Distribution Grid Impacts of Smart Electric Vehicle Charging From Different Perspectives

Else Veldman, *Member, IEEE,* and Remco A. Verzijlbergh

***Abstract*—As a consequence of the developments in electric transportation and the evolution toward smart grids, large-scale deployment of smart charging strategies for electric vehicles (EVs) becomes feasible. This leads to opportunities for different market parties to use the flexibility of EVs for various objectives that may be conflicting and result in a nonoptimal shifting of peak demands for the distribution grids. In this paper, we assess the financial impact of various EV charging strategies on distribution grids. We compare a strategy that minimizes network peak loads (from a network operators perspective) with a strategy to minimize charging costs (from the perspective of a commercial party). In a scenario with a high wind penetration in the system, the electricity prices are, for a significant part, determined by the instantaneous wind production. Therefore, we additionally study the effect of wind energy on electricity prices and, consequently, on the resulting EV load and network impacts. We obtain the network costs by calculating the impacts expressed in the net present value (NPV) of the investments costs and energy losses. We found that, in the case where EVs are basing their charge schedules on electricity prices, the increase in NPV compared with a no EV scenario was found to be 25% higher than in the case where the extra peak load due to EVs was minimized. The large difference in network impacts between the price based and network based charging strategies was only observed in the case with a high wind penetration. The results strongly suggest that the situation where EVs are controlled with a strategy to minimize charging costs that does not take the distribution grids into account may not lead to an optimal situation when the entire electricity delivery system is regarded.**

***Index Terms*—Electric vehicles (EVs), load management, power distribution system planning, smart grids.**

I. INTRODUCTION

WITH THE developments toward smart grids, customers are expected to take an active part in electricity markets which enables flexibility in electricity demand. In smart grids, that use information and communication technology to intelligently integrate the actions of the users connected to electricity distribution grid, flexible electricity demand may fulfill an important role as it can be used to balance demand and supply, maximize the utilization of renewable energy sources and optimize efficient use of the energy system. With the advent of electric transport, a significant part of the future electricity demand can be the flexible demand of electric vehicles (EVs). Although the development and speed of adoption of EVs is uncertain, the number of EVs can grow fast and the impact of these flexible demands on the electricity systems may be significant.

As a consequence of the developments in electric transportation and the evolution toward smart grids, large-scale deployment of smart charging strategies for EVs becomes feasible. This leads to opportunities for different parties to use the flexibility of EVs for various objectives. Strategies may for instance be employed to charge EVs to contribute to flattening peak demands. Shifting a part of the electricity demand to off-peak periods makes it possible to leverage (local) demand, allowing more energy to be transported without increasing the grid capacity to the level of high peak loads. Other objectives to apply charging strategies can be minimizing charging costs based on a certain real-time electricity price or using EVs for frequency regulation and/or real-time balancing of power. Such charging strategies have recently received much attention in [5] and [11] and the overviews of current research on this theme provided in [3] and [18].

One should realize that, in a liberalized electricity sector, the aforementioned objectives for applying charging strategies are in the interest of different parties. Maintaining the balance between demand and supply of electricity is primarily the responsibility of transmission system operators and/or balance responsible parties. Producers and commercial energy suppliers are market parties that aim to minimize production costs and/or the costs to serve their customers. However, the efficient use of electricity networks is the responsibility of network operators. As a consequence, load shifting strategies by commercial parties may cause large impacts on the distribution grid.

The misalignment of the objectives of network operators and commercial market parties is even more prominent in power systems with a high amount of wind generation. Because the variable output of wind generation is, in principle, uncorrelated with electricity demand, situations can occur in which electricity price is low in times of a high demand, because there happens to be a lot of wind available at that very moment. This effect, discussed in more detail in [13], implies that when responsive demand reacts to wind driven electricity prices, it can lead to very high peaks in network load.

In this paper, we therefore assess the impact of various EV charging strategies on distribution grids in power systems with a varying amount of wind generation. The main goal is to get

Manuscript received March 18, 2014; revised August 8, 2014; accepted August 22, 2014. Date of publication September 19, 2014; date of current version December 17, 2014. Paper no. TSG-00199-2014.

E. Veldman is with the Electrical Energy Systems Group, Eindhoven University of Technology, Eindhoven 5600 MB, The Netherlands; and also with the Asset Management Department, Enexis B.V., Hertogenbosch 5201 AW, The Netherlands (e-mail: else.veldman@enexis.nl).

R. A. Verzijlbergh is with the Energy and Industry Group, Delft University of Technology, Delft 2600 GA, The Netherlands (e-mail: r.a.verzijlbergh@tudelft.nl).

Digital Object Identifier 10.1109/TSG.2014.2355494

insight in the consequences, in terms of network impacts and related financial impacts, of different EV charging strategies and different wind scenarios. In particular, we compare a strategy that minimizes network peaks (from a network operators perspective) with a strategy to minimize charge costs (from the perspective of a commercial party), while an uncontrolled charging scenario and a scenario with no EVs are used as reference cases. This analysis can hence be regarded to be an important step toward the development of future grids in which the system-wide benefits of management of flexible loads like EVs in the distribution system can be obtained.

The method we employ in this paper is based on the methods applied in [12] and [15]. First, in Section II, the various charging strategies applied in this paper are described. Section III treats how the normalized EV charge profiles that are created for these strategies are, appropriately scaled, combined with the regular residential electricity demand to construct load profiles. These load profiles are subsequently used to perform a load flow analysis to assess the network impacts in terms of the loadings and energy losses of different distribution grid assets. By considering the necessary network reinforcements and energy losses, we obtain financial figures for the network costs that are needed to accommodate the new EV load. This is described in Sections IV and V. The last section presents the conclusions. In this paper, the method is applied to the case of The Netherlands. Though many variations exist in the distribution grids all over the world, the applied principles are the same and the uncertainties in future electricity demand for EVs and the possibilities to apply various charging strategies are not different in The Netherlands compared to many other developed countries.

II. Charging Strategies

In this section, we will describe various how objectives that may be adopted by different actors the electricity system lead to different charging profiles of EVs. We consider three different charging strategies: 1) minimizing charging costs; 2) minimizing network peak load; and 3) uncontrolled charging. For a more elaborate description of the methods to construct the charging profiles, we refer to [13], [14], and [16]. Below, we present the most important assumptions and a concise mathematical formulation of the optimization problems that correspond to the two strategies where charging costs and network peak load are minimized. We consider it appropriate to remark that these charging formulations and the resulting demand profiles can be considered idealized profiles since they assume, among other things, perfect knowledge of prices, driving patterns, and network load. Formulations that are applicable in practice would have to focus on handling uncertainty, IT and communication requirements, etc. Such issues are, however, regarded out of the scope of this paper.

