Comprehensive transportation and energy analysis: A price sensitive, time-specific microsimulation of electric vehicles

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ABSTRACT

Despite ambitious climate goals, the German transportation sector has failed to reduce emissions. As these emissions are dominated by personal vehicles, electric vehicles are central for achieving environmental objectives. To determine potential emission reductions from electric vehicles, a detailed analysis of the transportation and energy sectors is necessary. Thus we present a methodology to calculate charging demand of electric vehicles using a time and location specific microsimulation and probability estimation based on a utility function for charging behavior. The transportation model is coupled with a detailed energy model for Germany, which provides electricity generation per energy source on an hourly basis over a year.

We apply the methodology and models to the case study of Germany in 2030 for five scenarios. The scenarios represent difference pricing schemes reflecting policy options for electric vehicles. The results show that charging demand can be shifted using market incentives. We find that charging subsidies can shift charging demand to or away from peaks. We then combine charging demand with the energy model to quantify the CO_2 emissions. The results show that shifting charging demand can reduce emissions, albeit at a minimal level. For the entire year, shifting charging to the daytime can reduce emissions by 2%. New areas of research including bidirectional charging and hourly pricing are needed to ensure maximum emission reductions from electric vehicles.

Keywords: Electric vehicles, charging demand, charging behavior, sector-coupling, greenhouse gas emissions, price sensitivity

INTRODUCTION

It remains to be seen if the transportation sector can reduce greenhouse gas emissions in accordance with international agreements. In Germany, transportation greenhouse gas emissions are dominated by road transportation (96% in 2016; most recent year available) *(1)*. Furthermore, emissions from road transportation are not decreasing. Emissions in 2016 were 4 % higher (160 million (metric) tons CO_2-Eq.) compared to 1990 (154 million tons CO_2-Eq.) *(1)*. Due to these developments, the German Federal Government supports the uptake of electric vehicles and charging infrastructure as a primary means to achieve emission reductions *(2, 3)*. As of October 1, 2018, there are 86,540 batter-electric vehicles (BEVs) and 83,260 plug-in hybrid electric vehicles (PHEVs) for a total of 169,800 electric vehicles in Germany *(4)*.

Significant research has been conducted on the environmental impact of electric vehicles. Archsmith et al. show that electric vehicles have slightly lower emissions, while Holland et al. find that ninety percent of local environmental externalities from electric vehicles are exported to other locations *(5, 6)*. Weis et al. show that plug-in electric vehicles have higher life-cycle air emissions than hybrid electric vehicles, and Yuksel et al. determine that emissions depend on reginal factors (grid mix, ambient temperature, vehicle miles traveled, and city versus highway driving) *(7, 8)*. However, it is unclear if electric vehicles can deliver stated goals, which in turn requires detailed information on charging demand.

There are numerous approaches to estimating electric vehicle charging demand. Several studies utilize actual charging data to determine demand. Morrissey et al. examine charging data in order to determine infrastructure requirements *(9)*. Neaimeh et al. similarly use charging data, but focus on the impacts for the electricity grid *(10)*. Xyda et al. analyze real charging demand to determine useful charging information *(11)*. These approaches utilize data from present electric vehicle fleets to estimate charging demand for future scenarios. Also these studies consider usage patterns of early adopters and not an entire fleet.

Addressing these issues, other approaches determine charging demand utilizing transportation data (e.g., household travel surveys). This allows for flexibility in fleet size analysis and an understanding of potential emission reductions. Anderson et al. estimate time and location specific charging demand based on household travel survey data, technology assumptions, and static charging preferences *(12)*. Dong et al. use household travel survey data and an activity-based assessment to optimize infrastructure demands and indirectly estimate charging demand *(13)*. Arias et al. estimate charging demand using traffic and weather data *(14)*. Amini et al. forecast demand using daily driving patterns and distances *(15)*. Arias et al. create a time-spatial charging demand forecast model focusing on demand in urban areas *(16)*. Xu et al. combine multiple data sources (i.e., mobile phone activity, charging sessions, and electric vehicle surveys) to determine demand *(17)*. Yang et al. estimate future demand through the agent-based models *(18)*. These approaches reveal the usefulness of detailed transportation models to estimate future charging demand and the associated emissions of electric vehicles. However, these approaches are limited in their analysis as charging demand estimation requires insights into the complex charging behavior and the decision making process of vehicle users.

In order to incorporate other important attributes influencing charging behavior, nested logit models are useful. Berkelmans et al. use a nested logit model to maximize utility with socio-demographic information and past charging records *(19)*. This approach considers users and their charging attributes, but the model relies on observed charging data of a small group of early adopters. Sheppard et al. expand upon this approach by including user behavior *(20)*. The authors utilize an agent-based transportation model (MATSim) with a nested-logit model to provide insights into siting charging infrastructure and indirectly determine demand. In regards to user behaviors, the model allows for the analysis of trade-offs of time, costs, convenience, and range anxiety when deciding to charge, which is a significant advancement in charge demand modeling. These studies illustrate the necessity of including complex user behavior in charging demand estimation. In order to determine emissions it is necessary to account for the interplay between demand (i.e., charging behavior) and supply (i.e., electricity grid).

Extensive work has been carried out on modeling charging demand for electric vehicles. Determining demand is essential to understanding the contribution of electric vehicles to greenhouse gas emission reductions. The literature review reveals that initial work focused on analyzing actual charging data. This was followed by advancements in charging demand estimation via the use of detailed transportation models; thereby allowing for the estimate of future fleet size impacts. Further insights were gained by incorporating user behavior models with transportation models.

