Open access • Journal Article • DOI:10.1109/TPWRS.2009.2036481

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Published on: 01 Feb 2010 - IEEE Transactions on Power Systems (IEEE)

Topics: Electricity generation, Voltage, Energy consumption, Stochastic programming and Grid

The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid

Kristien Clement-Nyns, Edwin Haesen, *Student Member, IEEE*, and Johan Driesen, *Member, IEEE*

***Abstract*—Alternative vehicles, such as plug-in hybrid electric vehicles, are becoming more popular. The batteries of these plug-in hybrid electric vehicles are to be charged at home from a standard outlet or on a corporate car park. These extra electrical loads have an impact on the distribution grid which is analyzed in terms of power losses and voltage deviations. Without coordination of the charging, the vehicles are charged instantaneously when they are plugged in or after a fixed start delay. This uncoordinated power consumption on a local scale can lead to grid problems. Therefore, coordinated charging is proposed to minimize the power losses and to maximize the main grid load factor. The optimal charging profile of the plug-in hybrid electric vehicles is computed by minimizing the power losses. As the exact forecasting of household loads is not possible, stochastic programming is introduced. Two main techniques are analyzed: quadratic and dynamic programming.**

***Index Terms*—Coordinated charging, distribution grid, dynamic programming, plug-in hybrid electric vehicles, quadratic programming.**

I. Introduction

HYBRID electric vehicles (HEVs), battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) are becoming more popular. PHEVs are charged by either plugging into electric outlets or by means of on-board electricity generation. These vehicles can drive at full power in electric-only mode over a limited range. As such, PHEVs offer valuable fuel flexibility [1]. PHEVs may have a larger battery and a more powerful motor compared to a HEV, but their range is still very limited [2].

The charging of PHEVs has an impact on the distribution grid because these vehicles consume a large amount of electrical energy and this demand of electrical power can lead to extra large and undesirable peaks in the electrical consumption. There are two main places where the batteries of PHEVs can be recharged: either on a car park, corporate or public, or at home. The focus in this article lies on the latter. The electrical consumption for charging PHEVs may take up to 5% of the total electrical consumption in Belgium by 2030 [3]. For a PHEV with a range of 60 miles (100 km), this amount can increase to 8% taking into account a utility factor which describes the fraction of driving that is electrical [4].

From the distribution system operator point of view, the power losses during charging are an economic concern and have to be minimized and transformer and feeder overloads have to be avoided. Not only power losses, but also power quality (e.g., voltage profile, unbalance, harmonics, etc.) are essential to the distribution grid operator as well as to grid customers. Voltage deviations are a power quality concern. Too large voltage deviations cause reliability problems which must be avoided to assure good operation of electric appliances. Overnight recharging can also increase the loading of base-load power plants and smoothen their daily cycle or avoid additional generator start-ups which would otherwise decrease the overall efficiency [5]. From the PHEV owner point of view, the batteries of the PHEV have to be charged overnight so the driver can drive off in the morning with a fully-charged battery. This gives opportunities for intelligent or smart charging. The coordination of the charging could be done remotely in order to shift the demand to periods of lower load consumption and thus avoiding higher peaks in electricity consumption.

This research fits in a more global context where also other new technologies, such as small wind turbines and photovoltaic cells, are implemented in the distribution grid. In this optimization problem, only power losses and voltage deviations are minimized. Other aspects, e.g., power factor control, can be included as well. The proposed methodology can help evaluating planned grid reinforcements versus PHEV ancillary services to achieve the most efficient grid operation.

This article wants to emphasize the improvements in power quality that are possible by using coordinated charging or smart metering. It also wants to indicate that uncoordinated charging of PHEVs decreases the efficiency of the distribution grid.

II. Assumptions and Modeling

A. Load Scenarios

From an available set of residential load measurements [6], two large groups of daily winter and summer load profiles are selected. The load profiles cover 24 hours and the instantaneous power consumption is given on a 15-min time base as shown in Fig. 1 for an arbitrary day during winter.

B. Specifications of PHEVs

Each of the PHEVs has a battery with a maximum storage capacity of 11 kWh [5]. Only 80% of the capacity of the battery can be used to optimize life expectancy. This gives an available capacity of 8.8 kWh; 10 kWh is required from the utility grid, assuming an 88% energy conversion efficiency from AC energy absorbed from the utility grid to DC energy stored in the battery of the vehicle [4]. The batteries can only be charged

Manuscript received May 27, 2009; revised July 27, 2009. First published December 18, 2009; current version published January 20, 2010. Paper no. TPWRS-00097-2009.

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Digital Object Identifier 10.1109/TPWRS.2009.2036481

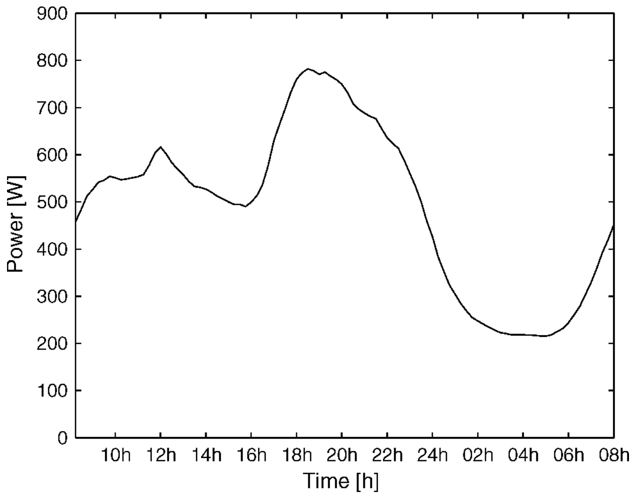

Fig. 1. Household load during winter [6].