A. Minimizing Charging Costs

From the perspective of an EV aggregator, the objective is to maximize profits. We assume that an aggregator has certain contractual agreements with its customers, the EV owners, such that revenues are fixed, for example because EV owners pay a fixed monthly fee to the aggregator. In this situation, the profit maximizing objective translates into minimizing the total costs for charging a fleet of EVs for a time-varying electricity price. Essentially, this boils down to postponing the charging until the moments with the lowest prices. The constraints that determine how long charging can be postponed are dictated by the driving behavior and battery limits of the individual EVs. Important to mention is that the driving behavior of the EVs is modeled based on actual driving data from a mobility survey that provides trip lengths, home departure times, and home arrival times [7]. To make the optimization problems computationally tractable, the fleet of EVs is represented using 25 typical drivers which are extracted from the travel survey using a clustering algorithm described in [16] and which is similar to the one described in [5]. Furthermore, the charging limits of the EVs in the two optimized charging scenarios are 0 kW (i.e., we do not allow for vehicle-to-grid services) minimum and 3 kW maximum. The value of 3 kW reflects the charge rate for a connection with a maximum current of 16 A at 230 V, that is common in many European countries. The battery capacity is assumed to be 24 kWh, reflecting a typical value of current EVs.

To obtain a future load profile of EVs charging according to this formulation, a future electricity price signal is constructed based on the merit order of power plants. This is done by expanding the current Dutch generation portfolio with extra wind capacity. The price signal reflects the net system demand (demand minus wind generation) that has to be met by the power plants. In this manner, we conserve the important property that electricity prices tend to be low when wind generation is high—a phenomenon already observed in countries with high penetrations of wind power such as Denmark. We emphasize that this formulation takes into account that the extra EV load itself alters the electricity prices, as was e.g., also considered in [5]. Below, we present a concise mathematical formulation of the complete optimization model.

The residual system demand of electricity $P_{D,k}$ is given by

$$P_{D,k} = P_{D0,k} - P_{\text{wind},k} + P_{\text{EV},k} \tag{1}$$

where $P_{D0,k}$ is the baseline demand, $P_{\text{wind},k}$ the instantaneous wind power production and $P_{\text{EV},k}$ the extra demand of the EVs at time-step k.

The charging costs of an EV aggregator charging its vehicles at some electricity price λ_k is simply the product of EV demand and price, so its objective function reads $f = \lambda_k P_{\text{EV},k}$. However, when the aggregator (or an ensemble of aggregators) actually influences the electricity price, that dependence needs to be taken into account. To this end, we use the following model for the time-varying electricity price:

$$\lambda_k = \alpha_k + \beta P_{\text{EV},k} \tag{2}$$

where α_k is the baseline electricity price at time-step k given by the intersection of the supply function (merit order) and the residual demand (without the EV part) which is assumed to be perfectly inelastic. The term $\beta P_{\text{EV},k}$ represents the EV dependent linear adjustment of the electricity price. As outlined in [13] and [16], the idea is to linearize the electricity price around the average price in the optimization period and use the supply function to estimate the sensitivity parameter β. This approximation allows for a quadratic programming formulation of the EV charging problem, while it still includes the feedback of EV charging on the electricity prices. If this feedback would not be taken into account, all EV demand would be programmed in a short time interval with the lowest prices in the optimization period, causing unrealistically high peaks in demand.

Each EV aggregator then performs the following optimization:

$$\min_{P_{\mathrm{EV},ik}} \sum_{k=1}^{N_k} \alpha_k P_{\mathrm{EV},k} + \beta P_{\mathrm{EV},k}^2 \tag{3}$$

$$\text{s.t.} \quad P_{\mathrm{EV},k} = \sum_{i=1}^{N_{\mathrm{EV}}} P_{\mathrm{EV},ik} \quad \forall k \tag{4}$$

$$P_{\mathrm{EV}_{\min},i} \leq P_{\mathrm{EV},ik} \leq P_{\mathrm{EV}_{\max},i} \forall i, k \tag{5}$$

$$E_{\mathrm{EV}_{\min},i} \leq E_{\mathrm{EV},ik} \leq E_{\mathrm{EV}_{\max},i} \forall i, k \tag{6}$$

$$E_{\mathrm{EV},ik+1} = E_{\mathrm{EV},ik} + \eta_c P_{\mathrm{EV},ik} \Delta t - d_{ik} \forall i, k \tag{7}$$

where optimization variable $P_{\mathrm{EV},ik}$ denotes the charge rate of vehicle i out of a total of N_{EV} at time k and state variable $E_{\mathrm{EV},ik}$ denotes the battery state-of-charge expressed in units of energy. Technical vehicle parameters are the following: η_c denotes the charging efficiency per vehicle, $E_{\mathrm{EV}_{\min},i}$ and $E_{\mathrm{EV}_{\max},i}$ the minimum and maximum state-of-charge and the charging power limits are given by $P_{\mathrm{EV}_{\min},i}$ and $P_{\mathrm{EV}_{\max},i}$. The state equation (7) relates battery state to charge rate and it implicitly contains the assumption that vehicles cannot deliver energy back to the grid: $P_{\mathrm{EV}_{\min},i} = 0$. Other limits are as described above. The term d_{ik} represents the discharges due to driving and thus depends on the driving patterns of the EV owners, which are thus assumed to be known over the optimization horizon. The time-step Δt is set to 1 h in the simulations we consider in this paper. Note that the above description does not require that all EVs are fully charged overnight as long as all planned trips can be made.

B. Minimizing Network Peak Load

For the case of EV charging from the point of view of a distribution grid operator, we assume the presence of some form of incentive regulation, as is common in many European countries, which incentivizes efficient use of network assets. The main costs of operating the networks consist of capital expenditures on grid assets and the costs for energy losses. It turns out that, for an given asset, minimizing peak load as well as minimizing the energy loss can be captured by minimizing the square of the combined network load of exogenous (uncontrollable) household load plus the (controllable) EV load. Again, constraints are the result of driving and battery parameters, so there is only limited room for the network operator to shift load. The network operator thus performs the following optimization:

$$\min_{P_{\mathrm{EV},ik}} \sum_{k=1}^{N_k} \sum_{i \in EV_l}^{N_l} R_l \left(P_{l,k} + P_{\mathrm{EV},ik}\right)^2 \tag{8}$$

where EV_l denotes the subset of EVs connected to a particular cable l and $P_{l,k}$ the inelastic baseline load on that cable. The same constraints on the battery limits given by (5) to (7) apply. The resulting EV profiles are such that the low network load during the night is now filled with the EV load.

