Effect of electric vehicles' optimal charging-discharging schedule on a building's electricity cost demand considering low voltage network uncertainties

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***Abstract*—Nowadays, one of the dominant reasons of excessive energy consumption is the high energy demand in corporate and/or public buildings. At the same time, electric vehicles (EVs) are becoming more and more popular worldwide being a considerable alternative power source when parked. In this work we initially propose an energy management framework which optimizes the control of the charging-discharging schedule of a fleet of EVs arriving at a university building for two typical load-days in February and May aiming at the minimization of the energy demand and, thus, the electricity cost of the building. To this end, a mixed integer linear programing (MILP) model containing binary and continuous variables was developed. Uncertainties in load, generation, and cost require modeling power systems with a probabilistic approach. In such a way, the probabilistic nature of demand side management (DSM) problem is also possible to be addressed. The integration of the EVs in the Low Voltage (LV) grid is simulated with a probabilistic analysis framework that uses real smart metering (SM) data. The stochastic character of the loading parameters at the network nodes is studied taking into account the charging energy needs of the corresponding EVs fleet.**

***Index Terms*-Plug-in electric vehicles; energy management; coordinated charging; Monte Carlo, low-voltage network, MILP**

I. INTRODUCTION

Electric vehicles (EVs) including hybrid electric vehicles (HEVs), battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) have been experiencing considerable development in recent years [1,2] and EVs are now commercially available from a number of car manufacturers worldwide. The benefits of using vehicle energy have urged many researchers to work on modeling several EVs concepts. Special attention has been given to charging and discharging algorithms for gridable vehicles (i.e. BEVs or PHEVs with grid capacity) [3], optimal scheduling for vehicle-to-grid (V2G) operation [4] and the impact of plug-in EVs on power systems [5–7]. The V2G concept could contribute to the increase of the quality and performance of a distribution network in terms of system efficiency, stability and reliability [8]. EVs can act either as distributed storage devices delivering power to a grid at peak hours or serve as load.

A PHEV, more specifically, is a hybrid vehicle equipped with a larger battery pack. It uses electricity when its battery state of charge (SoC) is high; otherwise its internal combustion engine is used consuming gasoline [9]. The impact on the distribution grid of PHEVs charging is non-negligible. PHEVs consume a large amount of electricity which could lead to high undesirable peaks in the electric consumption. It is estimated that the electrical consumption for charging PHEVs might take up to 5% of total electricity production in Belgium by 2030 [10]. The two main places to recharge PHEVs batteries are either at home or in a car park, corporate or public. In this article, we focus on the latter.

A V2G system could be used through a demand response (DR) mechanism to reduce peak electricity usage and to incentivize load shedding. Currently, the DR schemes are usually deployed through either incentive-based or time-based rates schemes. While in the incentive-based DR schemes customers enroll voluntarily in certain rewarding programs, time-based rates schemes rely on dynamic pricing of electricity to regulate electricity consumption. The time-based rates scheme can have many different forms. The most common but not limited to are the time-of-use pricing (TOUP), the critical peak pricing (CPP) and the real-time pricing (RTP) [11]. The power load could be managed by charging the PHEVs when the electricity price received from the utility is lower and discharge the PHEVs batteries to the grid when prices are higher. Shifting load can effectively reduce the impact of the PHEVs fleet on the grid and this task can be achieved by charging and discharging coordination.

In this study, we examine the effect of several PHEVs fleets, distinct by the number of vehicles, on the electricity demand profile of a university building in Mons, Belgium under a RTP scheme. Our goal is to optimize the charging-discharging process of the PHEVs so as to minimize the energy demand and thus the electricity cost of the building. Our second goal is to examine the impact of the charging process on the local low-voltage (LV) distribution network. A probabilistic analysis framework designed for the offline state estimation of LV networks has been used to evaluate the interaction of the PHEVs when they are connected to a LV feeder with distributed PV units [12,13]. This analysis framework uses 15-min nodal energy flow datasets recorded by smart meters (SM).

