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Methodology for modelling plug-in electric vehicles in the power system and cost estimates for a system with either *smart* or *dumb* electric vehicles

Juha Kiviluoma [a,*], Peter Meibom [b]

[a] *VTT Technical Research Centre of Finland, P.O. Box 1000, 02044 VTT, Finland*
[b] *Risø DTU, Technical University of Denmark, P.O. Box 49, DK-4000 Roskilde, Denmark*

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ABSTRACT

The article estimates the costs of plug-in electric vehicles (EVs) in a future power system as well as the benefits from smart charging and discharging EVs (smart EVs). To arrive in a good estimate, a generation planning model was used to create power plant portfolios, which were operated in a more detailed unit commitment and dispatch model. In both models the charging and discharging of EVs is optimised together with the rest of the power system. Neither the system cost nor the market price of electricity for EVs turned out to be high (36–263 €/vehicle/year in the analysed scenarios). Most of the benefits of smart EVs come from smart timing of charging although benefits are also accrued from provision of reserves and lower power plant portfolio cost. The benefits of smart EVs are 227 €/vehicle/year. This amount has to cover all expenses related to enabling smart EVs and need to be divided between different actors. Additional benefits could come from the avoidance of grid related costs of immediate charging, but these were not part of the analysis.

1. Introduction

Higher transport fuel prices due to oil scarcity and decreasing costs for plug-in electric vehicles (EVs) have the potential to roll-out EVs on a large scale. Large-scale introduction of EVs could bring major changes to the power system operations and to the power plant investments. This article attempts to explore the most important system-wide effects from both perspectives.

The charging of the vehicle batteries without any control is likely to result in a new peak in electricity demand during the late afternoon. The new peak could be avoided and the shape of electricity demand flattened with optimised timing of the battery charging, e.g. smart charging. Smart EVs could also bring other benefits to the power system by participating in ancillary services. In contrast, dumb EVs will start charging immediately after plugging in and would keep charging until their batteries are full. When comparing a power system to a hypothetical national car fleet consisting only of EVs, the vehicle fleet has much more power capacity than the power system. However, in most cases available capacity from EVs would be limited by household electrical wirings. These can usually handle much smaller power flows than the batteries could charge or discharge. Even when taking the limitations of EV grid connections into account, EVs potentially constitute a large resource of flexible demand suitable for providing up and down regulation and reserve power.

There have been several articles and reports about the possible benefits from the participation of EVs in the electricity markets. Articles [1–3] and dissertation [4] represent calculations of the possible benefits of using EVs and fuel cell vehicles as a new power source, in which the authors use power market prices as a reference. Several vehicle setups and electricity markets are analysed. In reports [5,6], a dispatch model is used to estimate the cost of charging plug-in hybrid EVs (PHEVs). The generation portfolio is taken from an external estimate and is not influenced by the introduction of the flexible demand from PHEVs. The PHEVs are dispatched according to a preset schedule, and no vehicle-to-grid (V2G) is considered. Article [7] considers the effect of EVs on future generation portfolios and uses a simplified model to dispatch EVs on top of the demand profile. V2G or the use of EVs as reserves was not considered. Report [8] estimated the effect of PHEVs on future generation portfolios and report [9] analysed how dispatch might be affected. Costs and benefits were not analysed. In article [10], the costs and benefits of the use of vehicle batteries for peak shaving were calculated. Article [11] simulated the effect of the electricity consumption from the EVs on the CO_2 emissions. The results were based on the assumption that the emissions of the marginal power plants would be allocated to EVs. Article [12] analyses the effect of smart EVs in integrating variable wind power.

* Corresponding author. Tel.: +358 20 722 6671; fax: +358 20 722 7048.
E-mail address: juha.kiviluoma@vtt.fi (J. Kiviluoma).

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Nomenclature

Indices

g, G vehicle groups
n, N stochastic scenarios
t, T hourly time steps
tArr(t) hours when vehicles arrive to the grid
tLeave(t) hours when vehicles leave the grid
day, D days within the optimization

Endogenous variables

$S^{Grid}_{g,n,t}$ storage level in grid-connected batteries
$S^{Leav}_{g,n,t}$ storage level in batteries leaving the grid
$S^{Arr}_{g,n,t}$ storage level in batteries arriving to the grid
$E^{Charge}_{g,n,t}$ charging
$E^{ChargeDayAhead}_{g,n,t}$ day-ahead scheduled charging
$E^{ChargeUp}_{g,n,t}$ increase to the day-ahead scheduled charging
$E^{ChargeDown}_{g,n,t}$ decrease to the day-ahead scheduled charging
$E^{Discharge}_{g,n,t}$ discharging
$E^{DischargeDayAhead}_{g,n,t}$ day-ahead scheduled discharging
$E^{DischargeUp}_{g,n,t}$ increase to the day-ahead scheduled discharging
$E^{DischargeDown}_{g,n,t}$ decrease to the day-ahead scheduled discharging
$E^{Motor}_{g,n,t}$ production of grid electricity with a motor in a plug-in hybrid
$S^{Add}_{g,n,tLeav}$ stored electricity above the required minimum for a group of vehicles leaving the grid at tLeav
$R^{PosNonSpin}_{g,n,t}$ positive non-spinning reserve by discharging
$R^{PosSpin}_{g,day}$ positive spinning reserve by discharging
$R^{NegSpin}_{g,day}$ negative spinning reserve by means of discharging less than originally committed
$R^{NegSpinChrg}_{g,day}$ negative spinning reserve by promising to increase the charging
$R^{PosSpinChrg}_{g,day}$ positive spinning reserve by promising to reduce the charging
$R^{PosNonSpinChrg}_{g,n,t}$ positive non-spinning reserve by promising to reduce the charging

Parameters

C_g maximum charge capacity
D_g maximum discharge capacity
$v^{Arr}_{g,n,t}$ share of vehicles arriving to the grid
$v^{Leav}_{g,n,t}$ share of vehicles leaving the grid
$v^{Grid}_{g,n,t}$ share of grid-connected vehicles
$v^{Arr}_{g,n,t,tLeav}$ share of vehicles arriving to the grid at hour t, that have left the grid at hour tLeav
$s_{g,min}$ minimum amount of stored electricity a vehicle group must have when it leaves the grid
$s_{g,max}$ capacity of battery storage in a group of vehicles
$V^{ArrCons}_{g,n,t}$ consumption of electricity during the road trip
Eff efficiency of the charge/discharge processes

This article tries to improve earlier work by using a stochastic mixed-integer unit commitment and dispatch model in combination with a generation planning model. The unit commitment and dispatch model is named wind power integration in liberalised electricity markets (WILMAR) [13,14] and the generation planning model is named Balmorel [15,16]. Balmorel takes into account that as the demand curve changes, the investment patterns into power plants will also change. This in turn will influence the total cost of the power system. Furthermore, increased demand-side flexibility will make investments in base load or variable production more competitive against intermediate and peak production plants. Up and down regulation of power production due to load and wind power forecast errors take place in WILMAR. Hence, it can quantify the value of EVs providing the needed flexibility to cope with the partial predictability of load and wind.