C. Uncontrolled Charging

The uncontrolled charging case, in contrast to the other two charging strategies, assumes that people charge their EVs regardless of any price signal or network load. We assume that every day they plug in their EV after their last arrival at home and start charging with a constant rate until the battery is full. The constant charge rate per EV has been set to a value of 10 kW, which is markedly higher than the maximum charge rate of 3 kW per EV in the controlled cases. This assumption has been made to clearly treat this case as a “worst case scenario” in terms of the expected network peak load. Because the evening peak load usually also occurs when people arrive back home, this method is expected to significantly increase the evening peak load. The maximum charge rate of 10 kW per EV does not, however, mean that the combined demand peak of a number of EVs is equal to 10 kW times the number of EVs, due to the randomness of the times at which different EVs start charging. In [14], where the uncontrolled charging profile is discussed in more detail, is was shown that the diversity factor, that expresses the ratio of the combined peak load of a large group of EVs to the sum of the charge rates of the individual EVs, lies around 0.1 for EVs charging with a rate of 10 kW.

III. Load Profiles

Based on the EV load profiles that result from the models described above, network load profiles for the three charging strategies have been constructed. This is done for the case of The Netherlands in 2030. The target set by the Dutch Government is to reach 200 000 EVs in 2020 and 1 million in 2025 [6]. If the development curve to reach these goals is followed, this means that, depending on the growth of the total fleet of personal cars, 40%–45% of all cars will be electric in 2030. Besides this, it is expected that the number of cars per household will grow; in an extensive scenario study performed by PBL Netherlands Environmental Assessment Agency the number of cars will grow toward 1.10–1.17 cars per household in 2040 [8]. Based on these figures, we assume a growth toward 1.10 car per household in 2030 and 43% of the total car fleet to be electric. This results in a penetration degree of 47% EVs per household. The residential demands besides the demand for EVs are based on the current average residential electricity demand plus a yearly demand growth of 1.0%.

For wind generation the expectations are that, if the policy set by the Dutch Government and that has been agreed on is carried out, 11 GW will be installed in 2020 and that, due to more offshore wind generation potential, this will grow further toward 2030 [1]. Therefore, 15 GW wind generation in 2030 has been assumed. The wind generation time-series show a capacity factor of approximately 0.2. Compared with an expected base load and peak load of around 10 and 20 GW,

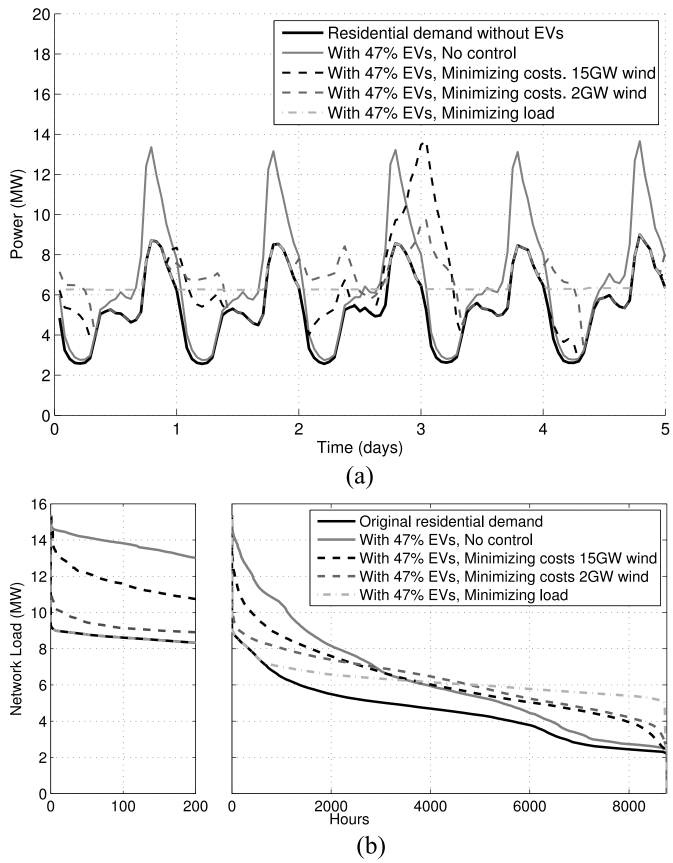

Fig. 1. (a) Load profiles during 5 days and (b) load duration curves of the residential demand of 10 000 households with and without the demand of 47% EVs per household resulting from three different charging strategies. Load profiles and load duration curves do not include wind generation.

respectively (currently, the peak load in The Netherlands lies around 17 GW, the base load around 8 GW and the average load around 12 GW), 15 GW wind generation with a capacity factor of 0.2 supplies approximately 20% of all electricity. At times wind generation will exceed demand, leading to very low electricity prices. To clearly observe the effect of the wind energy on the price-responsive EV profiles, we also study a scenario with a much more modest wind penetration. In this scenario, we assume an installed wind energy capacity of 2.4 GW, which is the reported value for 2012 [4].

The resulting load profiles during five days for a group of 10 000 households including the demand for EVs, as well as the load duration curves for the whole year[1] are depicted in Fig. 1. All three load profiles are based upon real-world driving patterns of conventional gasoline vehicles, so the implicit assumption is that EV driving patterns (i.e., daily driving distance, home departure time, etc.) will not change significantly. The average driving distance is 37 km per car [7]. For the EVs an efficiency of 5 km/kWh is taken. The load duration curves show that the high peak loads only occur during a relatively low number of hours; this is especially the case for the minimizing charging costs and the uncontrolled scenario.

[1]A load duration curve equals the load profiles, but the data is ordered in descending order of magnitude, rather than chronologically.

The differences between the profiles of the controlled charging strategies can be understood by realizing that the guiding "signals," i.e., electricity price in the cost minimizing scenario and network load in the peak minimizing scenario, could become less correlated when large amounts of intermittent renewable generation are present. In such a scenario, it is possible that electricity prices are relatively low, e.g., when there is surplus of wind generation, while the network demand of electricity is relatively high. This becomes particularly clear by comparing the profiles for the different wind capacities: the high peak in network load in the 15 GW case is absent in the 2.4 GW wind case.

IV. Impact on Loading of Distribution Grids

As the penetration of EVs grows, the share of EV load in the total demand in residential areas will increase and the load of distribution grids will grow accordingly. The required capacities of cables and transformers to support this additional load, is determined by the peak loads of the load profiles that result after applying various charging strategies. We model the future network load profiles by superposition of the EV profiles on the regular residential loads by the method described in [12]. This method implies that we multiply a normalized EV profile by the number of EVs per medium to low voltage (MV/LV) transformer. This number is the product of the share of EVs of the total personal car fleet, the numbers of cars per household and the number of households per transformer.

A distinction has been made between various residential areas, because the residential electricity demand as well as the car usage in a city can vary considerably compared to the car usage at the countryside. For five degrees of population density the average electricity demand, the average driving distance per car and the average number of cars per household are known [2], [7]. Table I presents the numbers for the various residential areas in 2030 that include a growth of 1.0% for the residential electricity demand (without the demand for the EVs) and an increase from on average 1.03 to 1.10 car per household.

The resulting load profiles are used as input for load flow calculations of an extensive set of typical medium voltage (MV) distribution networks in The Netherlands.

