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Integrating electric vehicles in electricity system models – representing individual driving patterns

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ABSTRACT: This study takes initial steps in developing a method that includes a representation of road transportation demand on individual EV level (based on GPS driving measurements) in an optimisation electricity system model to also represent the spread in the individual driving patterns. The main conclusions are that different driving profiles do have an impact on the charging and discharging back to grid depending on the individual driving distance, battery capacity and driving profile. This have shown to have an impact on, e.g. investments in peak power and the potential role of EVs facilitating the integration of more intermittent renewable power.

KEY WORDS: individual driving patterns, modelling, electricity system, vehicle-to-grid, variation management

1. INTRODUCTION

To enable meeting ambitious climate target, as agreed upon in the Paris agreement[(1)] and within the European Union framework[(2)], the transportation sector needs to replace current fossil energy supply with non-fossil options. Fulfilling such targets, will most likely lead to large scale employment of electric vehicles (EVs) deployed over the coming decades. Obviously, new EVs will cause a new electric load that is to be integrated into the electricity supply system. However, it is not obvious how these new loads will affect the electricity generation system, where for instance an unregulated charging can cause an increase in the electricity load during times when there is already a high demand[(3)]. Yet, if the integration of EVs include a strategy, the new demand can potentially offer benefits in terms of flexibility in the load, e.g. demand response services in the form of strategic charging and possibly also discharge back to the grid (i.e. vehicle-to-grid; V2G) according to what is most optimal from an electricity system point of view. Thus, it should be essential to investigate the potential gains from having a strategy in introducing EVs in the electricity supply system. Previous studies using modelling of the electricity system including smart charging of EVs are mainly based on data from traveling surveys aggregated to an entire EV fleet in the models[(3-6)]. There are few studies, if any, that include a representation of individual EV transportation demand profiles, which should be required for a realistic representation of the availability of the EVs in the electricity supply system. One reason could be due to the few available data sets of individual driving behavior. Another reason could be the increased number of decision variables in a model including individual driving patterns.

Data from self-reported traveling surveys are often underestimating the frequency of trips and focus on the travel behavior of persons during one day rather than the movement pattern of cars over longer time period[(7)]. Elango et al[(8)] have shown that individual car movements varies considerably from day to day, which might be important to include in the electricity system models in order to estimate the flexibility services that can be provided by the EV batteries over more than one day timespan. A more detailed measurement of individual car movement patterns can be achieve by measurement of time and position with Global Positioning System (GPS) equipment over a longer time period. Yet, there are a limited number of representative GPS-measured data sets for passenger vehicles gathered and available for scientific purposes, where most have been collected during a short time period and/or for a smaller geographical area[(9-13)].

This study takes initial steps in developing a method that includes such representation of transportation demand on individual EV level (based on real-time GPS driving data measurements) in an optimisation electricity system model to also represent the spread in individual driving patterns.

In particular this study attempts to answer the following:

✶ *How can individual EV driving demand patterns, be accounted for and included in electricity system optimisation models?*

✶ *What are the differences and benefits of including individual EV driving data in such models compare to use data for an aggregated fleet?*

2. METHOD

2.1. Model description

This study uses a cost-minimisation model of the electricity system (ENODE) that is designed to analyse transformation of the electricity system, while meeting assumptions on key scenario parameters such as a CO_2 emission target. The model is a Greenfield model (i.e., assuming an empty system as a starting point without any generation capacity in place) with an hourly time resolution, run for one year (Year 2050) and there is no inter-connection between regions. No net CO_2 emissions are allowed for the modelled year, corresponding to a 100% emission reduction by Year 2050 compare to Year 1990. The model is designed to analyse both investments in technologies to cover demand, as well as the hourly dispatch of different power technologies. Table 1 shows technologies and fuels to invest in, in the model. The model is explained to full extent including all mathematically equations in Göransson et al.[14]. Several model developments have taken place: (i) Garðarsdóttir et al.[15] added improved representation of thermal power plant flexibility, (ii) Johansson and Göransson[16] added different flexibility measures; and (iii) Johansson et al.[17] added new biomass and gasification generation technologies.