The remainder of this paper will is organized as follows. In Section II the mathematical formulation of the model is described along with the considered assumptions. In Section III the results of both the optimization process and the probabilistic analysis on the LV network are presented while in Section IV the conclusion is derived.

II. MODELING AND ASSUMPTIONS

A. Load Scenarios and Pricing

We chose two typical daily winter and summer electrical load profiles from an available set of a university building load measurements. The load profile covers 10 hours, from 8 am to 6 pm, and the electrical energy consumption is available on a 15-min time base as shown in Fig.1.

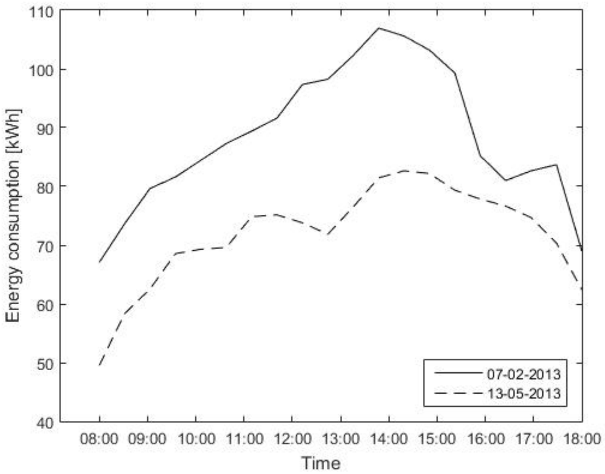

Figure 1 University building load during a typical day in February and May 2013

We considered this timetable taking into account the usual working hours at the university. The PHEVs charging-discharging optimization as well as the probabilistic analysis regarding the impact of the PHEVs on the LV network takes place during these hours. Fig. 2 shows the used pricing data. Electricity cost reaches its peak value between 4 pm and 7 pm.

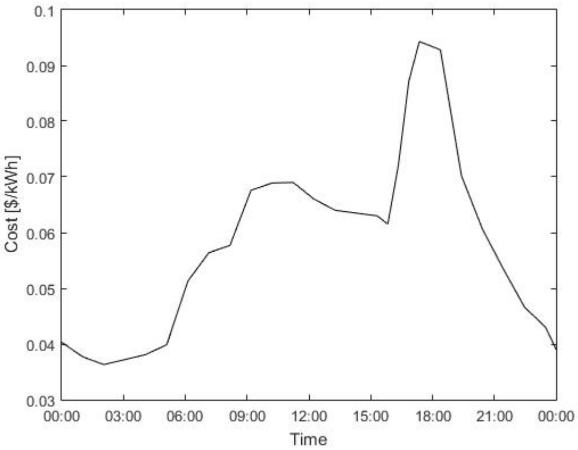

Figure 2 Electricity tariff (spot price) [14]

B. PHEVs Specifications

Each PHEVs battery is equipped with a maximum capacity of C^{PHEV} = 10.15 kWh and is characterized by its all-electric range (AER). AER is the total distance that the PHEVs can cover running on an all-electric mode. Different PHEVs require different amounts of energy based on their type. The energy required to accomplish their AER is called electrical energy per kilometer. In this work, it is selected equal to 0.37 kWh/km [15]. Assuming an energy conversion efficiency η^{PHEV} = 0.88 from the AC energy absorbed from LV to DC energy stored in the battery of the vehicle, a full charge would require 11.53 kWh. Among the different available standards and codes for the EVs charging, we have chosen the SAE J1772. More specifically the AC level-1 has been selected which defines single phase charging at 120V, 16A and 1.92 kW of power. This standard defines a common EV and supply equipment vehicle conductive charging method. Although this standard defines only the charging process (thus, a unidirectional flow of energy), in this study, we have considered a bidirectional energy flow of energy. It has been assumed that the discharging rate is equal to the charging rate. Note that fast charging was not considered as it requires higher voltage levels and a higher short-circuit power which induces extra investments increasing the total implementation costs.