A. *Topology and Operation of Medium Voltage Networks*

The typical topology of MV networks in The Netherlands is depicted in Fig. 2. An MV network is fed by a (regional) transmission network through a high to medium voltage (HV/MV) transformer. Typical primary voltages of HV/MV transformers in The Netherlands are 220, 150, 110, and 50 kV; typical secondary voltages are 25, 20, and 10 kV. MV transmission can be carried out either at the same voltage as MV distribution, in which case no MV/MV transformer is necessary in the MV/MV station, or at a higher voltage (e.g., MV transmission at 20 or 10 kV and MV distribution at 10 or 3 kV, respectively). MV distribution feeders are generally constructed as two half rings which are disconnected from each other.

TABLE I
NUMBERS RELATED TO THE ELECTRICITY DEMAND IN VARIOUS RESIDENTIAL AREAS IN 2030

	Residential electricity demand (kWh)	Driving distance per car (km)	Cars per household
Very high densely populated area	3261	32	0.81
High densely populated area	3762	37	1.02
Moderate densely populated area	4243	36	1.23
Low densely populated area	4486	38	1.34
Very low densely populated area	4752	39	1.45

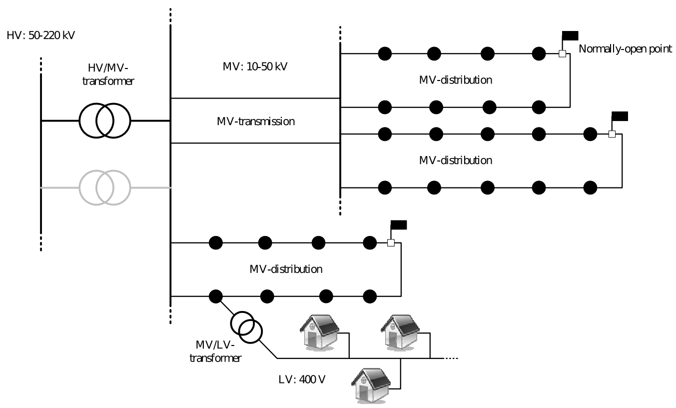

Fig. 2. Typical topology of MV networks in The Netherlands, with and without MV transmission.

In Fig. 2, MV networks with and without MV transmission are depicted schematically in their most straightforward form. More complex variations frequently occur, in which for instance an MV/MV substation is connected to several other MV/MV substations. Besides, many MV installations at HV/MV substations feed both MV transmission networks and MV distribution feeders and not all distribution feeders feature the pure ring shape. MV transmission networks normally meet the $(n-1)$ criterion, which means that when all (parallel) cable bundle circuits are in operation, any cable circuit in the bundle can be lost without causing an overload of any other cable and without any interruption of supply. Meeting the $(n-1)$ criterion also facilitates maintenance, as one circuit can be taken out of service for carrying out maintenance while continuity of supply is guaranteed.

B. Load Flow Calculations of Medium Voltage Networks

The selected grids for the analysis cover networks from 150 to 0.4 kV voltage level. The assets included in these networks are HV/MV transformers, 10 kV cables and MV/LV transformers. The number of assets under consideration in this research can be found in Table II. These numbers correspond with 48 MV networks that serve in total 920 000 residential customers. In order to identify the impact of future electricity demand for EVs on the MV networks, the loadings of these four types of assets are assessed with load flow calculations. This is done following the same procedure as presented in [12]. We emphasize that only the load profiles of the MV/LV transformers that supply residential areas are modified, the load profiles on the higher network parts are a result from the load flow analysis. The transformer substations in these networks supply on average 72 households.

TABLE II
OVERVIEW OF NETWORK DATA OF 48 MV NETWORKS THAT ARE ANALYZED

Asset type	Number of records
HV/MV transformers	122
MV transmission cables (MVT)	2,664 km
MV distribution cables (MVD)	14,004 km
MV/LV transformers	12,520

C. Component Peak Loadings

Fig. 3 shows the load percentages of the four types of assets that were included in this paper. The average peak loadings are presented in Table III. These results present the loading in the situation without any additional load of EVs, and four situations with a penetration degree of 47% EVs per household applying no control strategy, the strategy to minimize charging costs (15 and 2.4 GW wind) and the strategy to minimize network peak loads. Though the assets should be replaced in time to prevent them from overloading, these results give a good representation of the relative differences of the peak loading of the assets between the different cases.

The results show that if controlled charging to reduce peak load is applied, the peak loadings do not increase compared to the case without charging any EVs. In this case, more energy is transported without an increase in peak loadings because off-peak periods are used to charge the EVs. A side effect of higher grid utilization is that the assets have a flatter load profile. This will lead to a decrease in the maximum allowable loading and it will also affect energy losses. These issues will be paid attention to in the following section.

In the case of uncontrolled charging, the various assets are on average 6%–18% more loaded compared to the case without additional load of EVs. Charging EVs to minimize charging costs leads to load percentages that are even higher than the case of uncontrolled charging. In this latter case, the various assets are on average 10%–30% more loaded than in the case without EVs. The cost-minimization case with only 2.4 GW wind shows peak loadings that are only slightly higher than the peak minimization case.

V. FINANCIAL IMPACT

The charging strategy to minimize peak load enables a higher grid utilization, thereby deferring or eliminating the