Table 1 Technologies and fuels included in the model

Thermal technologies	Condensing and combined heat and power (CHP) with and without carbon capture, gasifiers
Renewable technologies (excluding biomass)	On-shore and off-shore wind power, solar PV, hydro power,
Fuels	Biomass, coal, gas, lignite, uranium, waste
Storage technologies	Flow batteries, Li-Ion batteries, hydrogen tank storage and hydrogen storage in lined rock caverns

In the present study, the model is expanded to include an electrified road transport sector in the form of controlled charging of passenger EVs, where the number of EVs and individual battery capacities are exogenously given to the model. Driving patterns determines when the vehicles are available for charging the EV batteries and the amount of discharging, i.e. V2G, that is possible while still fulfilling the driving need. The vehicles are assumed to be available for charging when they are parked for more than 1 hour. The model then optimises the amount and time of charging and discharging of the EVs according to some limitations: (i) the connection of the EVs to the grid; (ii) the charging power; and (iii) the battery storage capacity, see Taljegard[18] for a more detailed description of the equations. To enable answering the above given research questions, three different methods of integrating the EV driving data in an electricity system model have been applied: (i) aggregated vehicle fleet (AGG), (ii) representative daily driving profiles (DDP), and (iii) yearly driving profiles (YDP). The DDP and YDP approaches include individual driving patterns in the model, while the AGG approach uses average values from the measured individual vehicles.

2.2. Driving patterns

2.2.1 The car movement data base

This study applies measured traveling patterns from a measurement campaign performed in the region of Västra Götaland (western part of Sweden), i.e. GPS measurements of about 770 randomly chosen gasoline and diesel vehicles that completed 107 910 trips between Years 2010 and 2012[13,19]. The vehicles were randomly selected from the Swedish vehicle database and are representative for the region in terms of fleet composition, car ownership, household size, and distribution of larger and smaller towns and rural areas[13]. Out of the around 770 households, about 529 of them were logged for more than 30 days and 426 of these 529 have high-quality data in terms of, for example, for most trips the starting location of a trip matches the end location of previous trip. Each vehicle were measured for a period of about two months, yet different two-month periods for different vehicles. Thus, in total 27 879 measuring days were included in the data base. The measured vehicles are in this study used for describing the spread in the individual driving patterns, and thus, enable a realistic representation of when EVs can be assumed to be connected to the grid and the amount of driving per hour.

2.2.2. Aggregated vehicle fleet (AGG)

An aggregated vehicle fleet is the simplest and most common way to include EVs in electricity system modelling. Input data for the aggregated vehicle fleet implemented in the present model is based on the car movement data described in section 2.2.1. The yearly aggregated EV electricity demand in a region (E_r^{EV}) is calculated with following equation (Eq1):

$$E_r^{EV} = N_r \times vkm \times FC \qquad \forall\, r \in R \quad (1)$$

where N_r is the number of EVs in region r, vkm is the number of yearly kilometers per vehicle driven on electricity, and FC is the electricity consumption per kilometer. In these model runs, the average vehicle kilometer for all regions is 15 137 kilometer per year, which is the same as the average of the measured vehicle fleet in the car movement dataset. The share of the kilometers using electricity depends on the EV battery size, availability for charging and the charging power. For example with a charging power of 7 kW, which is assumed in this study, and applying the three different battery sizes of 10, 30 and 85 kWh, the distance covered by the battery per day is 65%, 92% and 97%, respectively. The model optimise the charging of the vehicle batteries with limitations to the share of vehicles available for charging and that the aggregated storage level of the EV batteries can never be negative or larger than the battery capacity. Since there is only an aggregated vehicle category (i.e. one category) in this approach, a share of the fleet is being parked and a share being out driving. Therefore, with this aggregated approach, there is a risk of a vehicle standing still can be charging for a vehicle being out driving and thereby overestimate the possibility to use the EV batteries for storage capacity. Fig. 2 shows the driving profile during an average day, but in the model, each day has a specific pattern in the aggregated approach according to the profile of the 426 measured vehicles.