The interaction between supply and demand is, however, absent from charging demand approaches with highly detailed transportation modeling. This feedback between demand and supply is critical to ensure emissions are actually reduced through electric vehicle use. Therefore, we present a detailed charging demand model integrated with the electricity grid via market mechanisms. Our approach offers new insights into potential emission reductions in the transportation sector.

METHODOLOGY

Calculating emission reductions from electric vehicles requires charging demand be coupled with information on the electricity supply. To do this we combine an electric vehicle charging model (CURRENT) with an electricity supply model (REMix), both developed by the authors, to determine the greenhouse gas emission impacts due to price sensitivity for vehicle charging. We aim to use market incentives (i.e., pricing) to encourage users to charge during times when electricity has a high percentage of renewable energy sources. We apply the methodology to Germany as a case study to illustrate the findings of the analysis.

Electric vehicle charging model – CURRENT

We determine charging demand using the model CURRENT (Charging infrastructure for electric vehicles analysis tool) *(12)*. This microscopic charging demand tool for electric vehicles provides time and location-specific charging details. This microscopic analysis requires data of single vehicle use, which are obtained from the latest available German household travel survey (MiD) *(21)*.

Two overarching assumptions form the basis for the charging model and allow us to utilize recent household travel data. First, we assume that electromobility only becomes a mass market if vehicle users do not have to change their travel behavior significantly. Thus the travel pattern of internal combustion engine vehicles is similar to electric vehicles and travel behavior does not change. Consequently, the second assumption states that vehicles predominantly charge where they already park. Thus only minor changes are made due to the vehicle being an electric vehicle (e.g., a supermarket with charging infrastructure is selected over a supermarket without infrastructure).

We determine the charging demand for an electric vehicle fleet using the charging algorithm. In order to do this we add specific information to each vehicle type (i.e., different electric range, maximum charging power). This results in an aggregated charging demand per hour of the week and per type of location for the entire fleet. A detailed summary of the model, data, and assumptions can be found in Anderson et al. *(12)*. In the following paragraphs advances in the charging algorithm are presented.

Utility function for charging behavior in CURRENT

The CURRENT model calculates charging demand for a specific electric vehicle fleet based on a static charging algorithm *(12)*. We expand upon this model to enable users to account for charging preferences and market mechanisms (i.e., pricing) in their decision algorithm, thereby creating a dynamic charging demand model. We use a utility based approach, which gives the probability of charging at each activity of the day. The utility function of each activity considers the preference of charging for each location and the price per kWh. The charging decision is made by a Monte Carlo simulation according to the charging probability at the charging point.

To simulate the charging behavior with the new utility based approach in CURRENT, a 24-hour vehicle diary is needed. Underlying different assumptions for BEVs and PHEVs, every vehicle must run through the charging algorithm as a BEV and PHEV. The vehicle types differ especially in electric range and possible maximal charging power. Figure 1 shows the charging algorithm, which every vehicle has to run through for every activity (i.e. trip and parking event) of the day.

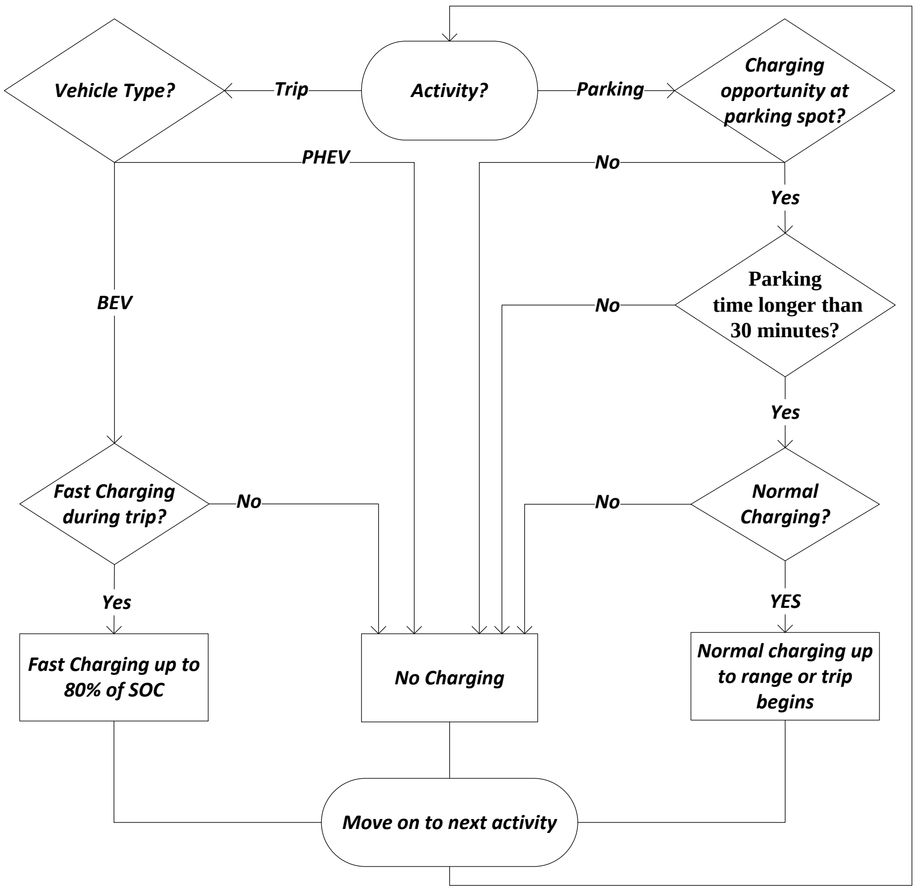

Figure 1: Charging algorithm for the transportation model CURRENT.

