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# The effect of price-optimized charging on electric vehicle fleet emissions

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***Abstract*—Aggregation of sufficiently large electric vehicle (EV) fleets and control over their charging schedules enables aggregators to utilise the flexibility of EV charging in the Day Ahead Market. Optimising the charge scheduling of such fleets enables time-shifting of electricity demand to hours when electricity is cheaper, reducing the electricity cost for charging the entire fleet. Time shifting with scheduled charging is expected to influence the average carbon intensity of the energy used by these vehicles. This work aims to quantify the change in the carbon intensity of energy used by smart charged vehicles. It uses real data collected from over 55,000 home charging sessions from 1031 chargepoints in the Netherlands in 2018. A simulation was made with a commercial smart charging algorithm to create a scheduled charging profile ex post from the historic EV charging dataset. The simulation resulted in an average price reduction of electricity for the fleet of about 25% relative to unscheduled charging of the same fleet over the same period. The time dependent average carbon intensity of electricity consumed in the Netherlands was used to calculate the mean carbon intensity of the electricity used to charge the fleet over the period in the scheduled and unscheduled charging cases. The results revealed a small decrease in carbon intensity by 1.2%. Analysis reveals that price optimisation can have large effects on the mean carbon intensity of individual sessions in the Dutch grid, but the net effect is averaged out over a large number of sessions and over the year.**

***Index Terms*—electric vehicle, scheduling, fleet emissions, well-to-tank**

## I. Introduction

In order to reduce emissions in the passenger mobility sector, average emissions of new vehicles in the EU are required to be limited to 95 $gCO_2eq./km$ [1]. Based on the EU electricity mix, electric vehicles (EVs) result in about 20% lower emissions over their lifetimes than internal combustion engine based vehicles based on Life Cycle Analyses [2], [3]. The adoption of electric vehicles (EVs) is thus widely supported as part of the shift to lower emission mobility.

Currently, most EVs charge in an unscheduled manner, beginning to charge as soon as they are plugged in. The alternative is scheduled or smart charging, whereby the charging profile is altered based on external data input. Scheduled charging is seen as essential once the fleet share of electric vehicles increases beyond a critical fraction. Alteration of the charging profile can allow vehicles to charge in response to price signals, to contribute to maintaining local voltage quality, reduce congestion in the distribution level network and to provide frequency reserves, among other services [4]. Smart charging to reduce the cost of EV charging is already a reality with aggregated groups of EVs participating in energy spot markets [5], [6].

Twenty-five of the twenty-six European aggregators surveyed by Poplavskaya et al. were found to include participation in energy markets as part of their value proposition [6]. Although the share of aggregated fleets is currently small, it is expected to rise in the future, together with the market share of EVs. Since the carbon intensity in the electricity grid varies with time, scheduled charging of fleets according to market prices is expected to have an effect on the net emissions of the fleet. The net emissions caused by use of EVs is highly dependent on the emissions caused by the generation mix of electricity used (Well-to-Tank emissions) [7], [8]. As such, estimation of this effect is of considerable interest for accurate assessment of current and future mobility related emissions.

This work aims to answer the question: How does the price-based scheduling of electric vehicle charging in the current Dutch grid affect the $CO_2$ emissions of the electricity used by the scheduled fleet?

A data-driven methodology is adopted in this investigation. We use charging data of around 55,000 unscheduled charging sessions of over 700 Dutch Battery Electric Vehicles (BEVs) in 2018. A commercial smart charging algorithm is used to build a new profile for the fleet ex post based on market based price optimized charging. The volume of electricity charged to EVs per charging session remains unchanged relative to the unscheduled case. The hourly emission intensity based on electricity consumed in the Dutch grid was used with the original and new profiles to calculate the mean carbon intensity of electricity consumed by the unscheduled and scheduled fleets.

The paper is structured as follows: Section II presents a description of the set-up considered and the data used. Section III describes the methods used for setting up the optimisation and the calculation of the emissions. Section IV provides the results and discusses their significance. Finally, Section V presents the conclusions of this work.

## II. System considered and scope

We consider 1031 electric vehicle chargepoints at residential locations in the Netherlands. Data was collected over eleven months in 2018 (data from August was not available) from these chargepoints. The chargepoints included single-phase charging with 16 and 32 A rated cables as well as three-phase charging with 16 A rated cables. These chargepoints were used by both Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), which were part of a leased EV fleet. The Well-to-Tank emissions of PHEVs are also influenced by the crude oil pathways for gasoline and diesel delivery in addition to the electricity factors associated with electric charging [1]. Since estimation of the emissions associated with fossil fuel pathways was considered out of the scope of this work, PHEVs were not considered in this study. The vehicle charging was unscheduled and charging session data was logged by the chargepoints for billing purposes.