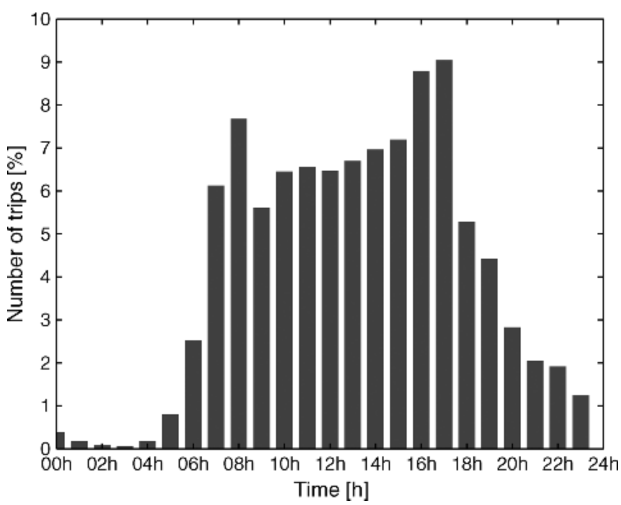

Fig. 2. Percentage of trips by vehicle each hour [8].

and not discharged, meaning that the energy flow is unidirectional and the vehicle-to-grid concept is not considered yet. The charger has a maximum output power of 4 kW. The charger of 4 kW is chosen because the maximum power output of a standard single phase 230 V outlet is 4.6 kW. Therefore, this is the largest charger that can be used for a standard outlet at home without reinforcing the wiring. Fast charging is not considered because it requires a higher short-circuit power which is not available at standard electric outlets in households. For fast charging, connections at a higher voltage level are indispensable. A higher voltage connection could be installed, but this is an extra investment for the PHEV owner. The maximum penetration degree of PHEVs is 30% by 2030 for Belgium as predicted by the Tremove model [7].

C. Charging Periods

It is not realistic to assume that PHEVs could be charged any place a standard outlet is present. Therefore in this article, the batteries of the vehicles are assumed to be charged at home. Fig. 2 shows the percentage of all trips by vehicle each hour. At that moment, they are not available for charging. Based on this figure, three important charging periods are proposed. The first charging period is during the evening and night. Most of the vehicles are at home from 21h00 until 06h00 in the morning. Some PHEVs are immediately plugged in on return from work in order to be ready to use throughout the evening. Thus the second charging period takes place between 18h00 and 21h00. This charging period coincides with the peak load during the evening. The number of vehicles that will be charged during this period will probably be smaller. One other charging period is considered, that is charging during the day between 10h00 and 16h00. The charging will occur in small offices in urban areas. It is assumed that only one vehicle per household or office can be charged. The charging of multiple vehicles at a household or office is not considered because it is not feasible to reflect all possible scenarios. However, the proposed methods are also valid for other periods and scenarios. In this article, the focus lies on charging at home, in weaker non-dedicated distribution grids.

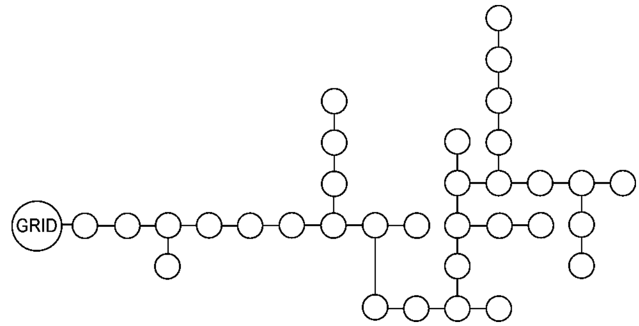

Fig. 3. IEEE 34-node test feeder [9].

D. Grid Topology

The radial network used for this analysis is the IEEE 34-node test feeder [9] shown in Fig. 3. The network is downscaled from 24.9 kV to 230 V so this grid topology represents a residential radial network. The line impedances are adapted to achieve tolerable voltage deviations and power losses. Each node is a connection with a residential load and some, randomly chosen, nodes will have PHEVs charging.

E. Assumptions

The exact advantage of coordinated charging depends on the assumptions made in this section. The household load profiles are typical for Belgium. Other regions may have other load profiles because of different weather conditions, such as an air conditioning peak in the afternoon for warm regions. Some regions will also have other grid voltages, such as 120 V. The IEEE grid is an example of a distribution grid, so the obtained results are only valid for this grid. The maximum power of the charger is determined by the maximum power of a standard electric outlet. Other parameters which affect the obtained results are the utility load cycle of the base-load power plants, incentives and the use of smart meters.

III. Uncoordinated Charging

At the moment, there is no smart metering system available for PHEVs, so the vehicles will be charged without coordination. Uncoordinated charging indicates that the batteries of the vehicles are either start charging immediately when plugged in, or after a user-adjustable fixed start delay. The vehicle owners currently do not have the incentive nor the essential information to schedule the charging of the batteries to optimize the grid utilization. The fixed start delay is introduced to give the vehicle owner the possibility to start charging using off-peak electricity tariffs.

A. *Load Flow Analysis*

A load flow analysis is performed to assess the voltage deviations and the power losses in the selected distribution grid. This analysis is based on the backward-forward sweep method to calculate the node currents, line currents and node voltages [10]. At the initialization step, a flat profile is taken for the node voltages. A constant power load model is used at all connections at each time step. In the backward step, the currents are computed based on the voltages of the previous iteration. In the forward step, the voltages are computed based on the voltage at the root node and the voltage drops of the lines between the nodes. The currents and voltages are updated iteratively until the stopping criterion based on node voltages is reached.

B. *Methodology*

At the start of a 24-h cycle, a daily profile is randomly selected from the available set belonging to a specific scenario (winter, summer) and assigned at each node. For each scenario, four cases depending on the penetration degree are selected. The first case, with no PHEVs, is taken as a reference case. The next cases have a PHEV penetration of, respectively, 10%, 20%, and 30% representing the proportion of nodes with a PHEV present. The PHEVs are randomly placed. Separated runs are performed for each charging period and the number of vehicles is varying between 0% and 30% for each charging period.