When the activity is a trip, we allow only BEVs to interrupt their trip for a fast charging event. Normal charging events are not possible due to the long waiting time resulting from the low charging power. Fast charging for PHEVs is prohibited, as only one PHEV (i.e., Mitsubishi Outlander) exists which can use fast charging *(22)*. We allow BEVs to charge fast with an weighted average charging power of 41.18 kW for up to 80% of their electric range during a trip *(12)*. If the electric range of a BEV is not sufficient to reach the next charging station, the probability of charging at a fast charging station during a trip becomes 100%. PHEVs, on the other hand, use their combustion engine to reach their trip destination if the electric range is insufficient and then charge at their next possible charging opportunity.

For parking events, every electric vehicle is able to charge, if there is a charging opportunity at a parking spot and the parking time is greater than 30 minutes. The average charging power is set to 2.86 kW at home and to 7.86 kW at other normal charging points to account for charging losses and different charging powers during the charging process *(12)*. The vehicle can be fully charged or charged until the next trip begins.

Besides the restrictive assumptions illustrated in Figure 1, the final charging decision for a fast or normal charging event at an activity depends on several additional factors. These factors are relevant for the charging behavior of the user and depend on their preferences. Specifically, how many potential charging points are there within the remaining electric range, the price per kWh at each charging location, and the preference of charging at the charging location. Beyond that there are many minor or major factors, like charging power, charging time, charging alternatives, actual electric range, etc., which also influence the charging decision. Due to a lack of knowledge about all the preferences for charging behavior, we consider only the main factors of a charging decision. Thus, the expected utility for each potential charging opportunity is given by the following equation:

$$U_{i,n} = \beta\_LOC_i + \beta\_PRICE * p_i + \varepsilon_{i,n} \quad (1)$$

$U_{i,n}$ is the utility of charging at activity *i*, for electric vehicle n, and depends on the preference of charging (β_LOC) at charging location *i*, and the price per kWh, *p*, for charging at location *i*, multiplied with the perception of the price (β_PRICE). We differentiate the price by location and not by time as time-specific electricity pricing is not currently permitted in Germany. We use a literature review to obtain *ß*-coefficients for the utility function (see Analysis below).

To predict the probability of a charging event, a multinomial logistic approach outlined by McFadden is applied *(23)*. Due to the fact that choice experiments are based on the Random Utility Theory *(24, 25)* it is assumed that an individual, in our case the user of an electric vehicle, gives every alternative a utility and chooses the alternative with the maximum utility. The utility function also consists of a stochastic term, $\varepsilon_{i,n}$, which is independent and identical distributed (i.i.d.) of extreme value type 1. Therefore, the probability can be calculated with a logit function, where $V_{i,n}$ is the deterministic part of the utility function.

At each possible charging point, *j*, the charging probability is related to all potential charging locations within the electric range. Therefore, we assume that the user of the electric vehicle knows their entire daily travel pattern. Thus we can use the observed travel data. The user only adapts their behavior by choosing for example a grocery store with charger instead of a grocery store without charger. The complete choice set of a charging decision includes all potential charging points, *j*, in the electric range on the same day. If the electric range is greater than the kilometers traveled by the end of the day, there is also a non-choice opportunity of not charging the vehicle on the same day. The dichotomous variable, $\gamma_{i,n}$, indicates the existence of the non-choice alternative by 1. Therefore, the utility for the non-choice alternative depends on the hypothetical remaining electric range without charging by the end of the day and is:

$$U_{nonchoice,n|i} = SoC_{nonchoice,n|i} + \varepsilon_{nonchoice,n} \quad (2)$$

The utility of charging not on the same day increases with a higher hypothetical $SoC_{nonchoice,n|i}$ at the end of the day and depends on the distance to travel from the choice location, *i*, to the location at the end of the day. Calibrating an average SoC at the end of the day of around 60% for the entire fleet, a constant is added by α (set to –1) to have a realistic probability for each alternative in the choice set. The final formula for the probability of charging at location, *i*, of vehicle, *n*, is:

$$P_{i,n} = \frac{e^{V_{i,n}}}{\sum_{j=1}^{J} e^{V_{j,n}} + \gamma_{i,n} * \left(e^{V_{nonchoice,n|i}} + \alpha\right)} \quad (3)$$

The final charging decision at each charging point is made using the Monte Carlo simulation by drawing a pseudo random number between 0 and 1 from a uniform distribution. Due to the fact that drawing one random number does not represent individual choices adequately, it is necessary to repeat the process several times respectively for several days of the microsimulation *(24)*. Therefore, we repeat the simulation 11 times, based on Vovsha et al. (2007) *(26)*. This also yields a sufficient convergence in the simulation according to the average SoC at the end of the day.

When starting the algorithm at the beginning of day one, the initial SoC is exogenously set either to half of the electric range or depends on the potential charging time over night *(12)*. In all other cases the SoC at the end of one day is the initial SoC for the next day. The first run of the simulation is excluded in order to have an endogenous SoC, which is on average almost the same (less than 1 percent difference) at the beginning and the end of the day. After running the simulation, we obtain a charging profile of one day of the week for each vehicle. Scaling and weighting the profiles for an entire fleet our simulation yields the charging demand of an entire electric fleet over the course of a week.