2.2.3. Representative daily driving profiles (DDP)

A more detailed approch, compared to the aggregated vehicle fleet, is to include individual driving patterns directly in the electricity system model. The main difference to the aggregated model setup is that the vehicles are divided into several representative daily driving profiles, where they in each category and time step are either parked or driving. This will thereby solve the problem with the aggregated approach where the collective idle car battery capacity can charged even though the energy is needed in cars on the road. Thus, the car movement database consist of 27 879 measured days (including both days where the measured vehicles are driving, as well as, not driving). In the present work a K-means clustering method[20] is applied to determine which of the daily driving profiles that, using weithing factors, are representative for the total number of daily profiles. Fig. 1 shows the share of the daily driving distance distributed over the day for sample sizes of 10, 50, 100, 200 and 500 days, as well as for the total 27 879 measured days. Thus, it can be seen that approximately 200 representative days out of the total 27 879 measured 1-day profiles is required for a decent representation in terms of distance and driving profile. Thus, the driving demand for EVs are approximated by 200 representative daily driving profiles. The drawback in the applied modelling methodology of using representative daily driving profiles is that it does not allow for electricity storage in the vehicle batteries from one day to another, i.e. even though there is good overall representation of the demand profiles from the representative days there is no information on the interlinkages between such representative days.

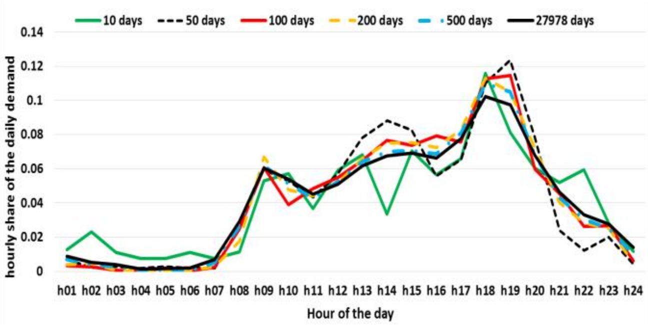

Fig. 1 The share of the daily driving distance distributed over the day for different number of sample sizes of representative days where 27 879 days is the full sample size.

2.2.4. Yearly driving profiles

The car movement data base includes, with high-quality data, 426 vehicles measured between 50-100 days per vehicle, i.e. no vehicle with a full year of logging. Another approach, than using representative days, is to use the measured driving period per vehicle and extrapolate it from the original period to 12 months. This means that the driving data for each vehicle was used repeatedly with respect to days of the week so that the driving data always is the same weekday as other data in the model. The main advantage with this method is that storing of electricity between days can be captured, without overestimating the potential of the batteries since individual driving patterns is included in the model. The main disadvantage with this approach is that for some yearly driving profiles the driving during certain months will represent the driving for all other seasons. The average yearly driving per vehicle for these 426 vehicles is 15 043 kilometer per year.

Fig. 2 shows the driving profile for an average day, i.e. share of the daily driving distance distributed over the day, for a number of representative daily driving profiles (200 days, 426 days and 27 879 days), as well as, 200 and 429 yearly driving profiles. As seen in Fig. 2, representative days or extrapolate the data to yearly driving profiles from the data set gives approximately the same average driving profile and thereby also the same average profile for the fleet connected to the grid.

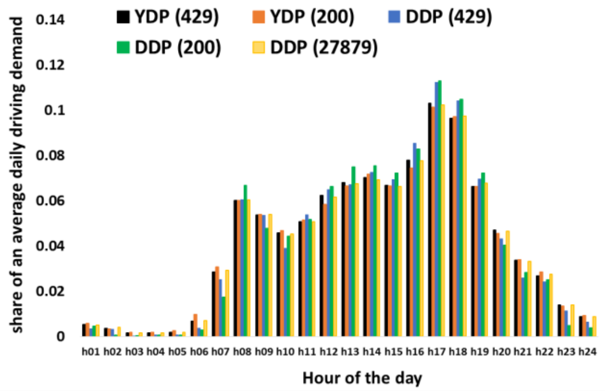

Fig. 2 Driving profiles for an average day (i.e. share of the daily driving distance distributed over the day) for 200, 429 and 27987 representative daily driving profiles (DDP), as well as, 200 and 429 yearly vehicle driving profiles (YDP).