The profile for charging the PHEVs is kept straightforward. Each individual vehicle starts charging at a random time step within a specific period of time such that the vehicles are still fully charged at the end of the charging period. It is assumed that the batteries of the vehicles are fully discharged at the first time step. For every quarter of an hour, the backward-forward sweep method is repeated to compute the voltage at each node until convergence is obtained.

C. *Results*

The impact of uncoordinated charging on the distribution grid is illustrated by computing the power losses and the maximum voltage deviation for the different charging periods. The number of samples is 1000, which is large enough to achieve an accurate average per scenario. Taking more samples does not change the results significantly.

The results for the 4 kW charger are shown in Tables I and II. Table I depicts the ratio of the power losses to the total load. The total load includes the daily household loads and the charging of the PHEVs, if present. In all cases, the power losses are higher in the winter season than in the summer season due to the higher household loads. The increase of the number of PHEVs leads to a significant increase in power losses. These power losses are important for the operator of the distribution grid. The distribution system operator (DSO) will compensate higher losses by increasing its grid tariffs.

TABLE I
RATIO OF POWER LOSSES TO TOTAL POWER [%] FOR THE 4 kW CHARGER IN CASE OF UNCOORDINATED CHARGING

Charging period	**Penetration level**	**0%**	**10%**	**20%**	**30%**
21h00-06h00	**Summer**	1.1	1.4	1.9	2.2
	Winter	1.4	1.6	2.1	2.4
18h00-21h00	**Summer**	1.5	2.4	3.8	5.0
	Winter	2.4	3.4	4.8	6.0
10h00-16h00	**Summer**	1.3	1.8	2.6	3.2
	Winter	1.7	2.2	3.0	3.6

TABLE II
MAXIMUM VOLTAGE DEVIATIONS [%] FOR THE 4 kW CHARGER IN CASE OF UNCOORDINATED CHARGING

Charging period	**Penetration level**	**0%**	**10%**	**20%**	**30%**
21h00-06h00	**Summer**	3.1	3.5	4.4	5.0
	Winter	4.2	4.4	4.9	5.5
18h00-21h00	**Summer**	3.0	4.4	6.5	8.1
	Winter	4.8	6.3	8.5	10.3
10h00-16h00	**Summer**	3.0	4.1	5.6	6.9
	Winter	3.7	4.9	6.4	7.7

Not only the power losses, but also the voltage deviations of the grid voltage (230 V) which are represented in Table II, are important for the DSO. An increase in the number of PHEVs leads to a significant increase in voltage deviations. According to the mandatory EN50160 standard [11], voltage deviations up to 10% in low voltage grids, for 95% of the time, are acceptable. Table II shows that for a penetration of 30%, some of the voltage deviations are close to 10%, especially during evening peak.

The power losses and the voltage deviations are the highest while charging during the evening peak, between 18h00 and 21h00. The reasons are twofold. In the first place, this charging period, wherein the batteries must be fully charged is rather short, only 4 hours. Therefore, the charger output power must be higher. Secondly, the household load during the evening is the highest of the whole day and the output power of the charger is added to the household loads. Charging during the day is a little more demanding for the grid compared by charging overnight. These results are directly related to Fig. 1.

Fig. 4 depicts the voltage profile in a node of the distribution grid for a penetration degree of 0% and 30% during winter night. This figure shows two charging examples and is not the average of several samples. Clearly, there is a decrease of the voltage in the presence of PHEVs during the charging period between 21h00 and 06h00. Between 23h00 and 04h00, most of the vehicles are charging and the voltage drop during these hours is the largest and deviates the most from the 0% PHEV voltage profile. The power needed for charging these vehicles is significantly higher compared to the household loads during the night. The small difference in voltage deviations during the rest of the day is caused by the different load profiles selected for both cases.

IV. COORDINATED CHARGING

In the previous section, the charging of the batteries of the PHEVs starts randomly, either immediately when they are

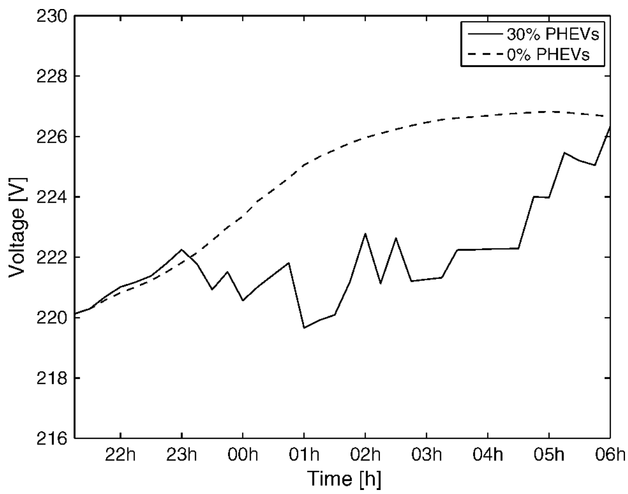

Fig. 4. Voltage profile in a node with 30% PHEVs compared to the voltage profile with 0% PHEV.

plugged in, or after a fixed start delay. The idea of this section is to achieve optimal charging and grid utilization to minimize the power losses. A direct coordination of the charging will be done by smart metering and by sending signals to the individual vehicles.

This optimization problem can be tackled with the quadratic programming technique (QP). This technique optimizes a quadratic function of several variables, in this case the power of the PHEV chargers at all time steps, which is subjected to linear constraints. In this section, the QP technique is applied to handle deterministic and stochastic household load profiles. The objective is to minimize the power losses.

A. Optimization Problem

By minimizing the power losses, the owners of PHEVs will no longer be able to control the charging profile. The only degree of freedom left for the owners is to indicate the point in time when the batteries must be fully charged. For the sake of convenience, the end of the indicated charging period is taken as the point in time when the vehicles must be fully charged. The charging power varies between zero and maximum and is no longer constant. The coordinated charging is analyzed for the same charging periods as described in the previous section. The range of PHEV penetration levels remains the same, and the vehicles are also placed randomly. The same IEEE 34-node test grid is used. For each charging period and season, the power losses and voltage deviations are calculated and compared with the values of uncoordinated charging.