Electricity model – REMix

REMix (Renewable energy mix for sustainable electricity supply) is a high spatial and temporal resolution energy system model developed to investigate cost-efficient integration of high shares of renewable energy into the energy system with a focus on power supply *(27, 28, 29, 30, 31)*.

The model optimizes the power generation for least-cost energy supply and is able to dimension the necessary installed generation, transmission, and other balancing capacities. The hourly dispatch is calculated simultaneously. The dispatch contains the composition of the power supply at each node for each hour in the simulation. This data set is then used to couple the REMix with CURRENT.

REMix is composed of two main elements: the energy data analysis tool REMix-EnDAT and the energy system optimization model REMix-OptiMo (Figure 2). REMix-EnDAT processes energy relates data such as hourly load data, temporally and spatially resolved meteorological data (e.g., wind speed, solar irradiance, temperature), and spatial information (e.g., maps of land cover type, altitude, slope, country borders, power system infrastructure). It calculates spatially and temporally resolved power and heat demand, as well as renewable energy potentials for user-defined regions. The results are used as input in REMix-OptiMo or other analyses that require spatially or temporally resolved energy data.

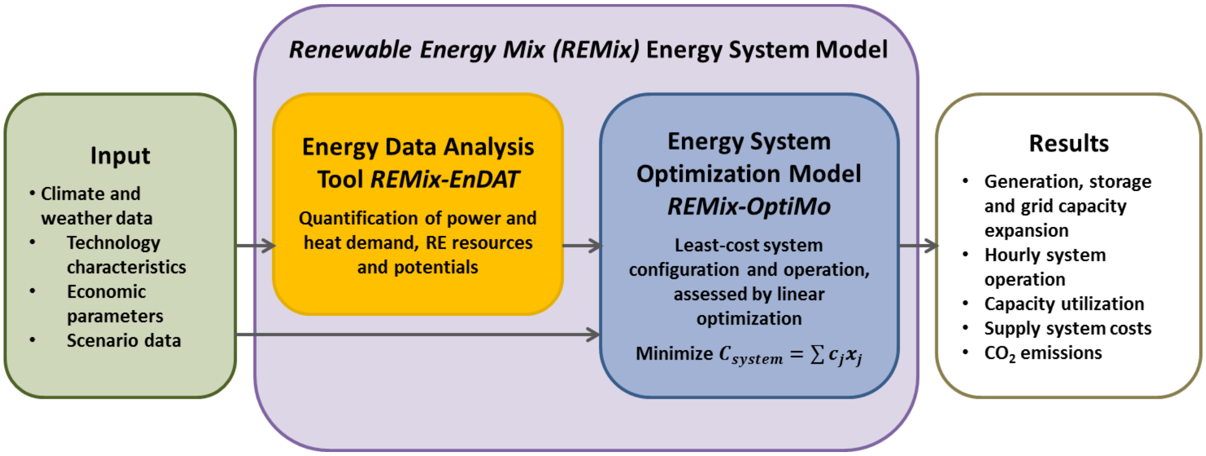

Figure 2: REMix model components and structure. For detailed information about the REMix model see *(27, 28, 29, 30, 31)*.

REMix-OptiMo considers hourly power generation restrictions for a whole year aggregated for user defined regions. The objective function is to minimize overall system costs, that is the sum of annuities of installed capacities, variable costs, fuel costs, and emission costs.

The objective function and system constraints are formulated as linear, deterministic equations, or inequalities. Given the high temporal resolution, linear modelling is necessary to keep running times as low as possible. The main constraint is the power balance which ensures that in each model node, power demand plus export equals power generation plus import. Balancing restrictions such as capacity installation limits due to area availability, power generation limits due to meteorological conditions, storage and demand response potentials are parametrized according to preceding energy data analyses *(28)*. A detailed discussion of mathematical equations representing the essential characteristics of power generation, storage and transmission technology modules can be obtained from *(27)*. REMix also accounts for demand from electric vehicles.

Integrating the transportation and energy models (CURRENT + REMix)
Next we couple the transportation model (CURRENT) and the energy model (REMix). From REMix we obtain the composition of the hourly power supply for an entire year and the associated CO_2 emissions. Emission factors are then determined for every hour of electricity produced over the course of the year based on the energy source. This results in average emission factors compared to marginal emission factors as identified by A.D. Hawkes *(32)*. We use average emissions as a first approach to integrate the models and understand the overall impact of pricing sensitivity in charging. This integration will later be expanded to include merit-order effects *(33)*. This will require iterative runs of CURRENT and REMix to see which additional power generation capacities are utilized by different charging patterns of electric vehicles.

The emission factors for every hour of the year are then combined with the charging demand from CURRENT for each scenario. This results in the hourly emissions for electric vehicles over the entire year. The emissions from each scenario can be compared on an hourly, weekly, or yearly basis. Also specific weeks of interest (i.e., the week with the most renewable energy, the most solar, the most wind, and conversely the lease renewable energy) can be evaluated.

The application of our methodology integrating the transportation model (CURRENT) and energy model (REMix) is presented below with the results and discussion of the case study for Germany in 2030.