We do not consider a specific EV fleet since there is no information on charging sessions of vehicles at chargepoints outside the 1031 under consideration. The scope, calculations and conclusions with regards to energy related emissions are therefore limited to the energy charged with these chargepoints. Three data sets were used in this study:

1) EV chargepoint data
2) Electricity market data
3) Time dependent carbon intensity data

### A. *EV chargepoint data*

The data collected during every charging session is shown in Table I

TABLE I
EV CHARGEPOINT DATA OVERVIEW

| No. | Chargepoint data |
|---|---|
| 1 | Unique charging session identifier |
| 2 | Unique chargepoint identifier |
| 3 | Unique vehicle charging pass identifier |
| 4 | Plug-in time |
| 5 | Plug-out time |
| 6 | Session plug-in duration |
| 7 | Session charging volume |

Certain charging sessions were considered to be the result of logging errors and were excluded from the dataset. The conditions for their exclusion from the dataset are given in Table II.

TABLE II
OVERVIEW OF CONDITIONS FOR EXCLUSION OF CHARGEPOINT DATA

| No. | Condition for exclusion |
|---|---|
| 1 | Session charging volume $<1$ kWh |
| 2 | Session charging volume $>100$ kWh |
| 3 | Session plug-in duration $>24$ h |
| 4 | Missing data |

The charging volumes lower than 1 kWh were expected to be cases where the user plugged in the vehicle by mistake and are therefore disregarded. Since the largest battery energy capacity among the vehicles considered in the study was that of the Tesla Model S at 100 kWh, it is not possible for charging volumes to have been larger than 100 kWh within a single plug-in session. Hence these values were excluded. Plug-in duration exceeding 24 hours were expected to be caused by users leaving the cables permanently plugged in rather than placing them in the vehicle when driving away. These could also have led to sessions with volumes greater than 100 kWh as they included many consecutive sessions. Since these sessions did not really represent the availability of the vehicle, they were left out. Finally, sessions where data from the chargepoint was missing in the data set were removed so as not to bias the results.

The processed dataset used in this study finally consisted of 55,610 BEV charging sessions.

### B. *Electricity Market price data*

The BEVs were scheduled to optimize their charging cost on the Dutch Day Ahead Market prices for the year 2018. This data set was taken from the European Network of Transmission System Operators for Electricity (ENTSO-E) for the year 2018 [9]. The Dutch Day Ahead Markets are currently open for aggregators to participate in with sufficiently large EV fleets.

### C. *Time dependent carbon intensity data*

We use the time dependent carbon intensity data of electricity in the Dutch grid from the open source project electricityMap Live. These values are based on realtime monitoring of power plants with hourly time resolution and take cross-border trade into account. The values account for emissions arising from the entire lifecycle of power plants involved, from construction to decommissioning. They are based on consumption of electricity rather than generation, which can create differences in numbers. Additional information on the data sources and methodology may be found in [10], [11].

A scatter plot of the Dutch Day Ahead Market prices and the time dependent carbon intensity in the year 2018 is shown in Fig.1 to illustrate the relation between these variables in the Dutch grid.

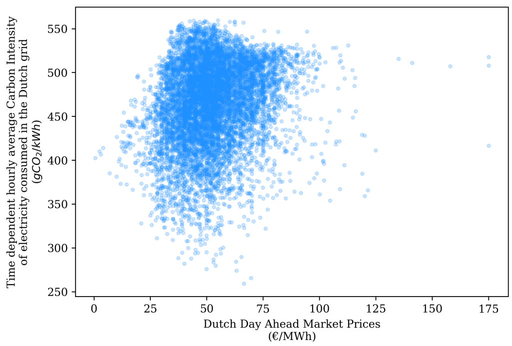


Fig. 1. Carbon intensity vs. Dutch Day Ahead Market prices in 2018

## III. METHODS

The study consists of two different phases, each with its own methodology. In section III-A, we describe the use of historic EV charging data to generate a cost optimized charging profile ex post for the plugged-in fleet. In section III-B, we describe the methods used to calculate the mean carbon intensity of electricity consumed by the EV fleet.