For this article, an EV model was developed and incorporated in WILMAR. The methodology includes more detailed data and equations of the vehicle behaviour than in previous studies. Furthermore, the operational model can utilize the EVs for correcting prediction mistakes in demand and in variable generation as well as for reserve purposes.

The purpose of the scenario runs was to examine the impact of various assumptions about the behaviour of the EVs and their use in the power system. How often the capabilities of smart EVs are really used is up to the functioning of the power system, which is largely determined by the markets that operate around the system. Benefits are estimated by comparing the costs of a power system with smart EVs and forced dumb-charging EVs. In addition, when compared with a scenario not having EVs, the smart and dumb EV scenarios also give lower and upper estimates for the increased cost of the power system with EVs. Respective market prices and CO_2 emissions of the vehicles are derived from the results. We also examined how the use of some modelling methodologies would influence the results.

It is clear that the benefits of smart EVs will be system-dependent. In the analysis of the results, the causes of the benefits are displayed, and this should increase understanding concerning which situations the benefits might be larger or smaller in, even if only one system is analysed. If EVs become commonplace, there will be a need for more detailed studies focusing on a certain power system during a specific period.

In Kiviluoma and Meibom [17], the effect of increasing the quantity of EVs in the system was calculated. The main conclusion is that the system benefits per smart vehicle decrease substantially with an increasing number of EVs. This paper continues the analysis by examining the sources of the benefits when the EV penetration is high (about half of the active personal vehicle fleet). We have estimated the share of benefits from various ancillary services and from the use of the V2G. V2G could increase the benefits of smart EVs by enabling the EVs to discharge their batteries to the power grid at times when it is economic to do so.

The article is structured in the following manner. The WILMAR model is described first. Then the equations to handle EVs in WILMAR are presented. The derivation of the data for the behaviour of EVs is next. It is followed by a description of the scenarios. The scenarios depict a hypothetical power system in 2035 based on results from Balmorel and data from the Finnish power system. Next, the results from the scenarios are presented. Lastly, the methodology and the results are discussed.

2. Methodology

2.1. Model description

The WILMAR model has been enhanced with an EV model. WILMAR analyses electricity markets based on a description of generation, demand and transmission between model regions in hourly time resolution and derives electricity market prices from marginal system operation costs. The unit commitment decision is most correctly modelled using binary variables leading to a mixed integer programming (MIP) problem. A linear approximation – where the model is allowed to bring only parts of a power plant online – has also been implemented, due to calculation time considerations. The model treats wind power production and electricity demand as optional stochastic input parameters. The stochastic scenarios for wind power and load are generated, but they mimic the characteristics of real forecasts and forecast errors. WILMAR optimises unit commitment in a day-ahead market and corrects for emerging prediction errors in intraday market clearings. It also sets requirements for spinning[1] and non-spinning reserve[2] capacity. It is assumed that the latter will be influenced by the predicted wind power production in the year 2035. Production of district heating or process heat in combined heat and power (CHP) plants is included in this model, as CHP plants are important in the case of Finland. The model handles the use of hydropower reservoirs through water values, which are derived by an algorithm ensuring that the reservoir levels in the model follow historical reservoir levels during the year. A more detailed description of the model is given in Refs. [13,14].

For current analysis, we have assumed no transmission bottlenecks. However, transmission bottlenecks are common in many power systems and can have important impacts on the benefits of EVs.

2.2. Data for the behaviour of the EVs

EVs need to be grid-connected in order to be charged or discharged. Since the number of vehicles is very large, statistical behaviour is rather predictable, though individual drivers might behave erratically. We assumed that there are two possible places where the vehicles might be plugged in: at work and at home. Most people would be plugging in only at home; some would do it at both locations and only a few solely at work. The data used for estimating the leaving and arriving vehicles was derived from the National Travel Survey conducted during 2004–2005 in Finland [19]. It provided information on the timing and distance of travel with personal vehicles as well as data on the purpose of all travel. Available travel data was one of the reasons to model the Finnish energy system. The information was processed to estimate when people driving cars may arrive at their workplaces as well as at home, and what kind of distances they had travelled before that.

It was assumed that people plug-in once they arrive and that 98% do this at home and 20% at work. The data was used to derive typical daily driving patterns on an hourly time scale, and these were modified to take into account typical differences between weekdays, Fridays, Saturdays, Sundays, holidays and weekdays between a holiday and a weekend. A weekly index which held the changes in driving over the year was multiplied into the data. The index was calculated from the same National Travel Survey. Then assumptions about specific consumption of grid electricity (0.2 kWh/km)[3] and plugging in were overlaid on the data. Vehicles arriving during different hours of the day have, on average, different trip lengths behind them, and this was also taken into account.

All this lead to a couple of full-year input time series on an hourly time scale for the power system model:

- Share of vehicles plugged in. This affects the size of the usable electricity storage and the charging and discharging capacities. ($v^{\mathrm{Grid}}_{g,n,t}$)
- Share of vehicles leaving the grid. ($v^{\mathrm{Leav}}_{g,n,t}$)
- Share of vehicles arriving to the grid and plugging in ($v^{\mathrm{Arr}}_{g,n,t}$)
- Arriving vehicles have partially empty batteries due to the consumption during driving. ($V^{\mathrm{ArrCons}}_{g,n,t}$)
- A link between vehicles leaving at certain hours and arriving at a later hour was established. A rather complex model was developed to create realistic schedules from the available data while ensuring consistency between the number of arriving and leaving vehicles. The model is not yet documented. ($\sum_{tLeav=t_0 \ldots t_{current-1}} S^{\mathrm{Add}}_{g,n,tLeav} \cdot v^{\mathrm{Arr}}_{g,n,t,tLeav}$)

Recharging is usually limited by the capacity of electric wiring or charger. Batteries could usually take more amperes, though many battery types can prolong their lifetime with slower charging. For PHEVs, charging capacity was set to an average of 4 kW per vehicle, and for full EVs (FEVs) that use only electricity (also known as battery EVs) it is 6 kW[4]. Average consumption of grid electricity was 0.2 kWh/km. The assumed usable size was 40 kWh for EV batteries to achieve a 200 km range and 20 kWh for PHEV batteries to achieve a 100 km all electric range[5]. On average, a vehicle makes three trips per day at a combined distance of 52 km and has a charge opportunity every 39 km. All the EV scenarios had one million EVs: a yearly consumption of half a million of FEVs amounted to 2.16 TWh, and the same for half a million PHEVs was 1.83 TWh.