ANALYSIS

Scenarios

To determine the impacts of pricing on electric vehicle fleet charging demand, we analyze five scenarios, which describe plausible future alternatives for charging pricing. Scenario 1 (Reference) utilizes actual pricing for all locations, no government subsidies are given, and private firms pass charging costs directly to users. This scenario serves as the reference case. Assuming that governments are not able to garner public funding for charging and there is no private sector interest in electric vehicles, this case assumes consumers must cover all costs.

Scenario 2 (Work) attempts to shift charging demand to the day by offering free charging at work (private and publically accessible locations). These costs could be covered by the government or government and employer subsidies. This scenario has been identified by Xu et al. to encourage commuters to charge at work locations and help shave peak power demand *(17)*. Scenario 3 (Home) provides free charging at private home locations. This scenario illustrates the outcome of public support of electric vehicle uptake by supporting users to charge at their preferred location – home *(34)*.

Scenario 4 (Public+Fast) presents an ambitious attempt to encourage the uptake of electric vehicles by subsidizing all public charging including fast charging. For this scenario the government covers all costs of users charging at public and publically accessible charging infrastructure. This represents a policy decision to dramatically support electric vehicles by free charging outside of the home. Scenario 5 (Public) again examines subsidizing all public charging, but excludes fast charging. It is the same as Scenario 4, but fast charging is no longer free. This allows us to analyze the influence of free fast charging on the charging profile. Prices for each scenario are listed in Table 1.

Case study

We now apply the dynamic charging demand model for electric vehicles to the case study of Germany to understand the influence of pricing on time and location of charging demand. We analyze the year 2030 with a fleet of six million electric vehicles per the stated goal of the federal government *(2)*. Based on the latest electric vehicle purchase data we assume the fleet is evenly split between battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) *(4)*. We assume that 73% of users have charging access at home *(21)*.

We increase the range of electric vehicles to account for anticipated technology changes between 2020 and 2030. While Anderson et al. assumed a range of 200 for BEVs and 40 km for PHEVs, we differentiate now based on vehicle class *(12)*. For BEVs, the assumed range is 200 km for small vehicles, 250 for medium vehicles, and 300 km for large vehicles. For PHEVs the electric range for small, medium, and large vehicles is 40, 50, and 60 km, respectively. Next we use beta-coefficients for the utility function estimates for charging in public (-3.37) and charging at work (-2.12), compared to charging at home, from findings by Jabeen et al. *(34)*.

Next electricity pricing data for different locations and accessibility requirements are determined. We examine a total of four locations (i.e., home, work, shops, other) each with up to three accessibility features (i.e., private, publically accessible, public) in addition to fast charging resulting in the cases outlined in Table 1. The value (-4.11) of the beta-coefficient for the price per kWh is derived from the price-coefficient of charging of Jabeen et al. *(34)*. The original value (-4.35) has been transformed with respect to the different perception of the price in Australian Dollar and Euro based on the exchange rate during the field phase (2012/09/24: 1 AUD = 0.8064 EUR) *(35)* of the survey of Jabeen et al. and an assumed price increase of 1.5% per year *(34)*.

Prices for the following cases are taken from data provided by Seum et al.: Home – Private; Work – Private; Work – Publically accessible; Shops – Private; Shops – Publically accessible *(36)*. These prices are nominal electricity prices for 2030 and account for all production costs, fees, taxes, and any other costs influencing the price. The prices are determined using an assumed price increase of 1.5% price increase per year. For all other cases, prices are based on actual 2018 charging prices from BMW Charge NOW in Germany *(37)*. These 2018 prices (0.05 €/minute for AC charging, 0.30 €/minute for DC charging) are then multiplied by average charging power to give prices in kWh and then an inflations rate of 1.5% is applied, per Seum et al. *(36)*, to get prices for 2030. All prices are summarized in Table 1.

Table 1: Nominal electricity prices for the scenarios: Reference, Work, Home, Public+Fast, and Public.

Price in 2030 (€/kWh)	**Scenario 1: Reference**	**Scenario 2: Work**	**Scenario 3: Home**	**Scenario 4: Public+Fast**	**Scenario 5: Public**
Home – Private	0.41	0.41	0.00	0.41	0.41
Work – Private	0.21	0.00	0.21	0.21	0.21
Work – Publically accessible	0.21	0.00	0.21	0.00	0.00
Shops – Publically accessible	0.21	0.21	0.21	0.00	0.00
Shops – Public	0.51	0.51	0.51	0.00	0.00
Other – Private	0.51	0.51	0.51	0.51	0.51
Other – Publically accessible	0.51	0.51	0.51	0.00	0.00
Other – Public	0.51	0.51	0.51	0.00	0.00
Fast charging	0.68	0.68	0.68	0.00	0.68

RESULTS AND DISCUSSION

Electric vehicle charging demand

We calculate the charging demand for the fleet of six million electric vehicles using CURRENT. The results for Scenario 1 (Reference) are shown in Figure 3. The figure illustrates the total charging demand for the fleet differentiated by location and accessibility over the course of an entire week on an aggregated level. The figure shows the charging demand for fast charging events (Fast), during work (Work), at home when parking at a private spot (Home, private), and at all other locations (Other). This calculation is also carried out for all the other scenarios.