B. Methodology

The objective is to minimize the power losses which are treated as a reformulation of the nonlinear power flow equations. This nonlinear minimization problem can be tackled as a sequential quadratic optimization [12]. The charging power obtained by the quadratic programming cannot be larger than the maximum power of the charger P_{max}. The batteries must be fully charged at the end of cycle, so the energy which flows to the batteries must equal the capacity of the batteries C_{max}. x_n is zero if there is no PHEV placed and is one if there is a PHEV

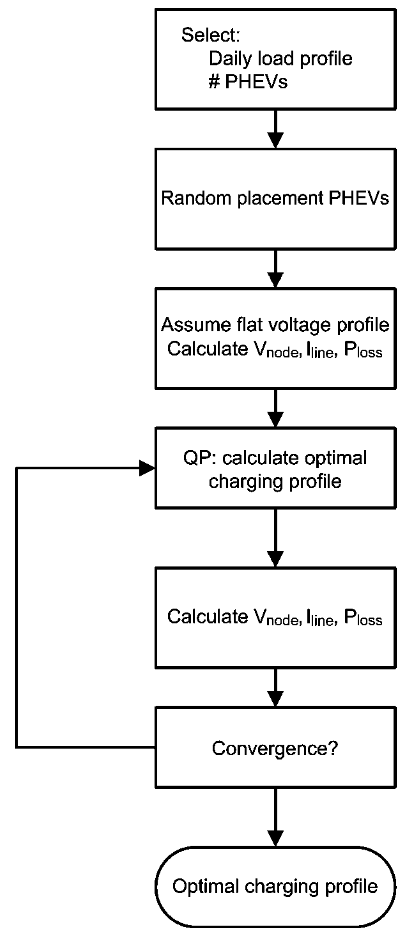

Fig. 5. Algorithm of coordinated charging.

at node n. The goal is to minimize power losses while taking into account these constraints. The quadratic programming uses (1) and (2):

$$\min \sum_{t=1}^{t_{max}} \sum_{l=1}^{lines} R_l \cdot I_{l,t}^2 \tag{1}$$

$$s.t. \begin{cases} \forall t, \forall n \epsilon \{nodes\} : 0 \leq P_{n,t} \leq P_{\max} \\ \forall n \epsilon \{nodes\} : \sum_{t=1}^{t_{max}} P_{n,t} \cdot \triangle t \cdot x_n = C_{max} \\ x_n \epsilon \{0,1\}. \end{cases} \tag{2}$$

C. Deterministic Programming

Fig. 5 represents the outline of the algorithm of coordinated charging. The vehicles are placed randomly after the selection of a daily load profile and the number of PHEVs. A flat voltage profile is assumed and the node voltages are computed with the backward-forward sweep method assuming that there are no PHEVs. The backward and forward sweep are formulated as a matrix multiplication. The quadratic optimization is performed in order to determine the optimal charging profile. Then, the node voltages are computed again. This process is repeated until the power losses based stopping criterion is reached.

This paragraph describes the results of the coordinated charging to illustrate the impact on the distribution grid. Table III and Table IV represent respectively the power losses and the maximum voltage deviations for the coordinated

TABLE III
RATIO OF POWER LOSSES TO TOTAL POWER [%] FOR THE 4 kW CHARGER IN CASE OF COORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	1.1	1.3	1.7	1.9
	Winter	1.4	1.5	1.8	2.1
18h00-21h00	Summer	1.5	2.3	3.7	4.7
	Winter	2.4	3.3	4.7	5.8
10h00-16h00	Summer	1.3	1.7	2.3	2.8
	Winter	1.7	2.1	2.7	3.2

TABLE IV
MAXIMUM VOLTAGE DEVIATIONS [%] FOR THE 4 kW CHARGER IN CASE OF COORDINATED CHARGING

Charging period	Penetration level	0%	10%	20%	30%
21h00-06h00	Summer	3.1	3.1	3.3	3.7
	Winter	4.2	4.2	4.2	4.3
18h00-21h00	Summer	3.0	4.1	5.8	7.2
	Winter	4.8	6.0	7.8	9.1
10h00-16h00	Summer	3.0	3.3	4.1	4.7
	Winter	3.7	4.0	4.9	5.5

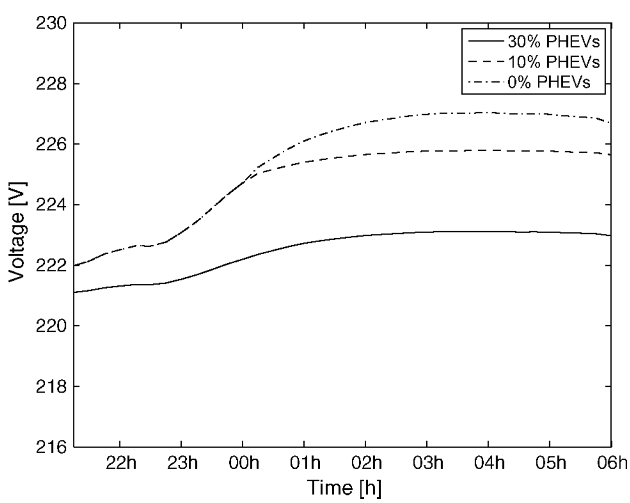

Fig. 6. Voltage profile in a node with 30% and 10% PHEVs compared to the voltage profile with 0% PHEV for coordinated charging.

charging during the different charging periods. These results must be compared with Table I and Table II. For all charging periods and seasons, the power losses are decreasing if the coordinated charging is applied. The voltage deviations are in accordance with EN50160 standard and the maximum voltage deviation for a penetration degree of 30% is now well below 10%. If there are no PHEVs present, charging during the day and the night gives more or less the same results. However, if the number of PHEVs is increased, the voltage deviations and the power loss increases are larger for charging during the day than during the night.