2.3. The EV model

The model for EVs treats the vehicles as electricity storages which are not always connected to the power grid and, while gone, spend some of their stored electricity. An important part of the model is the data for the share of vehicles arriving and leaving the network, which is described later.

Each vehicle type has its own general electricity storage pool in each model region. It would naturally be more correct to have separate storage for each vehicle, but the problem would not be possible to solve with thousands of vehicles, and some simplification has to be made. Restrictions were applied to keep the influence of aggregation small (Eqs. (12), (13) and (16)). Similarly, aggregation of storages is common in modelling reservoir hydropower.

When a vehicle leaves the network, it takes electricity from the storage pool and when it arrives in the network, it releases what is left to the pool (Eq. (1)).

$$S^{\mathrm{Grid}}_{g,n,t} = S^{\mathrm{Grid}}_{g,n,t-1} - S^{\mathrm{Leav}}_{g,n,t} + E^{\mathrm{Charge}}_{g,n,t} \cdot \mathrm{Eff}_g - \frac{E^{\mathrm{Discharge}}_{g,n,t}}{\mathrm{Eff}_g} + S^{\mathrm{Arr}}_{g,n,t} \quad \forall \ g \in G, n \in N, t \in T \tag{1}$$

[1] Spinning reserves in these model runs refers to the frequency controlled reserves (both normal operation and disturbance) that have been allocated to Finland by Entso-E Nordic [18].

[2] Non-spinning reserve or replacement reserve is the fast active disturbance reserve allocated to Finland by Entso-E Nordic [18]. They need to be available within 15 min.

[3] The estimate is somewhat high in comparison to the estimates quoted for the near-term EVs. However, the near-term EVs are usually small in comparison to average vehicle size and therefore not representative of the consumption in an average vehicle. It should also be noted that WILMAR requires the consumption of grid electricity and the estimate has to include charging and network losses. Rousseau et al. [20] provides estimates for pre-transmission energy consumption for midsize car, cross-over sub-urban vehicle (SUV) and midsize SUV and our estimate is in comparable range.

[4] It was assumed that it will be more beneficial for FEV users to install three-phase plugs, since they cannot rely on fuel if the batteries are not charged fast enough. One-phase 220 V connection with either 10 A or 16 A could provide 2.2 kW or 3.5 kW while a three-phase plug with 25 A could provide 10 kW.

[5] The ranges are higher than what are expected for the first series production EVs, but the analysis is made for 2035 and by that time batteries could be cheap enough to justify the higher range. PHEV prototype vehicle ranges are quoted in Bradley and Frank [21]. For EVs the average range will be very dependant on the highly uncertain battery cost as demonstrated by Kromer and Heywood [22].

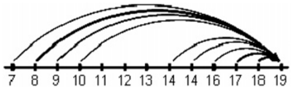

Fig. 1. Simplified example pattern of electric vehicles arriving at the power grid at 19.00 h. The thicker the line, the greater the share of vehicles which return to the network at that time.

Charging and discharging are divided into parts (Eqs. (2) and (3)). $E^{\mathrm{ChargeDayAhead}}$ is determined during the clearing of the day-ahead spot market. E^{ChargeUp} and $E^{\mathrm{ChargeDown}}$ can modify this during the intraday solves, taking updated wind power production and demand forecasts into account.

$$E^{\mathrm{Charge}}_{\mathrm{g,n,t}} = E^{\mathrm{ChargeDayAhead}}_{\mathrm{g,n,t}} + E^{\mathrm{ChargeUp}}_{\mathrm{g,n,t}} - E^{\mathrm{ChargeDown}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T} \tag{2}$$

$$E^{\mathrm{Discharge}}_{\mathrm{g,n,t}} = E^{\mathrm{DischargeDayAhead}}_{\mathrm{g,n,t}} + E^{\mathrm{DischargeUp}}_{\mathrm{g,n,t}} - E^{\mathrm{DischargeDown}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T} \tag{3}$$

The model includes a relation between the vehicle departure and arrival times. In Fig. 1 there is an example pattern of EVs that arrive at 7 pm in the network. Some of them had left in the morning and some of them during the afternoon. This influences the calculated consumption of electricity during the trip, since the distribution of trip lengths varies throughout the day. Furthermore, there can be system benefits if the batteries do not need to be completely full upon departure. Eq. (4) enables this option. The arriving storage content S^{Arr} is a sum of the electricity EVs took with them deducted by the consumption of electricity on the road. If EVs had to have full batteries on departure, the minimum level would be the same as the maximum, and variable s^{Add} would not be used. In the event that EVs are not required to leave with a full battery, the variable s^{Add} will hold the additional electricity above the minimum level required (Eq. (4)).

$$S^{\mathrm{Arr}}_{\mathrm{g,n,t}} = \nu^{\mathrm{Arr}}_{\mathrm{g,n,t}} \cdot s_{\mathrm{g,min}} + \sum_{\mathrm{tLeav} = \mathrm{t_0} \ldots \mathrm{t_{current-1}}} S^{\mathrm{Add}}_{\mathrm{g,n,tLeav}} \cdot \nu^{\mathrm{Arr}}_{\mathrm{g,n,t,tLeav}} - V^{\mathrm{ArrCons}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T} \tag{4}$$

Eqs. (5) and (6) set a minimum level for the leaving battery and a variable additional charge for the model to optimise. Partially full batteries can provide additional flexibility for the power system and be economic in situations where electricity prices have been exceptionally high during the previous charge opportunity. Partially full departing batteries can be realistic in situations where a person either owns a PHEV or normally drives short daily distances by means of an EV that has a long range. The equations mean that all the vehicles of same type join one electricity storage pool upon arrival.

$$S^{\mathrm{Leav}}_{\mathrm{g,n,t}} = \nu^{\mathrm{Leav}}_{\mathrm{g,n,t}} \cdot s_{\mathrm{g,min}} + \sum_{\mathrm{tArr\ iff\ tLeav = t}} s^{\mathrm{Add}}_{\mathrm{g,n,tLeav,tArr}} \quad \forall\ \mathrm{g} \in \mathrm{G}; \mathrm{n} \in \mathrm{N}; \mathrm{t}, \mathrm{tArr}, \mathrm{tLeav} \in \mathrm{T} \tag{5}$$

$$s^{\mathrm{Add}}_{\mathrm{g,n,t}} \le s_{\mathrm{g,max}} - s_{\mathrm{g,min}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T} \tag{6}$$

In the model, EVs are assumed to leave the network at the start of the hour. Therefore, batteries need to be charged during the previous hour. In real life, EVs leave all the time during the hour. This creates a small buffer, so that on average an EV has to be charged 30 min before it is actually used.