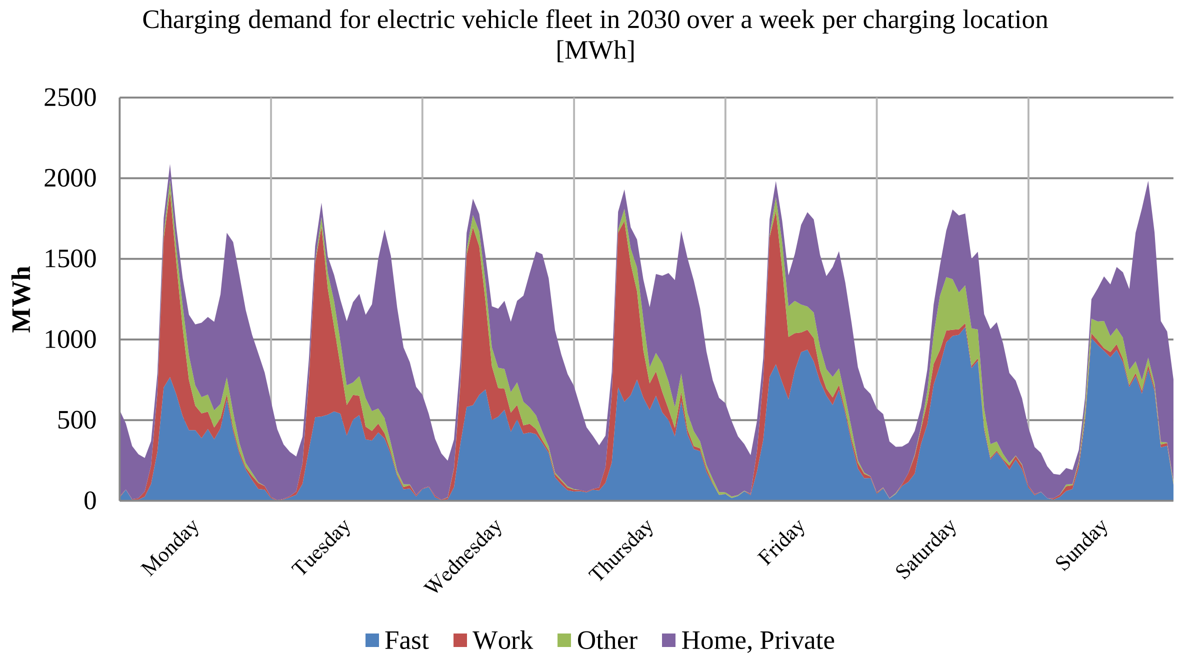

Figure 3: Total charging demand for six million electric vehicles for Scenario 1 (Reference) based on location and accessibility over the course of a week (Fast; Work; Other; Home, Private).

During the work week (Monday to Friday) the peak charging demand in Scenario 1 (Reference) is at 9 a.m. and most of the demand occurs at work. Fast charging events take place over the entire day with peak demand during the week at rush hour in the morning and afternoon. Most charging *events*, however, occur at home at the end of the day, when people end their daily trips. Due to the fact that the charging power is differentiated by location, the influence of fast charging events on the total charging demand is large despite the low number of events compared to charging at all other locations, especially at home. On the weekend, the most charging events take place after midday at other locations (i.e., while shopping, leisure activities) or during fast charging for other trips. In the afternoon there are increasing charging events at home with a low charging power.

This initial analysis reveals the importance in differentiating between charging demand (actual MWh charged) in comparison with charging events. We see that maximum charging demand and maximum charging events often occur at different times. This is due to two critical factors: charging power and actual charging time compared to charging point occupancy time (also including time when not charging).

To illustrate the difference in charging demand for the scenarios, total charging demand for all scenarios is shown in Figure 4. In this figure the charging demand is not differentiated by location or accessibility to ensure the figure is readable. The cumulative charging demand is composed of all demand per location and accessibility.