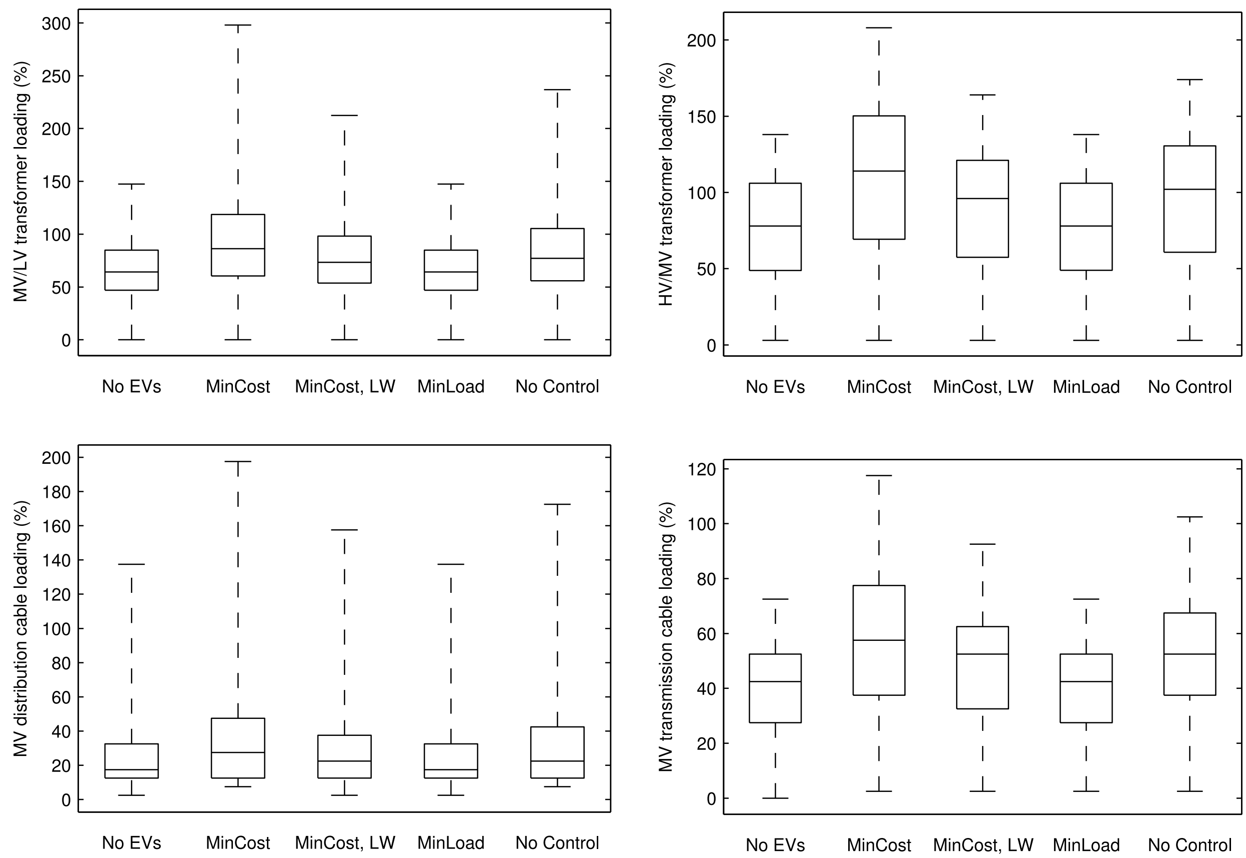

Fig. 3. Distribution of the peak loadings of the assets presented in Table II. The box-plots present the minimum and maximum values and the 25th, 50th, and 75th percentiles. The acronym LW in the case descriptions denotes the low wind (2.4 GW) case.

TABLE III
AVERAGE PEAK LOADINGS OF FOUR TYPES OF ASSETS IN 2030 IN THE VARIOUS CASES. ASSET TYPE ACRONYMS ARE AS IN TABLE II

Asset type	No EVs (%)	Min. costs (%)	Min. costs low wind (%)	Min. load (%)	No control
HV/MV	77	107	87	77	95
MVT	37	54	44	37	47
MVD	22	32	27	22	28
MV/LV	65	93	76	65	82

need for asset reinforcements and corresponding capital expenditures. Besides the effect of the various charging strategies on the required capacities of the network components, changing load profiles also affects the energy losses in the network. How the different charging strategies affect capital expenditures as a result of grid reinforcement as well as costs of energy losses is further explored in this section.

A. Capital Expenditures

To give an impression on what the required capacities for charging EVs in the various cases have on network investments, we calculate the cash flow of the reinforcements for the 48 MV networks including the assets that were presented in Table II. Based on current investment costs, taking no discounts rates, or price rises of material and labor costs into account, we calculate the cash flow of the reinforcements that are needed for upgrading the capacities of the existing assets, by replacing every overloaded asset with a new one. The reinforcements of HV/MV transformers and MV transmission cables are calculated for each single asset. For the MV distribution cables and MV/LV transformers, due to their large number, the reinforcement options are only calculated for a randomly sampled subset, and the results are extrapolated.

The overload criteria in normal operation for the assets are given in Table IV. For the case without additional load of EVs, the case of uncontrolled charging and the case of minimizing charging costs, the overload criteria follow the guidelines of the distribution system operator (DSO) involved in this research. These criteria are based on the nominal cable capacity and include a correction factor for the soil temperature, a correction factor for the thermal influence of parallel cables and the thermal resistance of the soil type. Besides this, a factor to incorporate the thermal dynamics of the cable is included; this factor is determined by the loading of the cable during $(n-1)$ situations in the grid [10]. For transformers a temporary higher loading than the nominal capacity is also allowed. This reflects the fact that we consider instantaneous peak values and transformers can sustain a peak higher than its nominal capacity for a while without problems. If the cables or transformers reach the values presented in Table IV in normal operation, the assets are upgraded.

TABLE IV
OVERLOAD CRITERIA IN NORMAL OPERATION

	Maximum loading in case of No EVs Minimizing costs and No Control (%)	Maximum loading in case of Minimizing load (%)
HV/MV transformers	120	110
MV transmission cables	59	50
MV distribution cables	101	92
MV/LV transformers	120	100

TABLE V
NUMBER OF REINFORCEMENTS UNTIL 2030 FOR ALL CASES

	No EVs	Min. costs	Min. costs. low wind	Min. load	No control
HV/MV trans. (#)	5	35	22	12	27
MVT and MVD cables (km)	321	2005	1074	550	1338
MV/LV trans. (#)	270	3651	1588	1129	2254

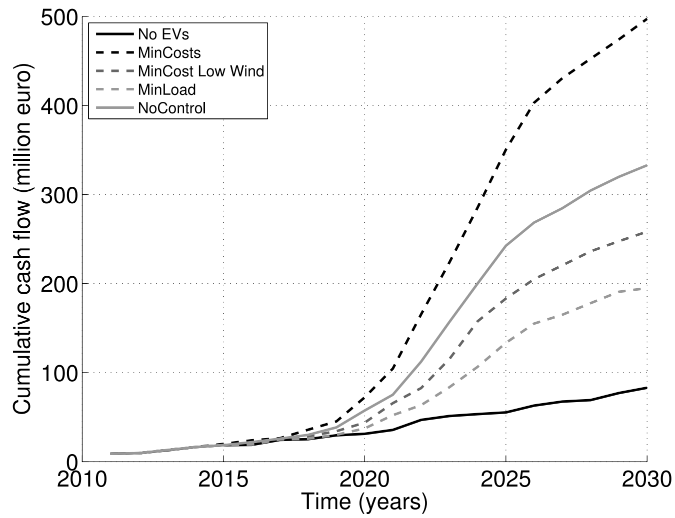

Fig. 4. Total cumulative cash flow of the reinforcements of the HV/LV transformers, the MV transmission and distribution cables, and the MV/LV transformers in the various cases.

The overload criteria for the case of minimizing peak loads are more stringent, because a flatter load profile of the assets reduces the room to utilize the heat capacity of the assets and hence the potential for exploiting thermal dynamics. Another issue is that because of the $(n-1)$ criterion, the MV transmission cables must be able to take over the load of parallel cables during an interruption; this reduces the maximum allowable loading in normal operation. To fulfill the $(n-1)$ criterion in case of HV/MV transformers spare capacity is present by additional transformers that are not in operation; this does not affect the overload criterion of the individual transformers. Note that when the transformers need to be upgraded the safe capacity that includes the capacity of the additional transformers is taken into consideration.