C. PHEVs Arrivals-Departures and Charging-Discharging Period

In this article we have considered that the batteries of all the vehicles have been fully charged when departing from home. It has been also assumed that all PHEVs run on an all-electric mode until they arrive at the university. Assuming that a fully charged PHEV drives s kilometers on electricity (which is nothing else that the AER), the SoC of a vehicle driven on a distance of d kilometers when arriving at university is calculated as:

$$\%SoC = \begin{cases} 100 \cdot \left(\dfrac{s-d}{s} \right), & \text{d} \leq s \\ 0, & \text{d} > s \end{cases} \tag{1}$$

In this work, the length of the trip and consequently the SoC of each PHEV upon arrival (S_i) is calculated using the normal distribution taking as base case (mean) value $\bar{d} = 10$ km [16] and standard deviation σ = 3 km. In this study, three different scenarios of PHEVs fleets have been considered, including 10, 20 and 50 PHEVs. The scheduling horizon is divided into a set of N time slots (having the same duration of 30 minutes). Thus, the duration of a 10 h period is divided into 20 time slots (N=20) for a more realistic and detailed time analysis. It has been also assumed that all the vehicles arrive at the university at the beginning of the time slot n=1 (8 am) and depart at the end of the time slot n=20 (6 pm). Upon their arrival the PHEVs are immediately available for charging-discharging or they can remain in standby mode, whatever the considered time slot n.

D. Problem Formulation

The objective is to find the optimum time slots during which the PHEVs should charge/discharge in order to minimize the building's energy demand under the current pricing scheme. A charging-discharging schedule of the PHEVs batteries is therefore to be determined in function of the pricing scheme and the current SoC of the batteries. Regardless the charging-discharging schedule during the day, a constraint is imposed which expresses that the SoC of all the batteries is at least 50% by the time the PHEVs depart (last time slot).

There exist two kinds of loads: fixed and adjustable. In this work, the fixed load is the building load demand and is characterized for each time slot n by the overall energy consumption p_F^n. On the other hand, the adjustable load is the charging load totalized for all the PHEVs (*i=1, …, I*).

In order to model the charging-discharging process of the vehicles, we introduce three sets of variables. First, we consider two sets of binary variables: ξ_i^n and σ_i^n which are defined for every vehicle and every time slot. If the *i-th* PHEV is charging during the time slot *n*, ξ_i^n is equal to 1, otherwise it is equal to 0. In a similar way, whether the PHEV is discharging or not, σ_i^n is equal to 1 or 0. The charging and discharging rates are constant and they are both worth 1.92 kW according to the SAE J1772. We denote as c^{PHEV} and d^{PHEV} the energy obtained and given from charging and discharging during one time slot respectively. The SoC of the *i-th* PHEV for the time slot n is represented by the continuous non-negative variable s_i^n .Recall that all the vehicles are characterized by their initial SoC (S_i .) The SoC of each PHEV in a time slot depends on its previous time slot and on the charging/discharging rates. It can be estimated according to the following equations and constraints:

$$s_i^n = S_i + \xi_i^n \cdot c^{PHEV} - \sigma_i^n \cdot d^{PHEV} \quad \forall i \in I, n = 1 \tag{2}$$

$$s_i^n = s_i^{n-1} + \xi_i^n \cdot c^{PHEV} - \sigma_i^n \cdot d^{PHEV} \quad \forall i \in I, n > 1 \tag{3}$$

$$\xi_n^i + \sigma_i^n \le 1 \tag{4}$$

$$s_i^n \le C^{PHEV} \tag{5}$$

$$s_i^n \ge S_i^{PHEV} = 50\% \cdot C^{PHEV} \tag{6}$$

Constraint (4) is very important as it guarantees that in every time slot, PHEVs can be only in charging, discharging or standby mode. The other constraints ensure that the SoC of the PHEVs cannot exceed the maximum battery capacity (see (5)) at any time and that the battery of each PHEV will be charged at least 50% of its total capacity before departure (see. (6)). The following constraint establishes the energy balance between the input and output electric power of the system in each time slot:

$$y^n + \sum_{i \in I} \sigma_i^n d^{PHEV} = p_F^n + \frac{1}{\eta^{PHEV}} \sum_{i \in I} \xi_i^n c^{PHEV} \tag{7}$$

where y^n is the energy required from the LV network at each time slot to cover its load demand and the PHEVs charging load. Finally, the objective function to be minimized is:

$$\min_y \sum_{n \in N} e^n y^n \tag{8}$$

where e^n is the cost of energy absorbed from the grid according to the current pricing scheme at time slot *n*. A mixed integer linear programming (MILP) model is run in order to schedule the energy usage plan over the time horizon *n = 1, …, N.*

III. RESULTS

A. Uncoordinated Charging

For the uncoordinated charging scenario, there is no control on the charging process. Uncoordinated charging indicates that the batteries of the PHEVs start charging immediately when plugged in. The vehicles in every case start charging at n=1 (i.e. 8 pm) and continue to charge until the SoC of the battery reaches 100%, regardless the cost of energy at any time slot. The impact of uncoordinated charging on the buildings' energy consumption from the LV network is shown in Fig. 3 and Fig.4.

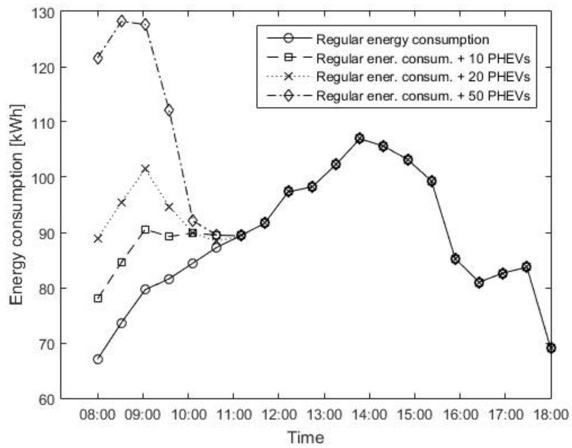

Figure 3 Energy consumption of the university building for uncoordinated charging (7th February 2013)

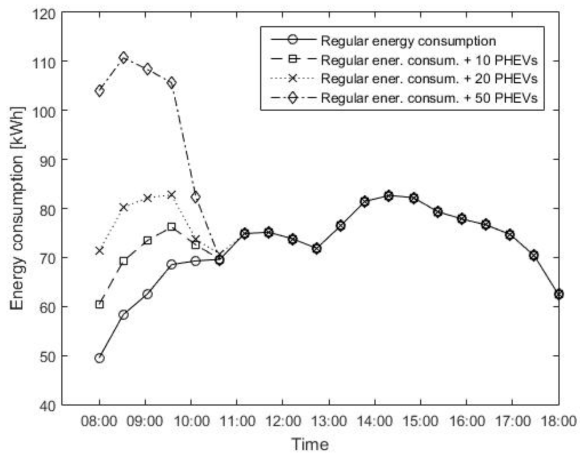

Figure 4 Energy consumption of the university building for uncoordinated charging (13th May 2013)

A similar pattern is observed in both Fig.3 and Fig.4. The total energy consumption includes the regular load demand of the building and the charging of the PHEVs. We can see that in both scenarios, due to the lack of any control in the charging process, all the PHEVs start charging when plugged in and until 11:00 a.m. all the vehicles have already been charged. As a result of this behavior, the total energy required is substantially increased during the first six time slots. After that, all the PHEVs batteries are fully charged and the energy consumption is normalized again. The increase of the number of PHEVs leads to a significant increase in energy demand. It should be noted that within this scenario, no PHEVs discharging takes place between 8 am and 6 pm and all the PHEVs are fully charged upon departure.