### A. Ex post EV scheduling

In this work, historic data was used to simulate real-time scheduled charging behaviour using a scheduling algorithm made by the commercial aggregator, Enervalis [12]. The process carried out is shown in Fig. 2. Initially, the Day Ahead Market prices together with the entry and exit times and electricity loads were input to the algorithm. A schedule was made for the EVs, whose aggregated demand volume was optimized for the lowest cost over the scheduling horizon (24 hours). In the charging sessions of individual EVs, the charging profile was assumed to follow the profile created as part of the collective schedule. The scheduling of the fleet resulted in an overall cost reduction of about 25% for charging the fleet over the year.

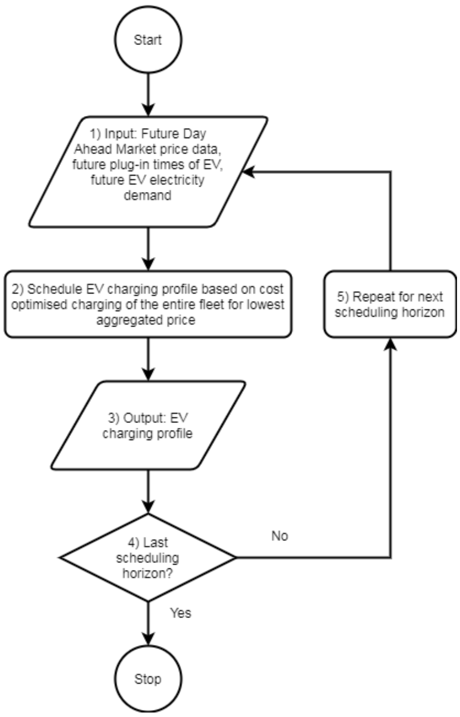


Fig. 2. Scheduling for each historic charging session

A Python script was used on an Ubuntu based laptop with an Intel® Core™ i7-7700HQ 2.80GHz CPU with 16 GB RAM. The problem was formulated as a Mixed Integer Linear Programming (MILP) problem and was solved using the open source CBC solver to less than 1% optimality gap. Eleven months of data were run as a simulation in this manner to produce the scheduled charging profiles of each charging session.

### B. Calculation of Carbon Intensities

The aim of this study is not carbon accounting for the entire fleet or on a per-vehicle basis but rather to quantify the relative change in emissions as a result of scheduled charging. Thus, we use the indicator of carbon intensity (CI), which we define as 'the total greenhouse gas emissions emitted per unit electricity consumed' measured in grams of $CO_2eq./kWh$ [13].

Most studies consider average annual values of carbon intensity (CI) to measure the emissions impact of the electricity [14]. This is primarily because it is a straightforward approach, understandable for stakeholders and can be easily performed ex-post with low data requirements. However, in countries where power plant portfolios having a mix of fossil fuels and variable renewable energies, there can be significant temporal variation (daily, weekly and seasonal) in the carbon intensity of electricity in the grid [15]. In our case, the time of charged electricity rather than its volume, is influenced by the scheduling. A purely volume-based approach, such as the annual average CI value, is not suitable for our case since there would be no change in emissions based on scheduling.

The use of carbon intensity which is based on the time dependent average electricity mix can lead to improved accuracy in the assessment of fleet related emissions [14]. The drawback of such an approach is that it does not consider the marginal emissions caused due to increased load at a given timestep, which depends upon the price-based merit order of power plants within the energy mix at each timestep as well as the capacity constraints of the highest cost deployed powerplant [16].

Calculation of the marginal emissions, however, requires either accurate energy modelling of the grid including the market dispatch or detailed data of local energy markets [14]. Further, there are many factors due to which the dispatch of powerplants is decided apart from merit order, including plant availability, transmission constraints and powerplant operational logistics [17]. Such an approach was considered out of the scope of this work. As such, we use the CI based on the time dependent average electricity mix. It is an approach which is well-suited for local analyses [18], as is the case here. Implicit in this approach is the assumption that the load profile being changed is not large enough to cause structural change in the electricity system under analysis. As our system is relatively small: 1031 chargepoints in the Dutch national grid, we take this assumption to be valid.