The network investment model can now be summarized as follows. The evolution of the peak load in all assets is estimated using an appropriate interpolation (that takes the introduction speed of the EVs into account) between the 2030 peak load and the current values that are the result of the load flow calculations described above. Based on this evolution of the peak, the year in which the overload criterion as defined in Table IV is determined, and in this year the asset is replaced by a heavier type. The replacement costs vary depending on the capacity of the specific asset that is replaced and the size of the project. To give an indication, the average costs lie around €12 000 for a MV/LV transformer, around €2 400 000 for an HV/MV transformer and between €225 000 and €350 000 per km MV cable. The number of reinforcements and the corresponding cumulative cash flow for the 48 MV networks can be found in Table V and Fig. 4.

B. Energy Losses

For efficient use of energy and reducing the costs related to energy losses, the annual energy losses in the networks should be minimized. System losses can be separated into so-called fixed losses and variable losses. The fixed losses are those due to the magnetization currents of such items as transformers and reactors, which are often referred to as iron or core losses and are practically independent of the load. The variable losses are those caused by the flow of current through the different items of equipment on the network, and are also termed load losses [19].

Core losses include hysteresis loss and eddy-current loss in the iron core of transformers, which depend on the type of steel used to fabricate the core. The hysteresis loss is due to the power requirement of maintaining the continuous reversals of the elementary magnets (or individual molecules) of which the iron is composed as a result of the flux alternations in a transformer core. The eddy-current loss is the loss due to the circulating currents in the core iron, caused by the time-varying magnetic fluxes within the iron [20]. The fixed energy losses in transformers can be estimated by

$$E_{\text{fixed loss}} = P_{\text{iron loss}} T_{\text{fixed loss}}. \tag{9}$$

The value of $P_{\text{iron loss}}$ is given by the supplier of the transformer and $T_{\text{fixed loss}}$ equals the annual service time of the transformer which in general will be 8760 h.

The load losses are due to the resistance of cables and of the primary and secondary windings in transformers, plus eddy-current losses in the windings and the core, tank and other metallic parts of the transformer caused by the leakage flux [19]. Power losses in a component having resistance R are proportional to the square of the current flowing through it ($P_{\text{loss}} = I^2 R$). The variable annual energy losses $E_{\text{variable loss}}$ can be determined by integrating the squared time function of the power flow

$$E_{\text{variable loss}} = \int_0^T P_{\text{loss}}(t)\mathrm{d}t. \tag{10}$$

In practice, the variable transformer losses are estimated by using the following formula:

$$E_{\text{variable transfomer loss}} = \alpha^2 P_{\text{nominal loss}} T_{\text{peak loss}}. \tag{11}$$

In this formula, $P_{\text{nominal loss}}$ is the power loss at full load which is given by the manufacturer of the transformer and α is the load factor of the transformer. $T_{\text{peak loss}}$ is the service time of the peak loss (i.e., the loss at peak load) which can be derived from the energy loss profile. This profile is related quadratically to the load profile.

Because of the squared relationship between the load and the loss, a flatter load profile in a component will mean that the load losses will decrease. It should be noted, however, that when replacing of the asset is delayed because the peak load is decreased due to shifting flexible demand of EVs, the energy losses may increase compared to a situation in which the asset would be replaced, because in the latter case the characteristics of the asset (i.e., the resistance) will change. Therefore, it is difficult to conclude in advance if changing load profiles in combination with the resulting reinforcement strategy will have a positive or negative effect on the energy losses in the network infrastructure.

Therefore, we will analyze how the energy losses in the transformers and cables of the 48 investigated MV networks change due to changing load of EVs in the various cases presented in this paper. We know the characteristics and peak loadings of the currently installed networks assets as well as of the assets with which the overloaded assets are replaced through the years. With this data we know the peak losses of the cables and transformers and can estimate the energy losses with the service times of these peak losses at the various network levels. The service time of the peak loss is determined by the energy loss profile that can be derived from the load profiles. The change in service time of the peak loss at the MV/LV transformers is determined by the known change in residential load profiles due to the residential load growth and EV charging profiles and the fact that 63% of the load of the MV/LV transformers is residential load. Also, for the higher network levels the service times follow from the relative sizes of the residential and industrial/commercial loads. In summary, the service time of the peak loss at the various networks assets in the initial year are known and are adjusted in the years after based on the changing load profiles at the MV/LV transformers as dictated by the changing load of residential load growth and EVs. The resulting annual energy losses in the investigated assets are presented in Fig. 5. This figure shows that the highest losses occur in the case of minimizing charging costs. The losses in the case of minimizing peak load are also higher than in the uncontrolled case, although the loss profiles are minimized by the charging strategy. This can be explained by the extra reinforcements made in the uncontrolled scenario, which lead to lower losses in the assets.

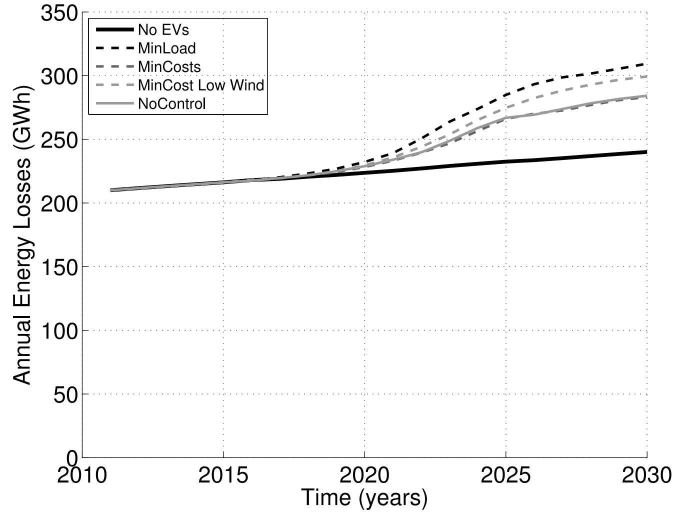

Fig. 5. Total annual energy losses for the HV/LV transformers, the MV transmission and distribution cables, and the MV/LV transformers in the various cases.

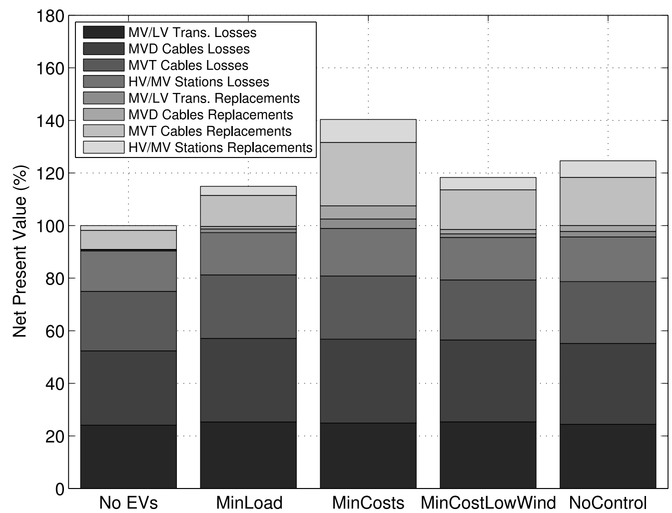

Fig. 6. NPV components of the capital expenditures and energy losses for the HV/LV transformers, the MV transmission and distribution cables, and the MV/LV transformers in the various cases. The values are normalized with respect to the NPV in the No EV case.

