular full

electric vehicles, and at least partly run on regular gasoline rather than on electric drive. Given that PHEVs profit from favorable tax incentives but may not always contribute to the objectives set by these taxes (increasing air quality and climate neutral mobility) this requires further investigation regarding the actual usage of PHEVs of charge stations.

This paper points to the merits of analyzing charge behaviour on different time scales, ranging from daily, monthly to yearly analysis. Plotting charge behaviour on daily basis provides opportunities for applying forecasting techniques; but requires to differentiate between weekdays and weekend-days given their different charge profiles. Monthly analysis, applied in a great deal of papers and monitoring reports, are useful for generating more general trends, but are limited to make comparable results, for instance given the different amount of days per month which inherently leads to errors up to 10% (28 days of February versus 31 days in March). Analysis on a weekly basis may provide a better time scale for identifying more general trends.

Care should be taken to generalizing the results of this study to other cities; contextual factors (demand driven policy regarding charge points, air quality problems in the municipality) and market factors (amount of electric vehicles on the market, car sharing program availability) play an important role in the success of the current growth in infrastructure and its use by EV-drivers. Comparing the results of this study to other cities would increase the value of this analysis and may lead to results that can also be generalized towards other cities and municipalities with an interest to stimulate electric mobility.

5 Conclusions

Facilitating the development of a public charging infrastructure by the municipality of Amsterdam has had a positive effect on the use the charging infrastructure. In the period of analysis a surge in the number of charge stations, charge sessions and unique users can be found. This has led to a significant amount of energy charged leading to zero emission driving. In order to facilitate policy makers in developing more effective policies for stimulating effective rollout of charging infrastructure this paper has identified a number of trends in charge behaviour, thereby updating earlier analysis of charge behaviour in [1]. Furthermore, using statistical analysis a number of

coefficient were identified which are independent on the charge stations in place, and which proved to remain fairly stationary over time. Based on this analyses we can conclude that around three quarters of all stations are used per day, the daily number of sessions is about one and a half times the total amount of stations and daily there is a load of around 15 kWh per station. This provides policy makers with a clear insight in what they expect when new charging infrastructure will be placed in terms of energy charged, amount of charge sessions, but also academics that develop smart grid models with information on actual charge *behaviour*. Lastly the data analysis suggests that plugin hybrid vehicles do not use the charging infrastructure as heavily as regular full electric vehicles. This shall be topic of further investigation in papers to come.

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statistics to students in Applied Mathematics.



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