The minimum storage content is restricted by the use of reserves. There has to be enough electricity in the batteries to be able to produce for a while, if there is a need to use the committed reserves (Eq. (7)).

$$S^{\mathrm{Grid}}_{\mathrm{g,n,t}} \ge R^{\mathrm{PosNonSpin}}_{\mathrm{g,n,t}} + R^{\mathrm{PosSpin}}_{\mathrm{g,day}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T}, \mathrm{day} \in \mathrm{D} \tag{7}$$

A set of equations restricting the abilities to charge/discharge and provide reserves according to available capacities are also required. The WILMAR model already incorporates electric storage and many of the equations used there also apply to EVs (Fig. 2).

Eq. (8) limits the sum of actual charging and negative spinning reserve that is based on increasing the charging of the vehicles. The limit is the charging capacity of the vehicles plugged-in during each hour.

$$E^{\mathrm{Charge}}_{\mathrm{g,n,t}} + R^{\mathrm{NegSpinChrg}}_{\mathrm{g,day}} \le C_{\mathrm{g}} \cdot \nu^{\mathrm{Grid}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T}, \mathrm{day} \in \mathrm{D} \tag{8}$$

Eq. (9) restricts the sum of positive reserves that are available from decreased charging. This has to be lower than the actual charging of the vehicles.

$$R^{\mathrm{PosNonSpinChrg}}_{\mathrm{g,n,t}} + R^{\mathrm{PosSpinChrg}}_{\mathrm{g,day}} \le E^{\mathrm{Charge}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T}, \mathrm{day} \in \mathrm{D} \tag{9}$$

In Eq. (10), the positive reserve from increased discharging of the vehicles has to be lower than the capacity of the vehicles to discharge, minus the current level of discharge.

$$R^{\mathrm{PosNonSpin}}_{\mathrm{g,n,t}} + R^{\mathrm{PosSpin}}_{\mathrm{g,day}} \le D_{\mathrm{g}} \cdot \nu^{\mathrm{Grid}}_{\mathrm{g,n,t}} - E^{\mathrm{Discharge}}_{\mathrm{g,n,t}} \quad \forall\ \mathrm{g} \in \mathrm{G}, \mathrm{n} \in \mathrm{N}, \mathrm{t} \in \mathrm{T}, \mathrm{day} \in \mathrm{D} \tag{10}$$

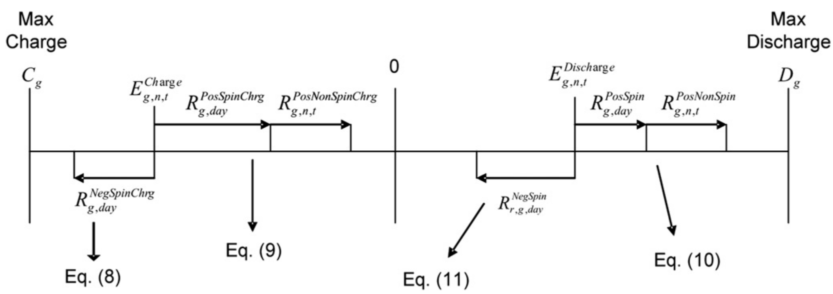

Fig. 2. Equations in WILMAR to limit the use of reserves based on electricity storages like EVs.

Negative spinning reserve from discharging requires that the discharging is decreased and this reserve should therefore be restricted to the level of discharging (Eq. (11)).

$$R^{\text{NegSpin}}_{g,\text{day}} \le E^{\text{Discharge}}_{g,n,t} \quad \forall \; g \in G, n \in N, t \in T, \text{day} \in D \tag{11}$$

These equations are designed for single large storage. However, the storage from EVs is formed from a large number of separate small storages. This will pose additional limitations to the use of the capacity from the storages. Individual vehicle storages do not fill up all at once – as single large storage would do. When the total storage level is for example 80% full, half of the vehicles might already have completely full storage, since the vehicles try to fill their batteries during the lowest prices. These vehicles cannot provide reserves that are based on increased charging. Therefore, a new Eq. (12) was introduced as shown by Fig. 3. There was no data available to estimate the form of the function. However, since it is apparent that more and more vehicles will have full batteries when the single large storage approaches full, a value for '*a*' and '*b*' in Eq. (12) had to be estimated. Both '*a*' and '*b*' were set to 1.6 for the scenarios presented in the results. By doing this we have assumed that after the single large storage is 38.5% full, the share of full vehicle batteries will start to linearly approach 100% and charging capacity will decrease accordingly. Similarly, discharging should be restricted, and this is presented in Eq. (13). When the model was used, Eq. (12) was often binding, while Eq. (13) was not.

$$E^{\text{Charge}}_{g,n,t} + R^{\text{NegSpinChrg}}_{g,\text{day}} \le C_g \times \left[-a \cdot S^{\text{Grid}}_{g,n,t} \Big/ \left(v^{\text{Grid}}_{g,n,t} s_{g,\max} \right) + b \right] \quad \forall \; g \in G, n \in N, t \in T, \text{day} \in D \tag{12}$$

$$E^{\text{Discharge}}_{g,n,t} + R^{\text{PosNonSpin}}_{g,n,t} + R^{\text{PosSpin}}_{g,\text{day}} \le D_g \times \left[\frac{a \cdot S^{\text{Grid}}_{g,n,t}}{v^{\text{Grid}}_{g,n,t} \cdot s_{g,\max}} \right] \quad \forall \; g \in G, n \in N, t \in T, \text{day} \in D \tag{13}$$

The model can handle both FEVs and PHEVs. In the data set, PHEVs have lower average consumption of electricity during road trips, since it is assumed that some part of the total mileage is done with the energy from the engine. This was calculated from the trip lengths in the vehicle travel data. Some share of PHEVs can also run their engine to produce power or ancillary services for the grid while being plugged in (Eq. (14)).