Fig. 6 shows that the maximum voltage deviation during overnight charging when no PHEVs are involved, occurs at the beginning of the charging period when the household loads are still high. A penetration degree of 10% gives the same voltage deviations, meaning that the vehicles are not charged

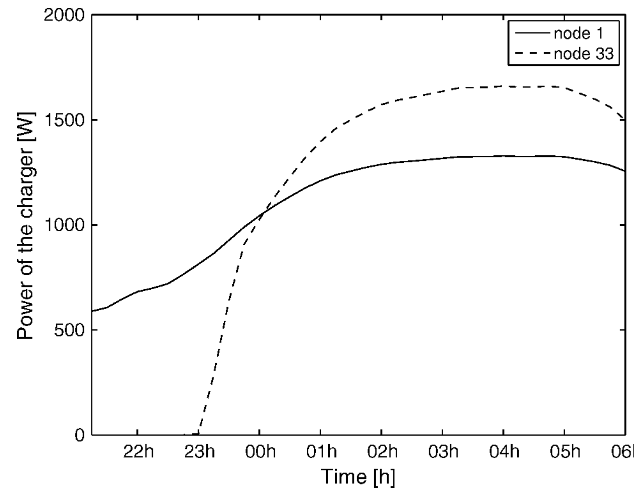

Fig. 7. Load profile of the 4 kW charger for the charging period from 21h00 until 06h00 during winter.

when the household load peak occurs. The vehicles cause an extra load during the off-peak hours to obtain the objective to minimize the power losses. The voltage deviations during these off-peak hours is smaller compared to the voltage deviations due to the household loads during the evening peak. For a vehicle penetration of 20% or more, the number of vehicles is increased, and the charging is more distributed. Some vehicles are charging during peak hours and this increases the voltage deviation and thus lowers the voltage.

Fig. 7 shows the load profiles of the nodes 1 and 33 of Fig. 3 with a penetration degree of 30% during the charging period from 21h00 until 06h00 during winter. The nodes are chosen at the starting and end point of the grid feeder. It is clear that the power output of the charger is not constantly 4 kW, but varies.

D. Stochastic Programming

The previous results are based on deterministic or historical data for the daily load profiles. So the essential input parameters are fixed. For this approach, a sufficient number of measurement data must be available. Most of the time, however, these measurements are not adequate to perform a perfect forecasting of the data. A stochastic approach in which an error in the forecasting of the daily load profiles is considered, is therefore more realistic.

The daily load profiles are the essential input parameters. The uncertainties of these parameters can be described in terms of probability density functions. In that way, the fixed input parameters are converted into random input variables with normal distributions assumed at each node. N independent samples of the random input variable ω^j, the daily load profile, are selected.

Equation (3) gives the estimation for the stochastic optimum $\hat{v}_n$. The function $g(P_{n,t}, \omega^j)$ gives the power losses and $P_{n,t}$ is the power rate of the charger for all the PHEVs and time steps. $\hat{f_N}$ is a sample-average approximation of the objective of the stochastic programming problem:

$$\hat{v}_n = \min\left\{ \hat{f_N}(P_{n,t}) \equiv \frac{1}{N}\sum_{j=1}^{N} g(P_{n,t}, \omega^j) \right\}. \quad (3)$$

The mean value of the power losses, $E(\hat{v}_n)$, is a lower bound for the real optimal value of the stochastic programming problem, v^* [13], as shown in (4):

$$E(\hat{v}_n) \leq v^*. \tag{4}$$

$E(\hat{v}_n)$ can be estimated by generating M independent samples $\omega^{i,j}$ of the random input variable each of size N. M optimization runs are performed in which the nonlinear power flow equations are solved by using the backward-forward sweep method. According to (5), $\hat{v}_n^j$ is the mean optimal value of the problem for each of the M samples. The optimal values of the M samples constitute a normal distribution:

$$\hat{v}_n^j = \min\left\{ \hat{f_N}^j(P_{n,t}) := \frac{1}{N}\sum_{i=1}^{N} g(P_{n,t},\omega^{i,j}) \right\}, \quad j = 1\ldots M. \tag{5}$$

In (6), $L_{N,M}$ is an unbiased estimator of $E(\hat{v}_n)$. Simulations indicate that in this type of problem, the lower bound converges to the real optimal value when N is sufficiently high:

$$L_{N,M} = \frac{1}{M}\sum_{j=1}^{M} \hat{v}_N^j. \tag{6}$$

A forecasting model for the daily load profile for the next 24 h is required. The daily load profiles of the available set are varied by a normal distribution function. The standard deviation σ is determined in such a way that 99.7% of the samples vary at maximum 5% or 25% of the average μ.

E. Results

For 2000 independent samples of the daily load profile, one optimal charging profile is calculated. This optimal charging profile is used to determine the power losses for the 2000 individual load profiles. This is the stochastic optimum. For each of these 2000 load profiles, the optimal charging profile and the corresponding power losses are also computed, which is the deterministic optimum.

The power losses of the deterministic optimum are subtracted from the power losses of the stochastic optimum and divided by the deterministic optimum, defined as ΔP. This is shown for a variation of the household loads of 5 and 25% in Figs. 8 and 9, respectively. The value of this difference is always positive. The forecasting of the daily load profiles introduces an efficiency loss because the charge profiles of the PHEVs are not optimal for this specific daily load profile. If the standard deviation of the normal distribution and thus the variation of the household load is reduced, the 2000 charge profiles of the deterministic optimum will converge to the optimal charge profile. The efficiency loss will also reduce indicating that the power losses of the differences will go down by a factor 25 as shown in Fig. 8 compared to Fig. 9.