C. Net Present Value

To compare the different scenarios, we calculate the net present value (NPV) based on the cash flow of the investment costs and energy losses presented above. The NPV associated with the reinforcements is calculated based on the annuity costs of the investments, using the method described in [15]. It should be recalled that by using this method, the reinforcement costs are spread out over the lifetime of the new assets. Since this is considerably larger than our 2030 horizon, a significant part of the investments costs falls outside the analysis.

Fig. 6 shows the NPV for the different cases and its breakdown in the different cost components. An interest rate of 3% is assumed. Furthermore, a 50-year lifetime for MV/LV transformers and MV cables, and a 40-year lifetime for HV/MV transformers are used. The costs due to energy losses are based on the current electricity price, which at moment lies around €0.06 per kWh for a DSO (energy taxes do not apply on this price).

It can be seen that the costs for energy losses dominate the total NPV. Moreover, the costs related to the MV distribution cables, are the largest component in the energy losses costs. Interestingly, the costs for the reinforcements of the MV transmission cables are (by far) the largest. This can be explained by the fact that there are many more MV distribution cables

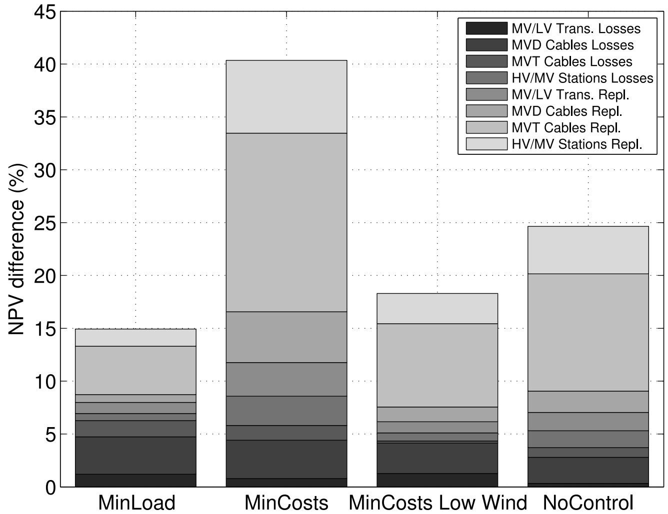

Fig. 7. Difference in NPV between EV scenarios compared to the case without EVs.

than MV transmission cables (see Table II) and hence many more losses in those cables. On the other hand, the MV transmission cables are loaded closer to their capacity and thus need to be replaced more frequently due to the extra EV load, resulting in a higher NPV due to reinforcements.

The NPV differences between the four different cases with EVs compared to the case without EVs are shown in Fig. 7. From this figure it can be concluded that while the losses dominate the total costs, the differences between the various cases are mostly caused by the reinforcement costs. Also noteworthy is the fact that the energy losses are smaller in the uncontrolled case than in the case of minimizing peak load strategy in which peak losses are minimized. This can be ascribed to the fact that when an extra capacity is added, energy losses are generally reduced. So the total energy losses in the uncontrolled EV scenario are lowered, but at the expense of higher investment costs.

We consider it worthwhile to compare the NPV figures presented above with other values found in the scientific literature. Although there have been many studies on grid impacts related to EV charging, only a few have considered the financial consequences. In [15], where a similar methodology and dataset compared to this paper has been used, the cost difference between uncontrolled charging and a controlled charging scenario comparable with our load minimizing scenario were found to be roughly 20%, whereas this difference in our case amounts to approximately 10%. Possible explanations for this deviation are differences in methodology and scope between the two papers such as are a longer time horizon in [15] (eventually leading to a higher EV penetration of 75%) and a different network investment model. A second study on the financial benefits of controlled EV charging was carried out in [9]. Here, the difference in investment and maintenance costs (not energy losses) between uncontrolled and controlled EV charging was found to be 7% and 20% for two different distribution networks. Given the fact that this includes no energy losses, this can be considered similar to the 12% difference in replacement costs that can be observed in Fig. 7. We conclude that, as far as differences in data, methodology and scope of other studies allow a comparison, the numbers are similar in magnitude.

The cost figures presented above provide strong evidence that some form of congestion management that limits the peaks caused by minimizing charging costs of EV demand is justified in a scenario with a lot of wind energy and volatile wholesale prices. Because the amount of hours where the EV demand leads to the high network peaks is very low, see Fig. 1, the extra electricity costs related to constrain the peak load at the network are expected to be very small. The additional costs due to extra network reinforcements compared to the case without EVs are roughly 25% higher than for the case where peak load is minimized. Furthermore, we observe that the high network costs in the cost minimization scenario can largely be ascribed to the effect that a large amount of wind energy has on electricity prices. In the low wind scenario, the network cost lie much closer to the peak minimization scenario.

VI. Conclusion

The research presented in this paper compares the distribution grid impacts resulting from various EV charging strategies. The results show that when EVs base their charging schedules on electricity price, which is for a significant part determined by the instantaneous production of wind energy, this leads to high peaks in network load and, consequently, high network investment costs. On the other hand, when EV charging is controlled with the objective of minimizing peaks in network load, we find that far less reinforcements are needed.

We calculated the network impacts expressed in the NPV of the annuitized investments costs and energy losses associated with the different EV charging strategies and found that in the case where EVs are basing their charge schedules on electricity prices in a scenario with a large share of wind energy, a roughly 25% higher NPV was found compared to the case with no EVs than in the case where the extra peak load due to EVs was minimized. The total cost figures are dominated by the costs for energy losses, which is partly the result of the fact that a large part of the investment costs (calculated as yearly annuity costs over the lifetime of the assets), fall outside the 2030 horizon of this paper. The cost differences, however, are largely caused by differences in reinforcements. We emphasize once more that the NPV related to a control strategy to minimize charge costs of EVs in the high wind energy scenario is even larger than the case with uncontrolled charging of EVs. This is a consequence of the EVs reacting to the same electricity price and therefore concentrating the EV load in the low price periods which leads to high peak loads. For a low wind scenario, the low price periods follow a more regular daily pattern and coincide mostly with moments of low network load. As a result, the large peaks in network demand caused by the EVs are absent in this case.