$$E^{\text{Motor}}_{g,n,t} + E^{\text{Discharge}}_{g,n,t} + R^{\text{PosNonSpin}}_{g,n,t} + R^{\text{PosSpin}}_{g,\text{day}} \le v^{\text{Grid}}_{g,n,t} \cdot D_g \quad \forall \; g \in G, n \in N, t \in T, \text{day} \in D \tag{14}$$

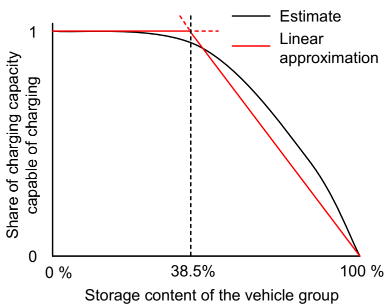

Fig. 3. Principle to limit the use of the aggregated battery storage when some of the batteries are full. Eqs. (9) and (13) constrain the charging and usage of increased charging to provide reserves to be below the red line in the figure. Realistic estimates were not available, which meant that an educated guess was made for this article. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Possible charge of the batteries should not exceed the capacity of the batteries (Eq. (15)). It is assumed that the maximum length for the actual use of reserves is one hour. In Eq. (16), individual vehicles are restricted from charging and discharging at the same time.

$$S^{\text{Grid}}_{g,n,t} + R^{\text{NegSpin}}_{g,\text{day}} \le S^{\text{Grid}}_{g,\max} \quad \forall \; g \in G, n \in N, t \in T, \text{day} \in D \tag{15}$$

$$E^{\text{Chrg}}_{g,n,t} \cdot \frac{D_g}{C_g} + E^{\text{Dischrg}}_{g,n,t} \le D_g \cdot v^{\text{Grid}}_{g,n,t} \quad \forall \; g \in G, n \in N, t \in T \tag{16}$$

In addition to these specific restrictions, the charging and discharging of EVs determined a day ahead are included in the day-ahead electricity balance equation and likewise with the up or down regulation of charging or discharging being included in the intraday electricity balance equations.

2.4. Scenarios

The purpose of the scenario runs was to examine the impact of various assumptions about the behaviour of the EVs and their use in the power system. By comparing different scenario runs the benefits due to smart charging could be split into benefits due to a) the ability to provide spinning reserves, b) providing non-spinning reserves and intraday flexibility by up and down regulation of charging and discharging schedules determined day-ahead, and c) being able to make an optimal day-ahead schedule for the charging and discharging. We also examined how use of the deterministic model influences the results. So far, only deterministic models have been used to study EVs, and this could have been a major weakness in the studies. WILMAR can be run in deterministic or stochastic mode. Stochastic mode takes the uncertainty in wind power production and in electricity demand into account. Stochastic forecasts are updated every 3 h and the power system is re-dispatched according to the new information. The influence of the modelling of unit commitment was also studied by comparing MIP model runs vs. linear programming (LP) model runs.

The analysis is performed on the power system of Finland. The Finnish system gets about 10% of its production from hydropower, with most of it being controllable. Finland is a northern country where heating is required during the winter. The country has many combined heat and power units for district heating. The model includes three heating areas for Finland, all of which have to fulfil their heating requirements separately. Large portion of the power plants were retired by the study year of 2035. Notable exceptions are 2440 MW of nuclear capacity, 1310 MW_{el} of natural gas capacity, all the hydropower plants and 2030 MW_{el} of industrial back pressure power plants using wood waste from industrial processes.

Scenarios were compared against the base scenario. The base scenario uses the power plant portfolio from Balmorel smart EV scenario, which is described in article [23]. The base scenario was run with MIP in stochastic mode. In the base scenario, departing EVs had to have full batteries and they were charged and discharged in optimal manner from the system perspective. Grid-connected EVs were able to provide reserves for the power system and all of them were capable of V2G. In addition, 10% of PHEVs were capable of E2G (engine-to-grid). Other scenario runs had some deviation from this basic setting as shown in Table 1 and described in the Results section. Dumb EVs start charging when they are plugged in, stop charging once they are full, and they cannot provide reserves. In addition, a scenario without EVs was run for both stochastic and deterministic model versions (not included in Table 1).

Table 1
Model properties in use in different WILMAR scenarios.

Scenario	Stochastic	Spinning	Intraday	Smart	Leaving full	MIP
Base	×	×	×	×	×	×
Det.		×	×	×	×	×
Add	×	×	×	×		×
No spinning	×		×	×	×	×
No flexibility	×			×	×	×
No V2G	×	×	×	×	×	×
V2G PHEV only	×	×	×	×	×	×
V2G PHEV + No E2G in PHEVs	×	×	×	×	×	×
LP	×	×	×	×	×	
LP Det.		×	×	×	×	
LP dumb	×				×	
LP Det. & dumb					×	
Dumb	×				×	×
Det. & dumb					×	×

Stochastic = model solved in stochastic or in deterministic mode.
Spinning = participation of EVs in the spinning reserve.
Intraday = participation of EVs in the intraday market to correct forecast errors.
Smart = smart or dumb EVs.
Leaving full = all EVs required to have full battery when leaving the grid.
MIP = model solved in MIP or in LP mode.

EVs capable of V2G can discharge their batteries to the grid, but there has to be an economic incentive for this to happen. In the modelling context, it was assumed that the cost of wear and tear on the batteries for the extra use is 10 €/MWh, and the roundtrip efficiency is 85% (same efficiency as in Peterson et al. [10]). There has to be a corresponding difference in power price fluctuations before the use of V2G for peak levelling is economical. Another use of V2G is the provision of the ancillary services. EVs with V2G could be especially useful as disturbance reserves[6] since these are rarely actually used, but the capacity has to be online. It was assumed that it does not cost anything extra to have the capacity online when the vehicles are plugged in. Therefore, more expensive sources of reserve capacity were replaced by the EVs.

In power markets, new electricity consumption will raise the prices in the electricity markets – all other things being equal. This in turn will attract new investments in power generation. New investments are also influenced by the retirement of old power plants and by policy. EVs will increase the electricity consumption and change the profile of the consumption. Four different situations are therefore analysed in terms of generation investments: no EVs, dumb EVs, smart EVs, and smart EVs without a capacity adequacy contribution. All of these will have induced a somewhat different power plant portfolio given enough time. The analysis tries to capture this by using a generation planning model (Balmorel) to estimate the different power plant portfolios. Two of the portfolio scenarios (no EVs and smart EVs) are borrowed from another article [23] and the details of the model assumptions and portfolios can be seen there.