B. Coordinated Charging-Discharging

In the previous section the charging process of the PHEVs occurred immediately after plug-in ignoring the pricing scheme. In this section, the idea is to show how the optimal charging-discharging control of the PHEVs leads to the minimization of the energy demand and thus of the electricity cost of the building. The charging-discharging times of the PHEVs are decided by the model along with the required energy to cover the building's load. The impact of the coordinated PHEVs charging-discharging on the building's energy consumption is illustrated in Fig. 5 and Fig.6.

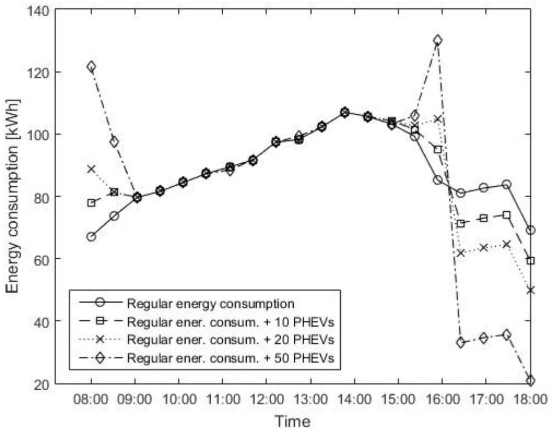

Figure 5 Energy consumption of the university building for coordinated charging-discharging (7th February 2013)

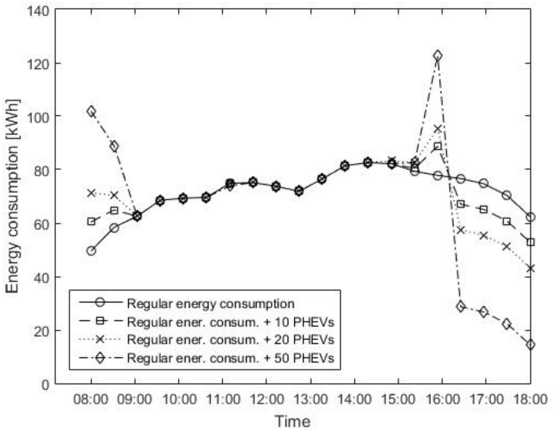

Figure 6 Energy consumption of the university building for coordinated charging-discharging (13th May 2013)

The two figures indicate one again similar patterns of the PHEVs charging-discharging process. The optimization algorithm tries to minimize the energy consumption when the electricity prices are high. Consequently, the PHEVs batteries charge mainly during the early hours and in the afternoon during the time-slots just before the electricity price starts to increase. During the electricity price peak hours (4pm – 7pm), the PHEVs mostly discharge resulting in a substantial decrease of the total required energy. The increase of the number of the PHEVs leads to a proportional and significant reduction of the total energy demand. Indicatively, the total energy requirement during the last time-slot (5.30 pm – 6.00 pm) for i=50 PHEVs in both scenarios (winter and summer) has been reduced more than 70%.

Another thing that should be mentioned is that in the coordinated charging-discharging control, the PHEVs are not forced to reach their maximum battery capacity level. The only applied constraint imposes that all the vehicles should be at least 50% charged before departure from the university. Thus, the PHEVs are either in stand-by mode (9 am -3 pm) or in charge mode when the electricity price is the lowest and in discharge mode when electricity price is higher (4.30 pm– 6.00 pm). Table I shows the total cost of energy per day for the simulated load scenarios under the current pricing.

TABLE I
TOTAL COST OF ENERGY FOR ALL SCENARIOS ($)

Mo-nth	Regul. load	10 PHEVs		20 PHEVs		50 PHEVs	
		Uncoor dinated	Coordi nated	Uncoor dinated	Coordi nated	Uncoor dinated	Coordi nated
Feb.	121.9	125.1	120.5	127.4	118.5	134.5	113.1
May	99.6	102.4	98.1	104.9	96.3	112.5	90.8

In all cases, the coordinated charging-discharging process results in the lowest cost/day. It is worth mentioning that the cost of the coordinated process (including the additional PHEV charging load cost) is even lower than the cost of the regular load (no PHEVs charging included). Finally, Fig. 7 illustrates the SoC of the batteries (for 20 vehicles) in the final time slot. It can be seen that in all cases, the PHEVs batteries are at least 50% charged (≥ 5.075 kWh).