2.3. Vehicle data

The passenger car fleet is assumed to increase by 35% until Year 2050 compare to Year 2016 and the EV share of the total fleet Year 2050 is set to 60%. The number of EVs in the model is 2.3, 1.7, 2.7 and 5.2 million in central-Sweden (SE2), Ireland (IE), Hungary (HU) and central-Spain (ES3), respectively. The rates of fuel consumption at the wheels are assumed to be 0.16 kWh per km for passenger EVs and the EV battery size is 30 kWh (i.e. a driving range of approximately 190 km) for all vehicles and varied in a sensitivity analysis assuming 10 kWh and 85 kWh.

2.4 Scenarios

The model is run assuming three different methods of integrating the EV driving data in a greenfield electricity system model: (i) aggregated vehicle fleet (AGG), (ii) representative daily driving profiles (DDP), and (iii) yearly driving profiles (YDP). Further, these three integrating approaches are compared assuming two charging strategies for passenger EVs: an optimisation of the charging time to minimise the cost of meeting the electricity demand (Opt) and a passenger vehicle-to-grid (V2G) strategy which also includes the possibility to discharge the EVs to the grid. All the scenarios are analysed for following geographical regions that have large differences in wind, hydro and solar resources: central-Sweden (SE2) with a lot of hydro power; Ireland (IE) with good wind conditions; central Spain (ES3) with good solar conditions; and Hungary (HU) a region with relatively poor conditions for wind and solar generation. It is assumed that Ireland, central-Spain and Hungary have the same driving patterns as the region in Sweden, where the data is collected.

3. RESULTS

3.1 Aggregated battery storage level and charging patterns

Fig. 3a shows the aggregated storage level of the EVs batteries in central-Spain (ES3) for a period of 90 days and the three different integration approaches (AGG, DDP and YDP) with a 30 kWh battery and the possibility to do V2G. DDP, without the possibility to store electricity between days, can only handle day-night differences in electricity generation and load (Fig. 3a). Day-night variations are important for integrating more solar PV in the electricity system. Thereby, with a DDP approach none of the hours uses the fully potential of the aggregated EV battery capacity (i.e. 155 GW in ES3). The YDP approach shows similar battery storage levels, as the AGG approach. The EV batteries are then used both to handle the day-night differences in solar PV generation and providing storage of electricity for several days (Fig. 3a). The possibility to store electricity for more than a couple of hours becomes important when providing system flexibility for wind power.

Fig. 3b shows the storage level of the aggregated EV batteries for three different battery sizes (10 kWh, 30 kWh and 85 kWh) assuming V2G, where the battery size 30 kWh is shown both for the charging strategies Opt and V2G. An optimised charging strategy without V2G, can still provide flexibility to the system in term of demand response for the charging, however, not to the same extent as with V2G (Fig. 3b). The maximum battery capacity with the larger battery sizes (30 and 85 kWh) are never fully used if storing of electricity in the EV batteries are limited to 24 hours, as with the DDP approach. However, as seen in Fig. 3b, the full battery capacity of also the larges battery size tested is used with the YDP and AGG approaches, for several hours during the year. Fig.3a also indicates that on an aggregated storage level, AGG and YDP provide similar result and AGG does not seem in this scenario to overestimate the use of the battery capacity to do V2G.

The same trends seen in Fig. 3 for central-Spain (ES3) can also be seen for the other regions investigated. Important to mention is also that Fig.3 gives the aggregated storage level, where large differences among the 426 profiles exists (see 3.2). The freedom to use the batteries for V2G as in Fig. 3, depends on assumptions of charging infrastructure access, number of EVs and the dimensioning of the battery relative to the daily driving distances. However, already with a 10 kWh battery (and definitely with a 30 kWh battery), the battery size is large compare to the average daily driving distance for a majority of the 426 driving profiles.

Fig. 4 shows the duration curves of the discharging back to the grid in central-Spain (ES3) for the aggregated fleet that reach zero after about 4392 hours. An 85 kWh battery size, for both YDP and AGG, can provide more peak power capacity of up to 12 GW, which can be compared to 10 and 8 GW for a battery size of 30 kWh and 10 kWh, respectively. The discharging to the grid in central-Spain, Ireland/Sweden and Hungary is ~9TWh, ~1TWh and ~4 TWh, respectively, assuming a battery size of 10 kWh, and increases with 13% to 100% if assuming 30 kWh and 85 kWh battery sizes.