In the smart EVs scenario of Balmorel, the EVs were considered to contribute to the power system capacity adequacy with 500 MW. The low electricity storage capacity of the EVs will limit the length of the production period and they cannot be trusted to provide energy for prolonged periods. For the smart EV scenarios in Balmorel, it was assumed that 1 h of non-spinning reserves could be maintained at the 500 MW level. In terms of capacity only, a V2G share of about 20% could provide 500 MW from the plugged-in vehicles during the highest net load hours. This 500 MW decreases the need for additional power plant capacity in the generation planning model. For comparison 500 MW of open cycle gas turbine (OCGT) would have an annuity of 16.3 M€/year in the model runs. In principle, the capacity effect could be assumed higher, if more EVs had V2G. In the WILMAR runs, it was possible to require the EVs to have enough stored electricity to provide the reserve for at least an hour (Eq. (7)).

Table 2 shows the differences in the power plant portfolios created by the Balmorel runs. The smart EVs reduce the need for power plant capacity through the timing of the charging as compared to their dumb-charging counterparts, since the dumb EVs create a new peak in the net load. The difference in the peak demand was 544 MW (in the WILMAR scenarios). The flexibility of smart EVs induced a larger proportion of variable wind power production, whereas inflexible dumb EVs leaned more on adjustable conventional power plants.

3. Results

WILMAR analyses only operational costs and does not include investment costs. These are estimated from the aforementioned Balmorel runs. The investment costs for new power plants required by the year under study, 2035, were 2.29 billion € in the scenario with smart EVs (Table 3). This was 91 M€ more than the investment costs in the scenario without EVs. This indicates that in the longer term, EVs attract more costly power plant investments, which in turn decrease the operational costs of the system. The overall result is lower average cost of electricity. In contrast, dumb EVs will increase the average cost of electricity.

There are differences between the two model setups, and the differences in costs and benefits are therefore only indicative. As expected, the more detailed WILMAR reveals costs that the Balmorel was unable to capture. With the smart EVs, these hidden costs are smaller, even though there is a higher share of variable wind power production in the smart EVs scenario. The smart EVs help the system to operate in a more efficient manner.

The difference between no EVs and dumb EVs gives the cost of electricity to provide necessary energy for the EV fleet. The difference between smart and dumb EVs gives the benefit of allowing the vehicle charging and discharging to be controlled in accordance with the market conditions. This benefit has to be shared between the vehicle owners and an entity that controls the charging in keeping with the market conditions and the needs of vehicle owners. This article does not consider how the benefit is shared; it only tries to estimate the magnitude of the benefit in different conditions. PHEVs will have additional costs due to fuel use when using the engine. As the PHEV fuel usage does not change, these costs were not considered.

For the rest of the article, the annual benefit of smart EVs compared with dumb EVs is used as a metric. The operational model (WILMAR) is used to estimate the operational costs and the costs for annualized power plant investments and fixed costs are taken from the difference between the generation planning model

Table 2
Capacity of new power plants in the different Balmorel scenarios.

Power plant type	MW of electricity			
	No EVs	Dumb	Smart	No 500
NatGas comb. cycle cond.	363	520	16	16
NatGas comb. cycle CHP	3	0	0	0
NatGas open cycle cond.	2861	3580	2519	3024
Nuclear	5312	5688	5312	5312
Wind	4705	5130	6122	6122
Forest residue CHP	1203	1206	1196	1192
Wood waste CHP	76	73	73	75

[6] Also known as contingency reserves or automatic frequency control reserves, which activate automatically following a fault in the system, if the system frequency drops below a certain threshold.

Table 3
Annualized system costs of the power system in various scenarios by using a generation planning model (Balmorel) and an operational model (WILMAR). The cost (€/MWh) is the total cost divided by the annual electricity consumption, which includes the new consumption from EVs.

	Balmorel no EVs	WILMAR no EVs	Balmorel dumb EVs	WILMAR dumb EVs	Balmorel smart EVs	WILMAR smart EVs
Investm. (M€/year)	2203	←	2370	←	2294	←
Fixed (M€/year)	485	←	528	←	501	←
Variable (M€/year)	1955	1976	2011	2034	1930	1900
Hydro (M€/year)	–	47	–	44	-	53
Total (M€/year)	4644	4713	4909	4976	4725	4749
Diff (M€/year)	68		67		24	
Cost (€/MWh)	41.1	41.8	41.9	42.7	40.4	40.7

The cost of hydropower in the WILMAR scenarios refers to the difference in the year-end hydro reservoir level compared to Balmorel runs, where this was fixed.

runs (Balmorel). The annualized investment costs and the fixed costs for the smart EVs scenario were 102 M€/year less expensive than in the dumb EVs scenario. As there are one million EVs in the scenarios, this means 102 €/vehicle/year. The investment and fixed costs for the smart EVs scenario were 106 M€/year more expensive than the scenario without EVs. These costs are included in the numbers presented later in this article.

3.1. Effect of modelling features on the calculated benefit from EVs

Since we analysed the operational costs of the power system with a stochastic unit commitment and dispatch model (WILMAR), we were able to compare the calculated benefits of the deterministic and stochastic modes (Fig. 4). In the stochastic mode, both wind power production and electricity demand have a probabilistic tree with 10 branches. The model has to optimise the unit commitment and dispatch with this uncertainty taken into account. In the deterministic mode, the model had a forecast error based on the average forecast from the stochastic scenarios.

In the stochastic mode, the model sees a distribution of possible outcomes and this additional information should help the model to make better unit commitment decisions, which will, on average, turn out to be more economic than in the deterministic mode. The stochastic mode reduced operational costs in no EVs, smart EVs and dumb EVs scenarios by 0.26%, 0.76%, and 0.35% respectively compared to deterministic results. This should be significant since 0.1% is more than 2 M€.

MIP and LP solutions were also compared. The assumption was that the MIP solution would increase the calculated benefit. Both models have a start-up cost, but in the LP model, it is possible to start up a fraction of a unit due to the linear simplification (described in Ref. [13]). In the MIP model unit has to start fully and this will be more costly than partial start-ups (MIP model is described in Ref. [14]). In the LP model, unit can reach full efficiency even if it is only partially started and this too increases the cost difference. Furthermore, in the MIP model, units operate more at partial load in order to avoid start-ups. These factors should increase the costs of the MIP model compared to the LP model. Smart EVs were able to keep the cost increase smaller and the system benefit of smart EVs over dumb EVs was about 2% larger in the stochastic MIP solution compared to the stochastic LP solution.