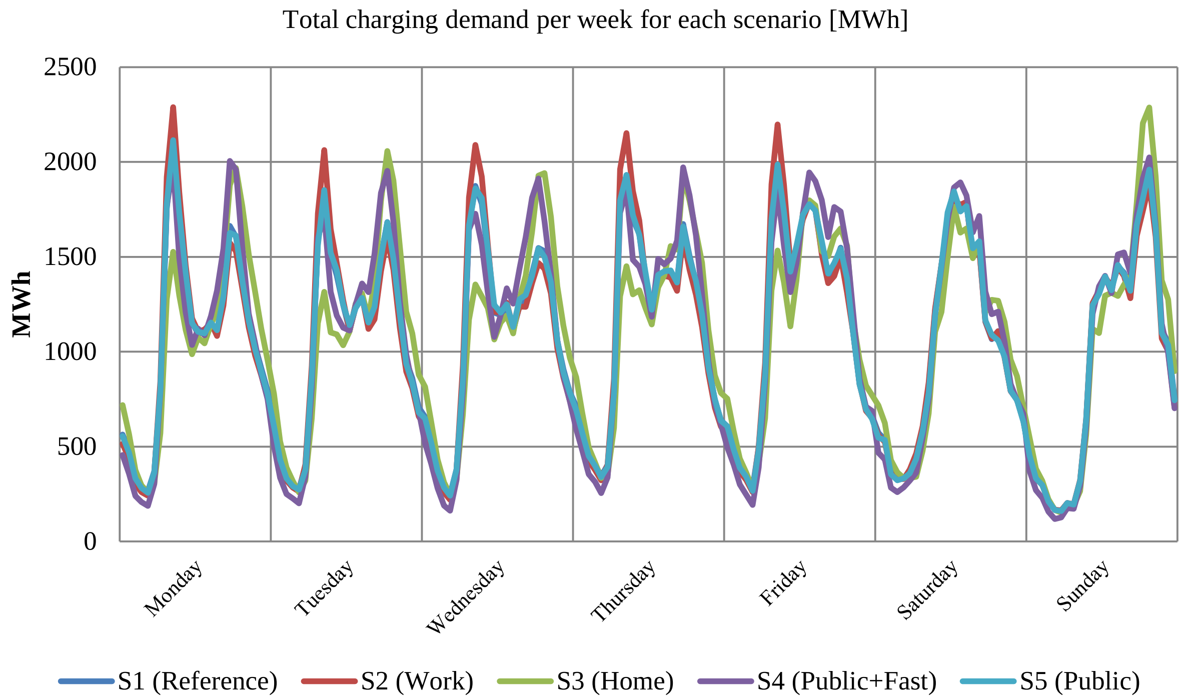

Figure 4: Total charging demand for all scenarios over the course of a week (Scenario 1–Reference, Scenario 2–Work, Scenario 3–Home, Scenario 4–Public+Fast, and Scenario 5–Public).

In Scenario 2 (Work), charging demand increases during the daytime as charging prices at work are set to zero. In addition, the number of vehicles charging at home in the evening is dramatically lower. An opposite trend can be observed in Scenario 3 when charging at home is free. Electric vehicle users prefer to charge at home at the end of the day and try to avoid charging during the daytime at work, shopping, or other activities. Thus total charging demand is shifted to the evening at home.

In Scenario 4 (Public+Fast) and Scenario 5 (Public) charging at public accessible charging points is free. The difference between the scenarios is that in Scenario 4 fast charging is also free. Figure 4 shows that Scenario 4 (Public+Fast) has more charging demand in the evenings compared to the Scenario 1 (Reference). As we can see in Figure 4, if fast charging is not subsidized (Scenario 5), the effect of free charging in public is minimal compared to Scenario 1 (Reference). However, in Scenario 4 (Public+Fast) users tend to use fast charging on their way home and avoid charging at work or late at night at home.

In order to better visualize the effect of pricing differences at different locations, Figure 5 shows the difference of each scenario (Scenario 2 to 5) compared to Scenario 1 (Reference). The trends and shifts in charging demand noted above are more readily apparent in Figure 5.

For S1 – S2 (Work) we see that charging demand increases during the day at work locations (charging here is free for Scenario 2) and charging demand falls in the evening. For S1 – S3 (Home) charging demand falls during the day and increases dramatically at night due to free charging at home. For S1 – S4 (Public+Fast) charging increases during the evening commute home to utilize free fast charging. Finally, S1 – S5 (Public) shows no significant difference to the Scenario 1 (Reference) indicating that S4 changes are driven by free fast charging rather than free public charging. Consequently, introducing pricing sensitivity allows for significant shifts in the charging demand profiles of electric vehicles.

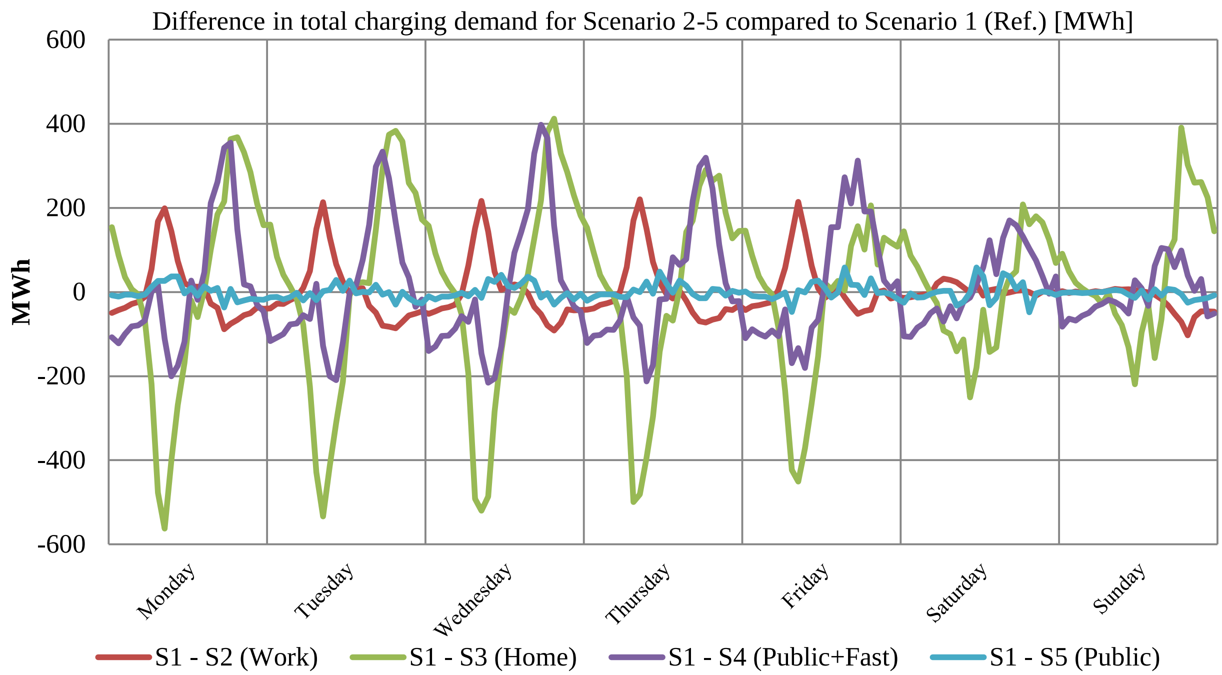

Figure 5: Difference of total charging demand of Scenario 2-5 (Work, Home, Public+Fast, and Fast) compare to Scenario 1 (Reference) over the course of a week.