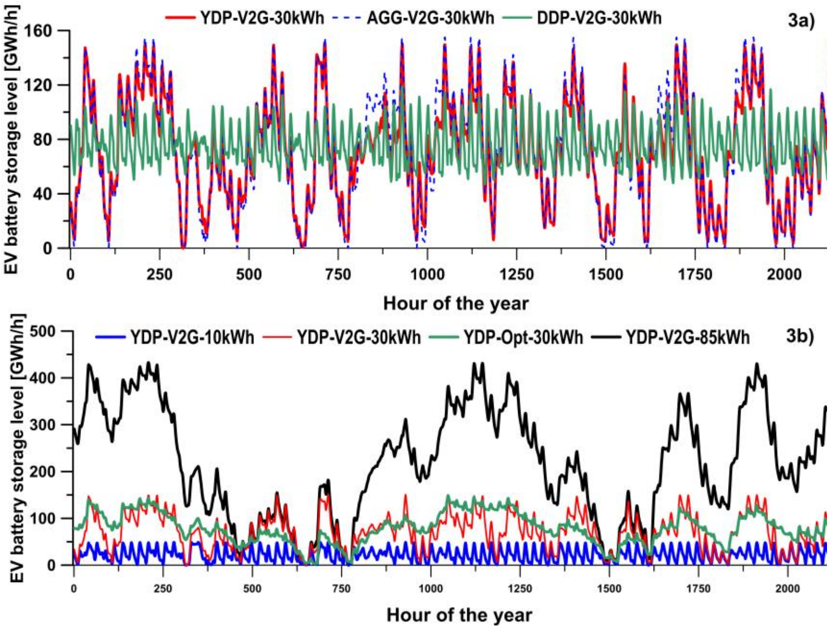

Fig. 3 Aggregated storage level of the EVs batteries for the first 90 days of the year in central-Spain (ES3) comparing the three different EV integration methods (AGG, YDP, DDP) for the scenario with 30 kWh battery and possibility to do V2G (a) and YDP comparing the three different battery sizes with V2G and Opt (b).

3.2 Individual battery storage level and charging patterns

The results from the modelling shows that the different individual EVs are charged and discharged very differently both assuming DDP and YDP. Fig. 5 shows the charging, transport energy demand (i.e. load) and discharging back to the electricity grid during 90 days (the same as in Fig. 3) for three out of the 426 YDP. The EVs with the largest yearly driving distance (~58432 km per year), Fig.2c) Maximum, have more limited possibility to store electricity for several days and discharge back to the grid due to limitations of the battery capacity, as well as availability in the electric grid. However, EVs with a low yearly driving distance (~1658 km per year), Fig.2a) Minimum, and the median EV driving distance (~ 15137 km per year) are to a large extent used for discharging back to the grid, since shorter driving distance means more time connected to the grid, as well as, less hours of the duration of charging the battery to be used for driving. In the Maxiumum, Minimum and Median cases, the amount of charging taking place at home is approximately XX%, XX% and XX%, respectively. The share of the home charging for all 426 profiles is XX% per year. The same numbers for discharging (i.e. share of the discharing at home location) are on average XX% per year. Thereby, the EVs vehicles need to, at a relative large extent, be connected to the grid also when not being home, to provide the optimal flexibility for the electricity system modelled in this study. The large differences in charging patterns for the three profiles in Fig. 5, gives an indication that there are scenarios where individual driving patterns are important to consider when doing energy system modelling, for example: (i) if there are a much less share of EVs than 60% of the fleet, and (ii) if also analysing the degradation impact on the batteries since the batteries will be cycled differently for the different driving profiles.