The difference between stochastic MIP and LP solutions is surprisingly small. Furthermore, there was no visible difference in the deterministic runs. The explanation is that there was a large number of small units (mainly open cycle gas turbines) as well as flexible hydropower. Even in the MIP mode, these provide a very economic combination to meet the changes in the net load. There is a small difference in the absolute cost when starting up a small unit fully or partially. This means that the difference between MIP and LP results could be considerably higher in a system with less flexible units.

The results from the Balmorel runs are rather different. The main reason is that units are simplified and more aggregated compared to the WILMAR runs. The benefits of smart EVs are smaller in Balmorel runs, since the units do not have minimum operation limits or part-load efficiencies, which create additional costs that the smart EVs could reduce.

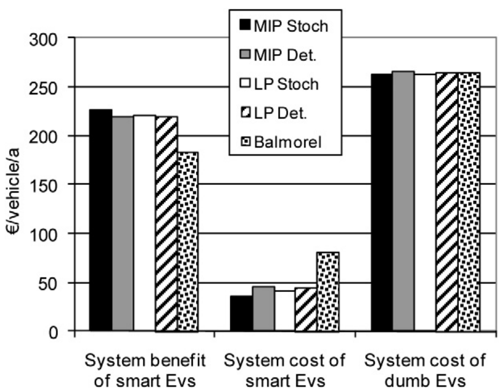

Fig. 4. The influence of various modelling methods on the simulated costs of the EVs. System cost of smart and dumb EVs is the additional total cost of the energy system compared to a situation without EVs. System benefit of smart EVs is the difference between the system cost of dumb EVs and the system cost of smart EVs.

3.2. Sources of benefits from smart EVs

Smart EVs can help the system in various ways (Fig. 5). The system benefit of smart EVs compared to dumb EVs was 227 €/vehicle/year in the studied system. Part of the benefits come from less expensive operations and part comes from smaller investment and fixed costs. To see the benefit of EVs in the spinning reserves, the base scenario was compared with a scenario where the EVs were not able to provide spinning reserves ('No Spinning'). The provision of spinning reserves benefitted 38 €/vehicle/year (17%). The model calculates only the reservation of the capacity and

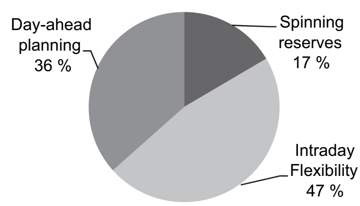

Fig. 5. The division of the benefit from smart EVs over dumb EVs between different components. The total benefit was 227 €/vehicle/year.

not the actual use. Intraday flexibility means that the EVs were allowed to correct the forecast errors in wind and load by up and down regulation of the charging and discharging schedules determined day-ahead. The benefit of intraday flexibility (47%) was calculated by comparing a scenario where the EVs were not flexible in the intraday ('no flexibility') with the scenario 'no spinning'. The 'no flexibility' WILMAR scenario used a power plant portfolio based on the Balmorel scenario where the EVs did not contribute to the power system capacity adequacy as reserves (scenario "no 500" in Table 2), because they are not able to provide non-spinning reserve without intraday flexibility. Day-ahead planning benefits (36%) are due to the more economic charging/discharging pattern decided day-ahead before the intraday adjustments. This was calculated by comparing the 'dumb' scenario with the 'no flexibility' scenario.

The model does not analyse intra hour load following or regulation, and possible benefits from these are missing from the analysis. Grid reinforcements were not taken into account, either. Due to the availability of flexible hydropower and OCGTs (open cycle gas turbines) the model was able to reserve the capacity for non-spinning reserves without extra cost at all times, and therefore EVs did not create cost savings for the provision of non-spinning reserves.

3.3. Benefits of vehicle-to-grid

The benefits of the V2G mostly derive from the provision of the reserves. Furthermore, most of the benefits can be achieved by having only a portion of the EV vehicle fleet capable of V2G (Table 4). This suggests that it does not make sense to equip all EVs with the V2G, because V2G capability will incur extra costs in the vehicles and in the grid connection. With E2G, 10% of the PHEVs (5% of all EVs) were assumed to have E2G. For most vehicles it is not possible to let the grid-connected car engines start by themselves when the power grid could use the power or the capacity. All the V2G scenarios were run with the same power plant portfolio based on the 'smart' Balmorel scenario. Balmorel was able to use the V2G, but not the E2G. The cost of the 'no V2G' scenario in the Table 4 should be lower, if the power plant portfolio was separately optimised for smart EVs without V2G.

In the 'battery not full' scenario of Table 4, V2G was fully allowed, but the EVs were not required to have completely full batteries when leaving the grid. FEVs had to have at least 80% full batteries and PHEVs at least 50% full batteries. The supposed benefit of this additional flexibility was lost within modelling inaccuracies.

3.4. Market prices

The analysis so far has concentrated on the system costs, which means that all the costs of running the system have been summed up. Another perspective is to look at the prices at the electricity markets (day-ahead and short-term markets). This reflects what the EV owners will have to pay for their electricity consumption. The costs here are based on the marginal cost of the model. If the market functioned perfectly and the cost assumptions were correct, the marginal cost should be the same as the market price. In reality, market prices are very likely to be at least somewhat higher. Furthermore, market prices are very sensitive to the actual capacity balance in the system. When there is a shortage of capacity, power plants with very high marginal costs need to be used more and the average market price can be much higher than if plenty of spare capacity existed.

In these model runs, the capacity balance is tight, since the generation planning model has invested in just enough capacity to cover for the worst situation plus some reserve margin. In reality, there could be too much or too little capacity due to investment uncertainty in combination with long building times.

Fig. 6 shows the results concerning market prices. The cost to buy electricity for smart EVs from the electricity markets was 157 €/vehicle/year. This takes into account the purchase of electricity for charging the battery as well as the sale of electricity by discharging or engine power. It does not take into account the sale of spare capacity as spinning reserve. If the shadow price of the equation requiring enough spinning reserves is taken as the market price for spinning reserves, then the sales would yield 1.7 €/vehicle/year.

In the operational phase simulated by the WILMAR runs, there were couple of hours where there was not enough available production capacity in the day-ahead spot market. This resulted in the use of dummy variables at a very high marginal cost. Since the values were unrealistic, a price ceiling of 400 €/MWh was used instead.

The average intraday market price in the WILMAR model with smart EVs and without EVs was almost the same (41.61 €/MWh vs. 41.62 €/MWh). This is despite the rather different power plant structure (Table 2). For comparison the average system cost of electricity was correspondingly 40.7 €/MWh and 41.8 €/MWh.