In general, the difference between the power losses of the stochastic and the deterministic optimum is rather small. It is clear that the error in forecasting does not have a large impact on the power losses. The daily household load profiles during the winter season show the same trend each day during winter season resulting in a optimal charge profile which resembles a deterministic charge profile of a specific day as shown in Fig. 10 for the last node of the test grid. Both charge profiles have the same trend. Therefore, the contrast in terms of power

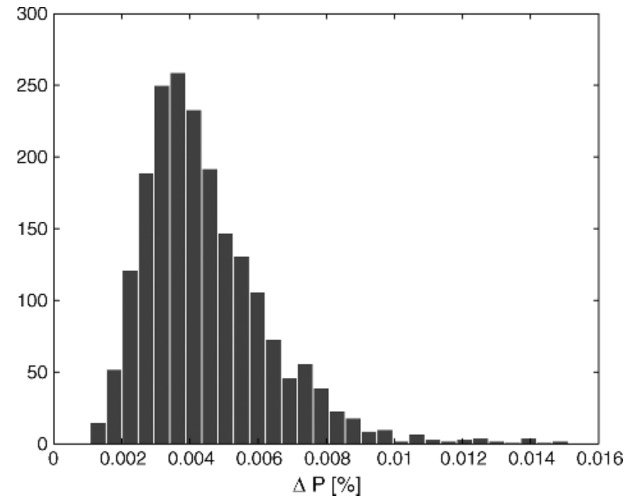

Fig. 8. Histogram of the efficiency loss of an arbitrary day during winter for a variation of 5%.

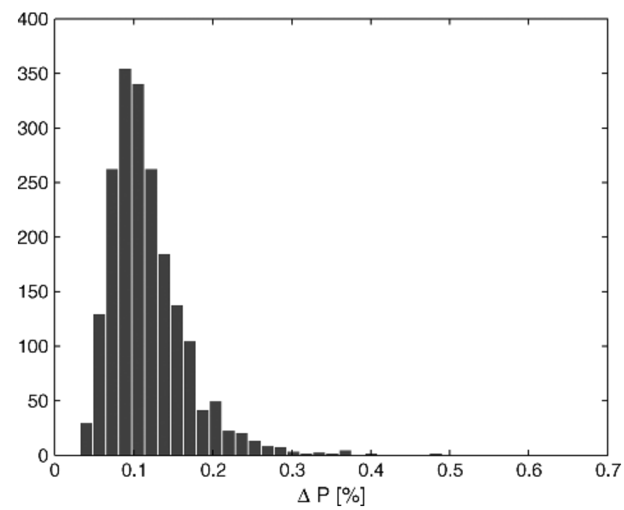

Fig. 9. Histogram of the efficiency loss of an arbitrary day during winter for a variation of 25%.

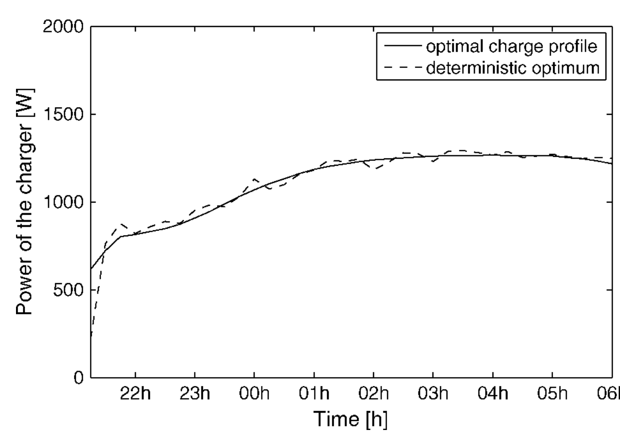

Fig. 10. Deterministic optimum and optimal charger profile for node 33.

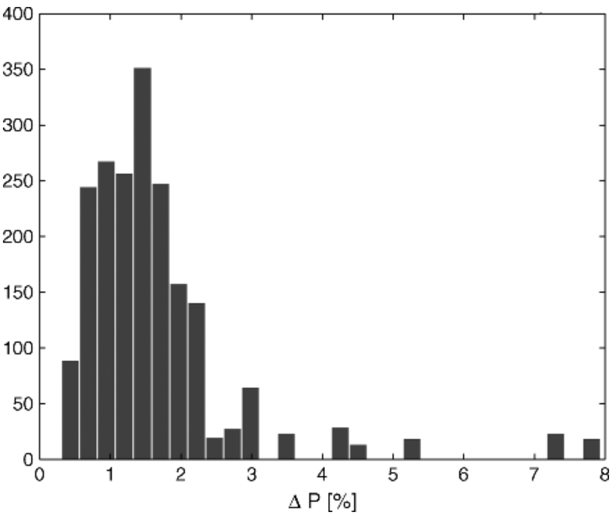

Fig. 11. Histogram of the efficiency loss of an arbitrary day during winter for other household profiles.

losses between the deterministic and stochastic optimum is not large. However, the difference between uncoordinated and coordinated charging is much larger because the charge profiles are more different. The uncoordinated charging has a constant charge profile for a specific amount of time.

In Fig. 8 and 9, a specific household load profile is assumed which is varied by a normal distribution function. In Fig. 11, the load profiles are randomly selected out of a database of household load profiles. This database contains profiles that differ more each day and are more peaked which increases the efficiency losses.

V. Dynamic Programming

The optimal coordination of charging PHEVs can also be tackled by the dynamic programming technique (DP). The QP and DP techniques are compared with respect to results, storage requirements and computational time. The DP technique decomposes the original optimization problem into a sequence of subproblems which are solved backward over each stage. A classical implementation of the DP technique is the shortest path problem. For the application of this article, the model is represented as a series of plug-in hybrid electric vehicles.

A. Methodology

There are Q vehicles with batteries charging and the maximum value of Q corresponds with a penetration degree of 30%. The battery content of these Q vehicles at each stage is the Q state variable, $S_{t,i}$. The number of stages T, is the number of hours of the charging period multiplied by four because the household loads are available on a 15-min time base.