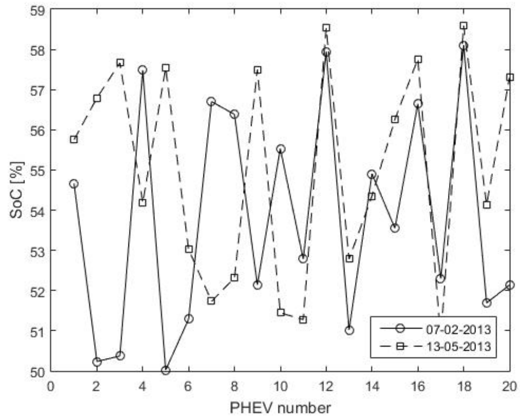

Figure 7 The final SoC for the 20 PHEVs case in both load scenarios

C. Impact on the LV Network

The presented problem formulation addresses the optimal time allocation of PHEVs charging so as to minimize the building's energy demand over the concerned period. However, the integration of a PHEVs installation in an LV feeder involves an extra complexity regarding the high volatility of loads and distributed generation over time. Let us consider the previous PHEVs charging schedule as a day-ahead schedule based on a day-ahead forecasting for a day in February and in May. The first goal is to determine the effect of network state uncertainty on the optimized parameters (that is the energy demand of the building in the presented formulation). The second goal is to investigate how PHEVs integration, with the proposed charging schedules (coordinated and uncoordinated) would impact the operation indices of the network.

To address these issues, the LV feeder of Fig. 8 is simulated in steady state operation with the use of a long-term observability algorithm for LV networks [12]. The algorithm uses Monte Carlo simulation and smart metering 15-min datasets for creating the statistical distributions of the random variables in each network state. In this case study, the algorithm elaborates nodal energy flow SM datasets, recorded at residential users in Belgium over a period of 1 to 3 years. The objective is to simulate the variability of nodal injections and consumptions based on the available datasets. Concerning the university campus, 15-min energy flow datasets are used, recorded in 2013-2014 at the previously considered building (Subsections III-A and III-B). One should note that the simulated feeder is a part of an LV network in Belgium of which the technical parameters are available to the authors. For this study, it is assumed that the university building is located in this feeder although this is not the case in reality. Given the size, the technical parameters and the voltage level of the network, the scenario of 50 PHEVs cannot be considered because it results in line congestion and important voltage dips. Only the scenarios of 10 and 20 PHEVs are therefore treated.

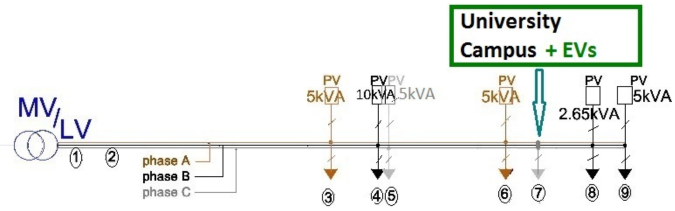

Figure 8 The simulated LV feeder

Fig. 9(i) and 9(iii) show the statistical distributions of the half-hourly energy demand in a typical February day for three different configurations. The first configuration is the base scenario and considers no PHEVs connected to the building. The other two configurations apply the uncoordinated and the coordinated charging schedule, each one considering both scenarios of 10 and 20 PHEVs fleets. The cumulative distributions functions (CDFs) of probability in Fig. 9(i) and 9(iii), in blue and green color, practically illustrate the distribution of values that the energy demand could take in case the uncoordinated and coordinated PHEVs charging would be applied in the building. Determining an expected range of values is possible thanks to the use of the Monte Carlo simulation. The reliability of the probabilistic state estimation is reinforced with the use of the SM input for the respective month.