For every electric vehicle charging session, we multiply the energy demand in each hour by the carbon intensity in that hour to get the net hourly emissions. The summed value across all sessions is the divided by the net energy demand to calculate the mean CI of electricity used. Mathematically, the average CI for $m$ charging sessions, each of which lasted $n$ hours, are calculated as:

$$\text{CI} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} CI_j E_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} E_{ij}} \quad (1)$$

where $E_{ij}$ is the energy demand of the $i^{th}$ chargepoint at the $j^{th}$ hour of the session in $kWh$
and $CI_j$ is the carbon intensity of electricity consumed in the Dutch grid at the $j^{th}$ hour of the session in $g.CO_2eq./kWh$

## IV. Results and Discussions

The mean carbon intensity of electricity used by the unscheduled BEVs was calculated to be 464 $gCO_2eq./kWh$, a value slightly lower than the annual average value of the Dutch grid, 468 $gCO_2eq./kWh$. The mean carbon intensity of electricity used by EVs scheduled according to prices in the Dutch Day Ahead markets was slightly lower, at 459 $gCO_2eq./kWh$. The effect of scheduling thus resulted in a 1.2% reduction in the mean carbon intensity of the electricity used - a relatively small change.

Given the data used and methodology, in the present Dutch scenario, the use of time dependent values of carbon intensity together with the charging times rather than average annual values with charging volumes does not make a large difference. This remains the case for both unscheduled and scheduled charging. In our approach, where the final value of carbon intensity was weighted by the hourly values and volumes when EVs were charged, the final results proved quite similar. This provides a validation of earlier studies considering annual average CI values. However, it should be noted that this is a reflection on the Dutch case rather than the methodology, as the use of time dependent CI values is expected to provide a better estimation of the Well-to-Tank emissions of electric vehicles.

Initial investigation suggests that the price optimisation of charging does not lead to large deviation from unscheduled charging in terms of mean carbon intensity. However, the annual mean value across all sessions does not reveal the variation in carbon intensities in individual charging sessions. Fig. 3 shows the difference in session CI between the scheduled and unscheduled cases.

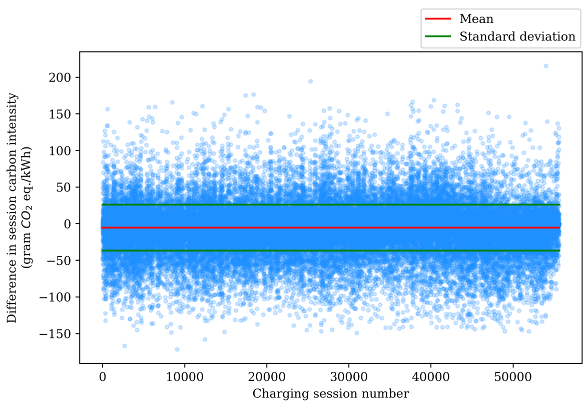


Fig. 3. Difference in carbon intensity between scheduled session and unscheduled sessions over all sessions considered

Fig. 3 shows that the effect of scheduled charging on the mean CI of individual sessions can be significant. The mean CI may increase or decrease in individual sessions, but these are balanced out over a large number of sessions and over the year. It reveals that price optimisation does have an effect on the reduction of $CO_2$ emissions, but only under certain conditions. Identification of the conditions under which price optimisation reduces $CO_2$ emissions may help scheduling of charging achieve multiple objectives and suggests a direction for further research.

The results further raise interesting questions related to the impact of price based charging in grids which include a greater fraction of renewable electricity. Higher price volatility may also be considered as an influencing factor on the emissions impacts of price based charging. Such investigations can lead to interesting future work.

## V. Conclusions

The study aims to investigate the effect of price optimized scheduled charging on the mean carbon intensity of EVs charged in the Dutch fleet. A data driven method is adopted, making use of the EV charging data of 1031 chargepoints at residential locations in the Netherlands over a year. A commercial charge scheduling algorithm was used to generate a new EV charging profile optimized for the Dutch Day Ahead market prices. The same volume of electricity was charged to the vehicles in both cases.

Time dependent average electricity mix based carbon intensity was used to calculate the mean carbon intensity of electricity over all the sessions in the two profiles. The results reveal that in the Dutch case, the use of time dependent carbon intensity does not have a large influence on the mean carbon intensity used by EVs in the Dutch situation, unscheduled or otherwise. Scheduling of charging based on price resulted in a small reduction of mean carbon intensity by 1.2%. The mean carbon intensity of individual sessions is found to vary considerable with price optimisation, but over a large number of sessions and periods of the year, scheduling does not have significant influence on mean carbon intensity of electricity consumed. Consideration of other schedules, locations with higher renewable shares and deeper analysis into the findings here represent avenues for future research.


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