Greenhouse gas emissions

Having determined the time and location specific charging demand, we combine these results with REMix to determine the CO_2 emissions for each scenario. We calculate the emissions for every hour of 2030 for the scenarios. In addition, we identify weeks of interest. Week 23 has the maximum solar energy. The week of maximum wind energy (combined onshore and offshore) (week 49) is also the week with the maximum renewable energy. The week with the least renewable energy is week 30. The findings are summarized in Table 2.

Table 2: Total emissions from electric vehicle charging for all scenarios for the 2030 case study in Germany. The week with the maximum renewable energy is the same week as maximum wind energy (week 49, starting 25 December 2030). The week with the maximum solar is week 23 (starting 3 June 2030). The week with the minimum renewable energy is week 30 (starting 29 July 2030). (Diff. – difference, Ref. – reference, renew. – renewable energy).

	S1(Ref.)	**S2 (Work)**	**S3 (Home)**	**S4 (Public+Fast)**	**S5 (Public)**
Total per year ($t\ CO_2$)	2,517,906	2,509,452	2,557,461	2,521,296	2,514,818
% diff. to Ref.		-0,34%	1,57%	0,13%	-0,12%
Average weekly ($t\ CO_2$)	47,508	47,348	48,254	47,572	47,449
% diff. to Ref.		-0,34%	1,57%	0,13%	-0,12%
Week max. renew. ($t\ CO_2$)	27,179	27,166	27,322	27,309	27,161
% diff. to Ref.		-0,05%	0,53%	0,48%	-0,06%
Week max. solar ($t\ CO_2$)	44,164	43,905	45,350	44,141	44,081
% diff. to Ref.		-0,59%	2,69%	-0,05%	-0,19%
Week min. renew. ($t\ CO_2$)	49,950	49,569	51,639	50,051	49,835
% diff. to Ref.		-0,76%	3,38%	0,20%	-0,23%

The results show that shifting charging demand can reduce emissions, albeit at a minimal level. For the entire year, shifting charging to the daytime (S2–Work) compared to overnight (S3–Home) can reduce emissions almost 2%. During the week with the maximum renewable energy, Scenario 2 (Work) compared to Scenario 3 (Home) results in a reduction of less than 1% in emissions. For the week with the maximum solar energy, Scenario 2 (Work) has 3.2% lower emissions than Scenario 3 (Home), and for the week with the minimum renewable energy, Scenario 2 (Work) has 4% less emissions.

From the charging demand analysis, we see that the scenarios yield significantly different charging profiles. Thus we are able to influence when and where charging occurs via price sensitivity. However, the same dramatic impacts are not seen in the emission results. The different charging strategies yield only minor reductions of emissions. Of the scenarios, the most promising is achieved by shifting charging demand to daytime hours (i.e., Work). However, REMix shows that wind dominates renewable electricity, which is also not fixed timewise. Consequently, the emission analysis reveals the limitations in influencing charging demand through fixed pricing. This is despite the significant impact we see in influencing the charging demand profiles.

CONCLUSION

This paper outlines an approach to integrate a microscopic transportation model for electric vehicles with a detailed energy model to determine impacts of policy decisions on greenhouse gas emissions. Specifically we use market incentives (i.e., pricing) and charging preferences to encourage users to charge during times when electricity has a high percentage of renewable energy sources (aside from Scenario 3). We apply our methodology for different scenarios to understand the role of varying pricing policies on the time and location of total charging demand.

The charging demand results show that using market mechanisms we are able to shift charging demand curves. Offering free charging at work shifts demand to the daytime and away from the night at home locations. Conversely, free charging at home shifts the demand curve to more charging at home at night. Free public charging has a negligibly effect on charging demand compared to the reference scenario. However, free fast charging increases charging in the evenings on the way home or during other activities (e.g., shopping, leisure).

The CO_2 emission results show we are able to minimally reduce emissions due to market mechanisms. However, these reductions are very small and illustrate the challenges in transfering shifts in charging demand to actual emission reductions. More complex analysis (e.g., merit-order, iterative analysis between the models) offers possibilities for greater reductions, which should be investigated in future work.

The methodology and findings have limitations. The results are specific to the German case study. Furthermore, there is limited information about charging behavior and preferences for a larger number of electric vehicle users in Germany. Although the major findings are applicable to similar countries, all assumptions and data sources must be examined in detail when drawing comparisons. Further as noted in the paper, average emissions, compared to marginal emission factors were used.

Future areas of research include a merit-order analysis for charging demand, the impact of hourly price differentiations, and the substitution of trips between household vehicles. Further, the role of smart charging and vehicle-to-grid schemes, varying electricity mixes, and different levels of electric vehicle adoption should be explored. Finally, additional future scenarios and the impact of increased electric range could be examined.

AUTHOR CONTRIBUTION

Study conception and design: Anderson and Steck; initial development of CURRENT: Kuhnimhof; further development of CURRENT and analysis: Steck; REMix analysis: Hoyer-Klick; analysis, results, and manuscript: J. Anderson and F. Steck.

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