Basically, the optimization algorithm of Subsection II.D can determine the optimal schedule for PHEVs charging based on day ahead forecasted values and the probabilistic analysis can provide estimation on the possible range of values that the various parameters might take in reality. Regarding energy demand, the CDFs of Fig. 9(i) and 9(iii) demonstrate that in 85% of the simulated network states the optimal coordination of PHEVs charging implies half-hourly energy demand values that are almost equal to the ones of the configuration without PHEVs. In 15% of the simulated network states, the coordinated charging leads to energy demand that is lower than the ones of the no PHEVs configuration. Similarly, Fig. 9(ii) and 9(iv) show that the optimal coordination of PHEVs charging reduces the daily cost for energy demand during PHEVs use hours in all the simulated typical February days. This reduction is in the range of 2$ and 5$ in the 10 and 20 vehicles fleets scenarios respectively, comparing to the case without PHEVs. Very similar outputs were obtained with the simulation of a typical day in May. The reduction is

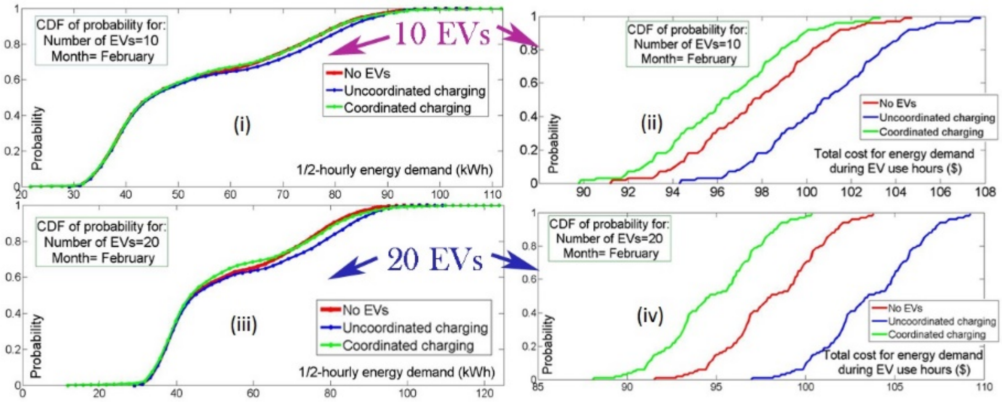

Figure 9: Half-hourly energy demand and total energy demand cost during the PHEVs use hours, in a typical February day, considering 10 and 20 PHEVs fleets.

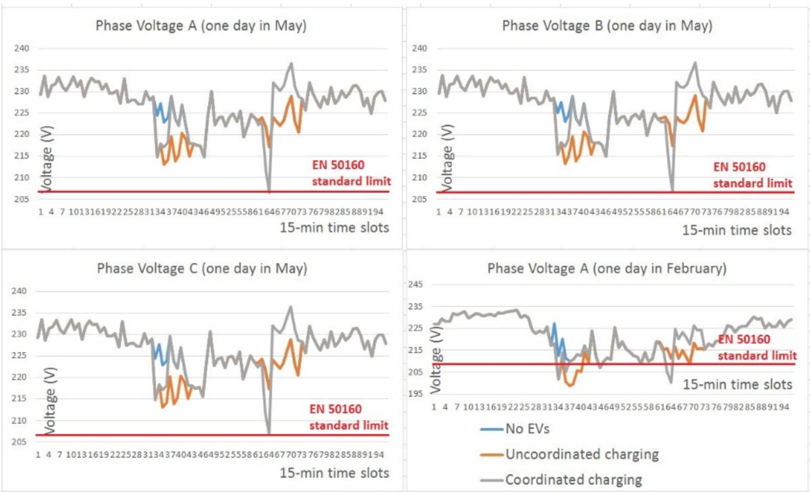

Figure 10: Phase voltage variation during a typical day in May ((i), (ii), (iii)) and EN 50160 standard violation (under-voltage) ιn a typical day in February (iv) at the PCC of the university building to the feeder