The backward recursive equations for the conventional dynamic programming technique are given in (7) and (8):

$$f_t = \min\left[L_t(S_t, P_t) + f_{t+1}(S_{t+1})\right] \quad t = 1, 2, \ldots, T \tag{7}$$

subject to

$$S_{t,i} = S_{t+1,i} - P_{t,i} \cdot \Delta t \quad \forall i = 1, \ldots, Q. \tag{8}$$

The function f_t represents the total optimal power losses from period t to the last period T. The vector S_t is a Q-dimensional vector of the R possible storage levels at time t. L_t is the power loss during period t and $S_{t,i}$ is the battery content of the ith vehicle at time stage t. The power of the chargers is represented by P_t and is also a Q-dimensional vector. So the first component of this vector gives the power of the charger for the first PHEV. The output of the charger is not continuous, but has a step size of 400 W. This is relatively large, but smaller step sizes would lead to too much computational time which is proportional to R^T [14]. As such, the battery content is also discrete. The constraints of the problem remain the same and are shown in (9)–(11):

$$0 \le S_{t,i} \le C_{max} \tag{9}$$

$$0 \le P_{t,i} \le P_{max} \tag{10}$$

$$S_{T,i} = C_{max} \quad \forall i = 1, \ldots, Q. \tag{11}$$

The power loss is the objective function which must be minimized. The storage vector S_t is a Q-dimensional vector and thus "the curse of dimensionality" [15] arises which is handled by modifying the original dynamic programming technique.

The dynamic programming technique successive approximation (DPSA) decomposes the multidimensional problem in a sequence of one-dimensional problems which are much easier to handle [16]. The optimizations occur one variable at a time while holding the other variables at a constant value. All the variables are evaluated that way. This technique converges to a optimum for convex problems. This method will be used for the deterministic and stochastic programming.

B. Deterministic Programming

A daily load profile of the selected season is chosen and the vehicles are placed randomly. The DPSA technique needs initial values of the state variables to start the iteration. These values are generated by calculating the optimal charge trajectory for each PHEV separately without considering the other PHEVs. These optimal trajectories are put together into one temporary optimal trajectory and thus one Q-dimensional state vector. All the components of the state vector are held constant, except the first one. The optimal charge trajectory for the first component of the state variable is defined. The new value is ascribed to the first component and the procedure continues until the last component of the state vector is optimized. This procedure is repeated until convergence is obtained. The problem is switched from a multidimensional problem to a sequence of one-dimensional problems. The algorithm of dynamic programming successive approximation is represented in Fig. 12.

C. Stochastic Programming

The uncertainties of the household loads must also be implemented in the DP technique. Two thousand stochastic household load profiles are generated and the mean power losses of these loads are used to determine the total power losses f_t as presented in (12):

$$f_t = \min\left[E\left(L_t(S_t, P_t)\right) + f_{t+1}(S_{t+1})\right] \quad t = 1, 2, \ldots, T. \tag{12}$$

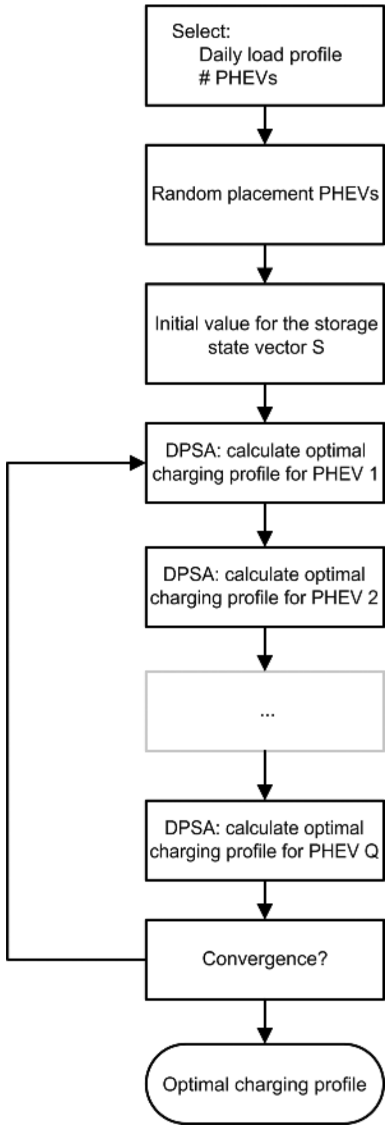

Fig. 12. Algorithm of DPSA charging.

The same stochastic load profiles as produced in the stochastic programming of the QP technique are applied to make the comparison more clear. One optimal charge profile is generated for these 2000 stochastic household loads with the DPSA technique. The power losses are calculated separately for the 2000 household load profiles and the single optimal charge profile. This is the stochastic optimum. For the deterministic optimum, the optimal charge profile and power losses are determined for each of the 2000 stochastic household load profiles, giving 2000 optimal charge profiles. The power losses of the deterministic optimum are subtracted from the power losses of the stochastic optimum and divided by the deterministic optimum for a variation of the household loads of 5 and 25%.

D. Results

In Fig. 13, the charge profiles for the QP and DP technique are compared. In general, the difference between the results of the DP and QP techniques is negligible, although the QP technique gives more accurate results because the values of the charge profile are continuous in that case. The DP technique, where a step size of 400 W is introduced for the power of the charger, gives a discrete charge profile. Reducing the step to an infinitesimal value would give the same result as the QP technique. This step size is taken rather large in order to reduce the number of levels and thus computational time and storage requirements. The storage requirements are heavier for the DP technique compared to the QP technique because every possible path over each stage must be stored. Since this leads to very large matrices and increased computational time, the DP technique is slower.