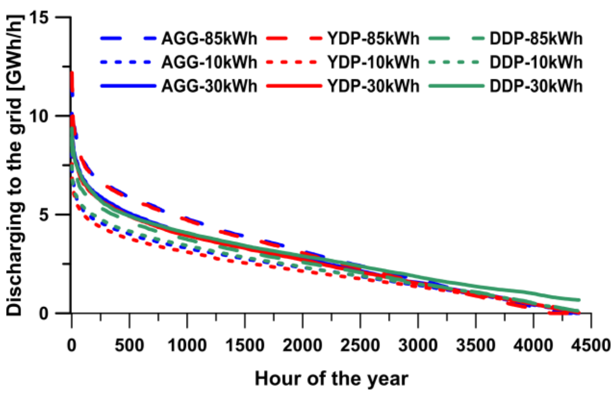

Fig. 4 Duration curve of the discharging to the grid in central-Spain (ES3) for the hours of the year with highest values.

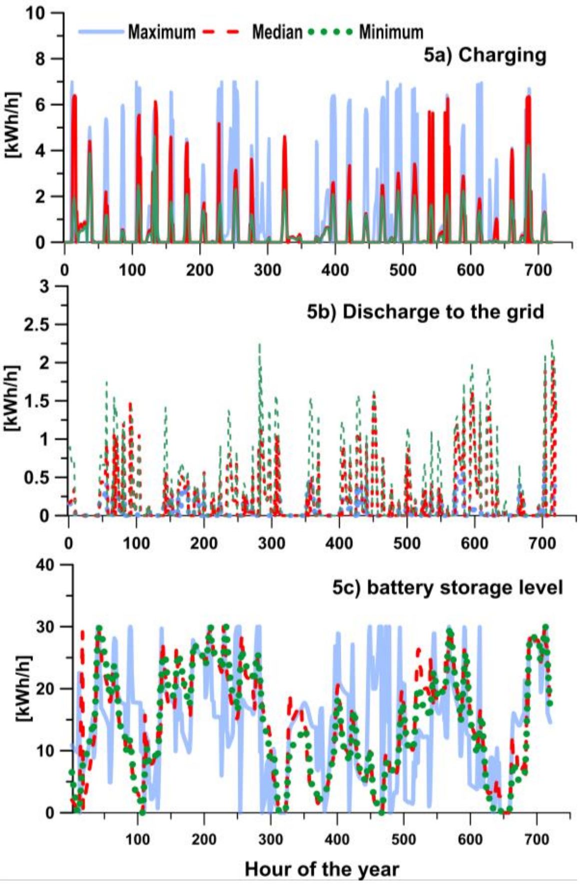

Fig. 5 Charging (a), discharging to grid (b) and battery level (c) for the first 30 days for 3 out of the 426 yearly driving profiles. The profiles chosen are one with longest (Maximum), shortest (Minimum) and median (median)yearly driving distance.

3.3 Investments in capacity and renewable electricity

Fig.6 shows the investments in peak power, renewable power (wind and solar) and other storage technologies (batteries and hydrogen) for a scenario without EV, different EV scenarios and regions. There are several interesting results shown in Fig. 6: (i) with the DDP approach more investments in peak power and gasifiers are needed to supply the hours with the highest demand compared to the YDP and AGG approaches, (ii) without EVs and with an optimisation charging strategy (Opt) investments in other storage technologies (i.e. stationary batteries in central-Spain and hydrogen storage in Ireland) are important to provide flexibility to the electricity system, but with a V2G strategy the EV batteries can provide that flexibility instead of other storage technologies, and (iii) to increase the investments in wind power, the battery size and the possibility to store electricity between days (as with YDP and AGG) becomes important, and thus, the methodology of describing the transportation need as well as how to represent the EV batteries.. In Ireland, with relative poor solar conditions, the investment in solar power is decreasing with V2G and larger batteries (Fig. 6), mainly due to solar power acting as a peak power technology.

Fig.7 shows the share of variable electricity generation (vRE, i.e. generation from solar and wind power) for the different regions and scenarios (both with and without EVs). The share of vRE is higher in all scenarios with EVs compare to the scenario without EVs. DDP shows in Fig. 7 a lower share of generaton from solar and wind power than YDP/AGG for the same battery size and charging strategy (Opt/V2G). This is mainly due to the possibility to store electricity for longer time periods with YDP/AGG. As seen in Fig. 7, the share of solar and wind power, also increases if (i) V2G is applied compare to only optimising the charging, and (ii) with larger battery size since more electricity can be stored during days with high output from wind power and discharged back to the grid at days with low wind power generation. For example increases the share of the electricity generation from variable renewable electricity sources in Hungary from 42% without EVs, to 47%-72% with EVs, depending on scenario (Fig. 7). The curtailment of solar and wind power decreases also when introducing EVs, which makes vRE more economical profitable.