3.5. CO_2 emissions

There has been considerable interest in the future CO_2 emissions from the EVs. For conventional vehicles it is relatively straightforward to calculate the emissions from the use of the vehicles. It is not so with the EVs. The authors believe it would be misleading to assess marginal emissions in a long-term study, since emissions due to EV electricity consumption should not be more marginal than any other electricity consumption in the long term. It would be more appropriate to use average emissions. Based on the scenario results, the average emissions in 2035 were 29.2 $kgCO_2$/MWh in the dumb EVs scenario and 26.0 $kgCO_2$/MWh in the smart EVs scenario. This would result in CO_2 emissions of 104–117 $kgCO_2$/vehicle/year for FEVs. PHEVs would have larger emissions, since they will also use fuel when driving. In comparison, a future hybrid vehicle with specific emissions of 90 gCO_2/km and annual driving distance of

Table 4
Cost of scenarios compared to the base scenario, in which V2G was fully allowed.

Scenario	Cost over base (€/vehicle/year)
No V2G	53
V2G half of the vehicles	6.7
V2G half, no E2G	8.0
Battery not full	0.4

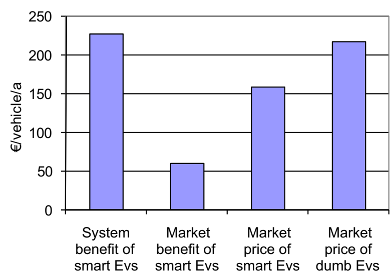

Fig. 6. Market benefits and prices of smart and dumb EVs. Market price of smart and dumb EVs is the sum of hourly market prices for charging the EVs in these scenarios. This includes revenue from discharging in the smart EVs scenario. Market benefit of smart EVs is the difference between the dumb and smart scenarios.

20,000 km would cause emissions of 1800 $kgCO_2$/vehicle/year. The large difference between FEVs and regular hybrids is due to the very low carbon intensity of electricity production in the model scenarios. This was a result of the CO_2 price, which caused minimal investments in power generation with CO_2 emissions.

However, there is another relevant approach. It is a comparison between the scenario where there was no EVs and the scenarios where there are EVs. The changes in the emissions of the whole power system can be seen as a consequence of the introduction of the EVs. In the case of dumb EVs, this change was +169 $kgCO_2$/vehicle/year. In the case of smart EVs, the change would be −211 $kgCO_2$/vehicle/year. The smart EVs would make the power system emit less CO_2 by enabling a higher share of CO_2 free production (wind and nuclear).

4. Discussion

The cost estimates would change from power system to power system. The analysed system had about 3000 MWs of reservoir hydropower with an electricity production share of about 8%. Flexible hydropower and smart EVs compete by providing similar services to the system. If there was less flexibility from the hydropower, smart charging would be more beneficial than it was. Benefits could be higher also if the system had grid bottlenecks, as these often limit the efficient dispatch of power plants. Smart EVs could bring local flexibility and therefore ease bottleneck situations. On the other hand, conventional power plants built in the future could be more flexible to operate than current power plants – especially when the growing share of variable generation (e.g. wind power) increases the need for economic cycling. This would decrease the benefits of smart EVs. The benefit would also change, if the capacity balance was different. If the capacity balance was less tight, changing the charging time of EVs would in many situations move production from intermediate power plants to base load power plants instead of peak power plants to intermediate power plants. This would yield less cost savings.

The changes in the system costs are different from the changes in the market prices, because system costs just sum the total costs whereas market prices take into account how the costs and benefits are shared between the market participants. The prices in the electricity market provide the reference price for the agents selling power to EV owners. The smart EVs will buy electricity at a different price than the dumb EVs due to the different time of charging. The smart vehicles can also benefit from the sale of electricity, if they have V2G. While the results provide an estimate how the market prices would affect EVs, market prices have a very large uncertainty. Nevertheless, the estimated cost difference between smart and dumb EVs was about 59 €/vehicle/year. This should cover for the expenses of the smart charging system. The remainder has to be divided between the vehicle owner and the entity acting between the vehicle owner and the wholesale power markets. Then the question becomes: for how many vehicle owners is the benefit large enough to compensate for any inconvenience caused by the postponed charging as well as the battery degradation in case of discharging? The size of the compensation appears to be such that not all vehicle owners will sign in. However, this means a larger piece of the cake for those who do participate in smart charging.

In the current model, all vehicles of the same type joined one single pool of electricity storage. An improved solution would be to have a separate pool for each hour of leaving vehicles. All vehicles arriving during certain hour should be divided into the hourly pools of leaving vehicles based on the patterns of driving behaviour. This would restrict the model from creating electricity transfers that would not necessarily be possible in the real world. This is to be implemented, but is not present in results of the article.

As usual, future fuel costs and investment costs of the power plants would also influence the results. The transmission links to other systems are also very relevant and variable from system to system. The analysis of all relevant sensitivities and uncertainties would require a very large number of burdensome model runs. Those should be done only when all the relevant characteristics of the EVs and the energy system are factored into the models. The improvements to the modelling presented here are a step closer, but more remains to be done. There is a need to increase the accuracy of the driver behaviour and account for the grid improvement costs as well as intra hour balancing benefits.

5. Conclusions

The analysis has estimated two extremes of EV charging intelligence and how these might influence the total costs of an optimised future power system. The methodology employed brings rigour to the way the costs should be estimated. The results of the article demonstrate that it is not enough to assess operational costs – also impacts of the new consumption patterns in the development of the long-term power plant portfolio should be taken into account. In the estimation of operational costs, stochastic model with binary unit commitment decisions was used to achieve more accurate results compared to previous studies.

The results exclude grid and intra hour balancing related costs and benefits. Furthermore, the restrictions in the use of the flexibility of the smart EVs are not as binding as they are likely to be in the real life. This includes the omission of uncertainty in driving behaviour, although the model had a safety margin for filling up the batteries.

In the case of smart EVs, the system cost to charge an EV was around 36 €/vehicle/year. In the case of dumb EVs the system cost was around 263 €/vehicle/year. Depending on the share of smart EVs vs. dumb EVs, the realised average cost should fall between these extremes – excluding the uncertainties in the article results. Most of the benefits come from the smart timing of charging. This can be divided between the benefits accrued on the day-ahead planning phase and the intraday adjustments to mitigate the forecast errors of electricity demand and variable generation.

Acknowledgements

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