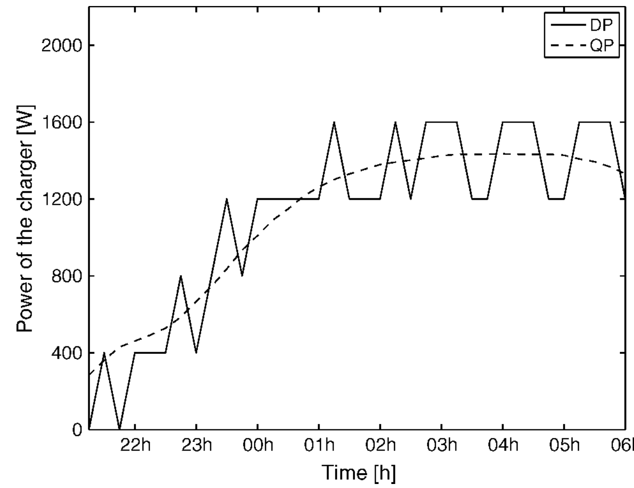

Fig. 13. Charge profile for node 1 for the QP and the DP program technique.

TABLE V
POWER QUALITY AND LOSSES FOR THE TEST GRID

Parameters	**Without PHEVs**	**Uncoordinated charging**	**Coordinated charging**
Peak load [kVA]	23	36	25
Line current [A]	105	163	112
Node voltage [V]	220	217	220
Power losses [%]	1.4	2.4	2.1

VI. Impact on the Distribution Grid

Uncoordinated charging of the batteries of PHEVs has a non-negligible impact on the performance of the distribution grid in terms of power losses and power quality. Both power quality and power losses are represented in Table V for three cases: without PHEVs, uncoordinated and coordinated charging. The power quality is given as the average of 1000 samples of the maximum load, voltage drop and line current for the IEEE 34-node test feeder during winter season for a penetration degree of 30%.

The power losses are the ratio of the power losses to the total load. With respect to uncoordinated charging, the coordination of the charging reduces the power losses. Power quality is improved to a level which is similar to the case where no PHEVs are present. Because the extra loads for charging PHEVs remain in the case of coordinated charging, additional losses are still higher.

The coordination of the charging can be done by a smart metering system. The distribution grid must be enforced to cope with the increased loads and voltage drops caused by charging PHEVs if this coordination system is not applied. Both scenarios will introduce extra costs for the distribution system operators and eventually for the customers.

A global estimation is performed in order to indicate the level of upgrading needed for a small distribution grid. For the argumentation, the IEEE 34-node test feeder is connected to each phase of a three phase transformer of 100 kVA, forming a global grid of 100 nodes. When no PHEVs are present, the maximum load for the three grids together is 69 kVA. Considering no PHEVs in the future, the transformer has enough reserve capacity for this global grid to meet additional peak load and load growth for the next ten years, which is predicted to be a few percent. A $4 \times 50\ \mathrm{mm}^2$ Aluminum underground conductor of 400 V is standard. The maximum capacity of these conductors is about 160 A [17]. For the case without PHEVs, the standard underground conductor would be sufficient.

If 30% PHEVs are introduced, the power for the global grid increases to 108 kVA, which is out of range for the 100 kVA transformer. This transformer must be replaced by a standard transformer of 125 kVA to deal with extra PHEVs, load growth and additional peak load. Due to the PHEVs, the line current increases to 163 A. The maximum capacity of the current conductor is not enough and must be replaced by a $4 \times 95\ \mathrm{mm}^2$ Aluminum underground conductor with a capacity of 220 A.

Voltage deviations up to 10% in low voltage grids are acceptable for 95% of the time according to the EN50160 standard which is mandatory in Belgium. In the case of uncoordinated charging, this limit has been reached for charging during the evening and action must be taken to reduce the voltage drop. The problem of the voltage drop can be tackled by placing a capacitor bank or a load tap changing transformer. Although the latter is not common at low voltages, it may be necessary in the future, especially for the vehicle-to-grid concept. This type of transformer can handle voltage variations of plus and minus 10% by adjusting among 32 tap settings built into the windings [18]. There is also another cost involved: the power losses. These losses increase reasonably in the case of uncoordinated charging. The power losses and loads must also be produced and transported over the transmission lines.

A smart metering system must be implemented to control the coordination and communication between the PHEVs individually, the distribution system operator and the transmission system operator (TSO). The vehicles could also be grouped and represented by a fleet manager to communicate with the DSO and TSO. Smart metering will lead to opportunities to make PHEVs a controllable load, to apply the vehicle-to-grid concept and to combine PHEVs and renewable energy. This technology is available for implementation, but capital investments by the utilities are necessary [19]. For the implementation of smart metering, also other incentives, such as real-time pricing and integration of renewable energy, are important.

Less grid enforcements are necessary with the coordination system. The maximum load is lower because the vehicles are not charging if the household loads are peaking. Therefore, the voltage drops, line currents and power losses are considerably reduced. The cost of upgrading the grid must be compared with the cost of the execution of smart metering. In both cases, the cost for the implementation and the possible additional power production will be passed on to the customers. In practice, it would be no difference for the DSOs which technology is implemented, as they are allowed to have a fair rate of return in a cost plus mechanism. With this mechanism, the DSOs are not strongly pushed towards the use of the most efficient technologies. The tariffs and the performance of the grid are more important in a price cap mechanism. The realization is favorable if the smart metering system helps a significant deferral of grid investments compared to the enhancement of the grid.

VII. Conclusion

In general, coordinated charging of plug-in hybrid electric vehicles can lower power losses and voltage deviations by flattening out peak power. However, when the choice of charging periods is rather arbitrary, the impact of the PHEV penetration level is large. The implementation of the coordinated charging is not without costs.

In the first stage, historical data are used so there is a perfect knowledge of the load profiles. In a second stage, stochastic programming is introduced to represent an error in the forecasting which increase the power losses. This efficiency loss is rather small if the trend of the household load profiles is known, so charging during the peak load of the evening can be avoided.

These results are obtained with the quadratic programming technique. The dynamic programming technique is also implemented but does not improve the computational time nor the achieved accuracy. The applied techniques and methods can be extended to other objective functions, such as voltage control by PHEV reactive power output control and grid balancing.

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