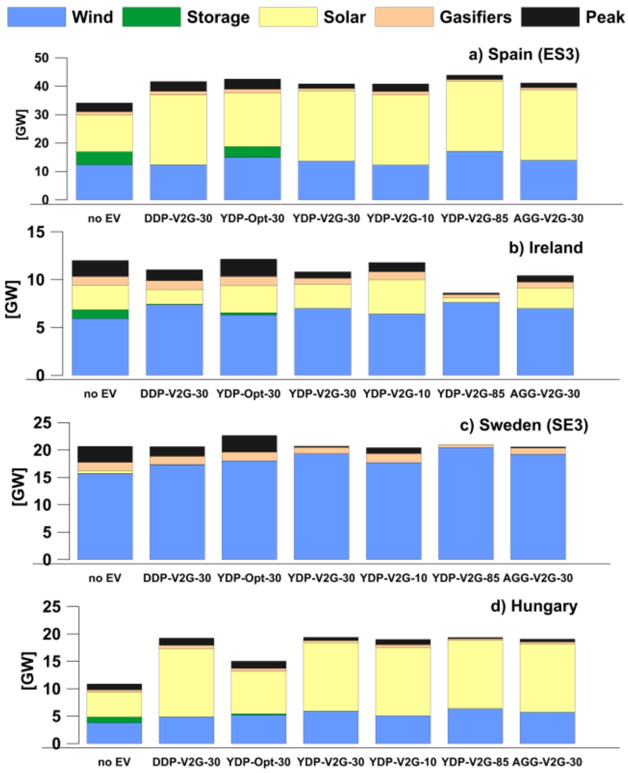

Fig. 6 Investments in peak power, variable renewable power and other storage technologies for a scenario without EV, different EV scenarios and regions. The number on the x-axis represents battery sizes.

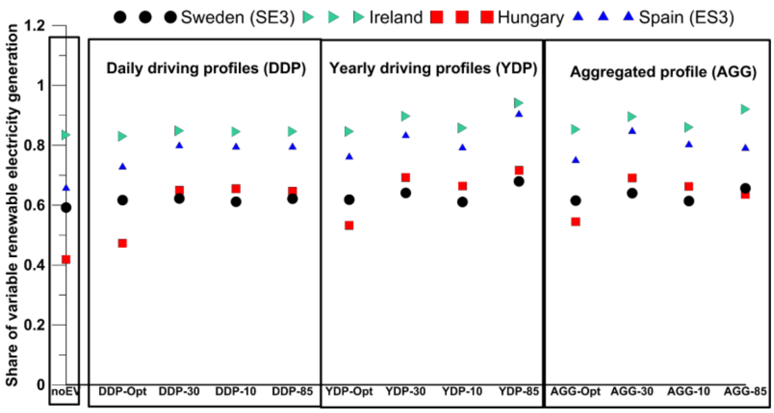

Fig. 7 Share of the electricity generation from variable renewable electricity sources (solar and wind power) for the different regions and scenarios. The number on the x-axis represents battery sizes.

4. CONCLUSION

This study shows how three different methods of integrating EV driving data in electricity system models can be done, where two of the methods includes individual driving patterns (i.e. 200 daily driving profiles and 426 two-months profiles extrapolated to a full year driving profiles). Individual driving patterns are necessary to represent the spread in driving patterns, in terms of diversity on longer time scales than one day, and thereby enable a realistic representation of battery availability in the electric grid. The main conclusions are that different driving profiles have a clear impact on the individual charging and discharging back to grid depending on the daily driving distance, battery capacity and the driving profile. However, an aggregated approach can be a good proxy in the event of relatively large total battery capacity present in the electricity generation system compared to the services required from them. Sufficient battery capacity will have an impact on the electricity system, e.g. in investments of peak power capacity, and thus, there is a potential role of EVs to facilitate increased employment of variable renewable power, such as wind and solar power.

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