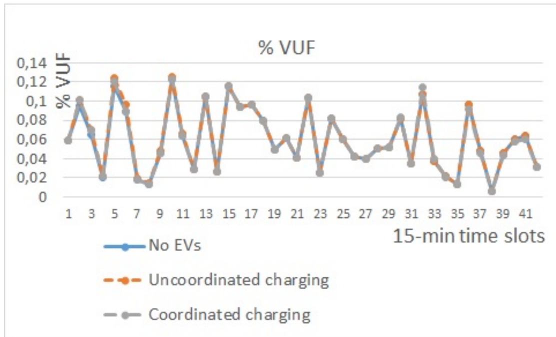

Figure 11: %VUF variation during EVs use hours in a typical day in May at the PCC of the university building to the feeder

even more decisive when one compares with the respective outputs for the uncoordinated PHEVs charging case as shown in Fig. 9(ii) and 9(iv).

Regarding the impact of PHEVs integration on the operational indices of the feeder, the voltage variation snapshots of Fig. 10(i), 10(ii) and 10(iii) show that both the coordinated and the uncoordinated charging strategies affect phase voltages at the point of common coupling (PCC) of the university building with the feeder (node 7), in a typical day in May, during a few time slots. The uncoordinated charging induced significant voltage dips during consecutive time slots in the morning. The coordinated charging pushes voltage magnitudes close to the lower acceptable limit of EN 50160 standard in the afternoon. Given the even higher energy demand in February, the added demand for PHEVs charging may lead to more frequent under-voltage events. For a set of consecutive simulated network states in February, Fig. 10(iv) shows that the voltage dip at node 7 is bigger and longer in case of uncoordinated PHEVs charging while it can be avoided by applying the coordinated charging strategy, in morning hours. The coordinated charging leads to under voltage during one time slot in the afternoon.

Concerning the impact on the voltage unbalance factor (%VUF) at the PCC of the university building with the network, the integration of EVs does not significantly affect this parameter (Fig. 11). According to the EN 50160 standard, %VUF should not exceed the value of 2% during more than 5% of the operation time. This condition remains quite far from being violated before and after the integration of EVs. One should note that although all residential users are connected to the feeder in single-phase mode, the university building is connected in three-phase mode given its higher energy demand compared to them. As far as congestion risk is concerned, it has been computed that the integration of PHEVs only slightly increases line current values, given the three-phase connection of the university building.

Based on the outputs of the probabilistic analysis, one can conclude with two principal outcomes concerning PHEVs integration in such an LV feeder. Firstly, the simulation of a large range of possible network states demonstrated that applying optimally coordinated charging is very valuable as it can ensure the cost-effectiveness of PHEVs integration for the respective network user. Secondly, the importance of including network operation parameters in the formulation of the problem is highlighted and greatly recommended. In such a way, PHEVs integration can be profitable for the respective user without inducing power quality problems to the other users and high operational expenses to the DSO.

IV. Conclusion

This study examined the effect of several fleets of PHEVs, distinct by the number of vehicles, on the electricity demand profile of a university building as well as the impact of the PHEVs charging process on the local LV distribution network. To model the coordinated charging-discharging process of the vehicles, a MILP optimization model was developed aiming at the minimization of a building's energy demand for two typical days in February and May. The conducted analysis showed that in case of coordinated charging-discharging control, the PHEVs batteries as an alternative power source, contributed in all simulated scenarios to a significant reduction of the building's energy demand (mainly during peak-pricing periods) resulting in a considerable decrease of electricity cost. Results also indicated a relation between the integration of the PHEVs on the LV network and the impact of such integration. More specifically, it has been concluded that under-voltage is more likely to occur in the case of uncoordinated PHEVs charging, while to a countable extent (15%), the coordinated PHEVs charging-discharging control resulted in lower total energy demand compared to the regular building load. Finally, it was pointed out that the integration of PHEVs did not significantly increased congestion risk, given the three-phase connection of the university building.

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