Furthermore, the results strongly suggest that the situation where EVs are controlled with a strategy to minimize charging costs that does not take the distribution grids into account may not lead to an optimal situation when the entire electricity delivery system is regarded. A form of congestion management for responsive demand where the distribution networks are somehow taken into account therefore seems a cost-beneficial way to optimally exploit the flexibility of EVs. In [17], it was shown that an adequate congestion management mechanism that limits responsive EV load to free network capacity increases energy costs only marginally. The results of our study essentially complete the argument for congestion management by showing that the network costs caused by price-responsive EV demand are significant in a scenario with a high wind energy penetration. An important aspect of future work in this area would be related to the extent to which a decentralized approach to apply congestion management mechanisms is feasible, since it likely has advantages in terms of communication infrastructure requirements and driver satisfaction. Another issue to take into account is the uncertainty related to network load, wind forecasts, electricity prices, and EV driving behavior, which could make some solution approaches difficult to apply in practice.

In a broader perspective, this paper contributes to the research questions what the implication of active participation of customers, in this case electric car owners, in electricity markets are on different levels of the entire electricity delivery system and how various demand response strategies can lead to more efficient use of electricity grids and facilitate the integration of renewable energy sources in smart grids in an optimal way. The question in which way the demand for EVs can be managed in practice to achieve the results presented in this paper is beyond the scope of this paper, but requires further attention. The results presented in this paper are relevant input for this discussion.

REFERENCES

[1] Energy Research Centre of the Netherlands and PBL Netherlands Environmental Assessment Agency. (2012). *Referentieraming Energie en Emissies: Actualisatie 2012—Energie en Emissies in de Jaren 2012, 2020 en 2030* [Online]. Available: http://www.ecn.nl/publications/ECN-E--12-039

[2] Government of the Netherlands. (2012, May). *WoonOnderzoek Nederland 2009* [Online]. Available: http://www.rijksoverheid.nl/onderwerpen/woningmarkt/woononderzoek/woononderzoek-nederland-won

[3] R. C. Green, II, L. Wang, and M. Alam, "The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook," *Renew. Sustain. Energy Rev.*, vol. 15, no. 1, pp. 544–553, 2011.

[4] Global Wind Energy Council (GWEC). (2013, Oct.). *Global Wind Statistics 2012* [Online]. Available: http://www.gwec.net/wp-content/uploads/2013/02/GWEC-PRstats-2012_english.pdf

[5] T. Kristoffersen, K. Capion, and P. Meibom, "Optimal charging of electric drive vehicles in a market environment," *Appl. Energy*, vol. 88, no. 5, pp. 1940–1948, 2011.

[6] Ministry of Economic Affairs, Ministry of Infrastructure and the Environment, and Ministry of the Interior and Kingdom Relations of the Netherlands. (Oct. 2012). *Plan van Aanpak Elektrisch Vervoer: Elektrisch Rijden in de Versnelling* [Online]. Available: http://www.rijksoverheid.nl/documenten-en-publicaties/richtlijnen/2011/10/03/bijlage-2-plan-van-aanpak-elektrisch-vervoer-elektrisch-rijden-in-de-versnelling.html

[7] Ministry of Infrastructure and the Environment. (2013, Jun.). *Mobiliteitsonderzoek Nederland 2009* [Online]. Available: http://www.scp.nl/Onderzoek/Bronnen/Beknopte_onderzoeksbeschrijvingen/Mobiliteitsonderzoek_Nederland_MON

[8] PBL Netherlands Environmental Assessment Agency and CPB Netherlands Bureau for Economic Policy Analysis. (2006). *Welvaart en Leefomgeving: Een Scenariostudie voor Nederland in 2040* [Online]. Available: http://www.pbl.nl/publicaties/2006/Welvaartenleefomgeving

[9] L. Pieltain Fernandez, T. Gómez San Román, R. Cossent, C. Domingo, and P. Frias, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, Feb. 2011.

[10] J. G. Slootweg, A. Postma, and F. de Wild, "A practical approach towards optimizing the utilization of MV cables in routine network planning," in *Proc. Int. Conf. Elect. Distrib. (CIRED)*, Vienna, Austria, 2007, p. 4.

[11] E. Sortomme and M. A. El-Sharkawi, "Optimal combined bidding of vehicle-to-grid ancillary services," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 70–79, Mar. 2012.

[12] E. Veldman, M. Gibescu, J. G. Slootweg, and W. L. Kling, "Scenario-based modelling of future residential electricity demands and assessing their impact on distribution grids," *Energy Policy*, vol. 56, pp. 233–247, May 2013.

[13] R. A. Verzijlbergh, Z. Lukszo, and M. Ilic, "Comparing different EV charging strategies in liberalized power systems," in *Proc. 9th Int. Conf. Eur. Energy Market (EEM)*, Florence, Italy, May 2012, pp. 1–8.

[14] R. A. Verzijlbergh, Z. Lukszo, E. Veldman, J. G. Slootweg, and M. Ilic, "Deriving electric vehicle charge profiles from driving statistics," in *Proc. 2011 IEEE Power Energy Soc. Gen. Meeting*, San Diego, CA, USA, pp. 1–6.

[15] R. A. Verzijlbergh, M. Grond, Z. Lukszo, J. G. Slootweg, and M. Ilic, "Network impacts and cost savings of controlled EV charging," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1203–1212, Sep. 2012.

[16] R. A. Verzijlbergh, "The power of electric vehicles. Exploring the value of flexible electricity demand in a multi-actor context," Ph.D. dissertation, Dept. Tech., Policy Manage., Delft Univ. Tech., Delft, The Netherlands, 2013.

[17] R. A. Verzijlbergh, L. J. De Vries, and Z. Lukszo, "Renewable energy sources and responsive demand. Do we need congestion management in the distribution grid?" *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2119–2128, Sep. 2014.

[18] D. B. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration," *Renew. Sustain. Energy Rev.*, vol. 19, pp. 247–254, Mar. 2013.

[19] E. Lakervi and E. J. Holmes, *Electricity Distribution Network Design*, 2nd ed. London, U.K.: Peregrinus, 1995.

[20] T. Gönen, *Electric Power Distribution Power Engineering*, 2nd ed. Boca Raton, FL, USA: CRC Press, 2008.

Else Veldman (M'08) received the M.Sc. degree in mechanical engineering from the University of Twente, Enschede, The Netherlands, in 2006, and the Ph.D. degree in electrical engineering in the field of smart grids from the Electrical Energy Systems Group, Eindhoven University of Technology, Eindhoven, The Netherlands, in 2013.

She is currently a Manager with the Innovation Department of Enexis B.V., Hertogenbosch, The Netherlands, one of the largest distribution network operators in The Netherlands, which formulates and realizes innovation projects and essential research. Her current research interests include energy transition, including smart grids and the integration of distributed generation and electric vehicles in the electricity distribution networks.

Remco A. Verzijlbergh received the M.Sc. degree in applied physics from the Delft University of Technology, Delft, The Netherlands, in 2009, where he received the Ph.D. degree (*cum laude*) in smart energy systems from the Energy and Industry Group, Department of Technology, Policy, and Management, in 2013.

His current research interests include operations and economics of power systems, integration of electric vehicles, and renewable energy sources in power systems.