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OPTIMAL CHARGING OF ELECTRICAL VEHICLES IN THE SMART CITY FOR LOSS MINIMIZATION AND VOLTAGE IMPROVEMENT

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Abstract

The world is two-thirds of the way through a century-long cycle of rapid urbanisation, at the end of which more than 70% of people will live in cities (World Health Organization, 2014). The urban transformation has become a major contributor to economic, demographic, social and environmental change. Electric vehicles (EVs) have become increasingly popular over the last few years and are considered as an important means to mitigate air pollution problems in big cities around the world. With their onboard batteries, EVs also present an opportunity to serve as a demand response tool in supporting future smart grid where there is usually high penetration level of renewable energy (RE) sources.

In this paper, we consider the coordinated charging control of electrical vehicles in the charging stations. The goals are to illustrate how the integration of EVs at the urban area improve the overall load schedule of the distribution network.

Key words: Smart City; Smart Grid; Electric vehicle (EV); charging stations; Vehicle to Grid (V2G); Grid to Vehicle (G2V)

1. Introduction

In the twenty-first century, global urbanization must be shaped and managed so that cities fully achieve their potential to increase prosperity and social cohesion, bring out improved standards of environmental efficiency, citizen health and well-being, and strengthen international relations. If it is not managed, and if suitable local financing and investment tools are not achieved, rapid urbanization could prove a major threat to both modern society, and to the world’s environmental fabric [1].

“Smart city” is originated from IBM’s “smart planet”, through the application of a new generation of information technology, managing the state of the production and life more refined and dynamic. It is realized by embedding sensors and equipment to every corner of the global power systems, water supply systems, transportation systems, buildings and oil and gas pipelines and other objects of production and living system, forming an internet of things which combined with the internet, to achieve the integration of human society and the physical system, then by supercomputers and cloud computing integrate with the internet of things [2].

The climate change and the environmental degradation have become increasingly prominent, and the concept of low carbon economy gets more and more attention, being characterized by low emission, low pollution, and low energy consumption [3].

According to International Energy Agency (IEA), the transportation is the second largest industry of the carbon emissions, which is only smaller than the electronic industry, accounted for 21% of total carbon emissions.

Smart transportation is one vector of the smart city. Due to the low efficiency, the transportation has become the second largest industry of carbon emissions, thus affecting the environment and the cities. The smart grid and EV represent an evolution of technology in the power grids which is expected to lead to a more efficient use of the energy resources by integrating of renewable energy sources and providing advanced solutions for reliable operation.

2. Literature review

Among the large number of applications, the Smart City concept implies the use of fast charging and slow charging stations of the electric vehicles. Both fast and slow public charge stations should be installed in great proximity of the transformer substations. In turn, such positioning allows to reduce power losses, to lower financial expenses, and, in the case of need for additional wiring – to install supplementary charging stations (not to overload the existing cables).

The fast public charge stations are used twenty-four hours a day. Commonly, they are installed at paid parking lots situated in proximity of the power stations of a micro-district, or near office buildings, shopping malls, garages, or governmental or social establishments [4].

In [5] the distribution network expansion planning problem considering the siting and sizing of EV charging stations is solved. The objective function considered for the integrated distribution network and the EV charging station expansion planning includes the investment cost and the operational cost. In [6], the same problem is solved considering minimizing the integrated cost of charging stations and consumers as the objective function. An integrated framework for planning of public charging spots and roadside fast charging stations in an urban area is proposed in [7]. The planning objective considered is to minimize the social costs of the whole PEV charging system. In [8] the objective is to find the best location for an EV in a distribution grid to support the voltage profile by charging and discharging process.

The literature on EV charging can be separated into two parts: unidirectional and bidirectional smart charging algorithms. Strategies to increase the penetration of PEVs without additional grid investments are proposed in [9-11]. Voltage profile control and losses minimization algorithms are proposed in [12-15]. The economic approach is not excluded because some algorithms integrate charging cost minimization [16-21].

3. Problem formulation

This study aims at identifying the effects of EV charging on the distribution grid, with regard to voltage profile and power losses. Other technical or economic aspects may be taken into account, such as those in Figure 1, but they are not considered here for the sake of simplicity.

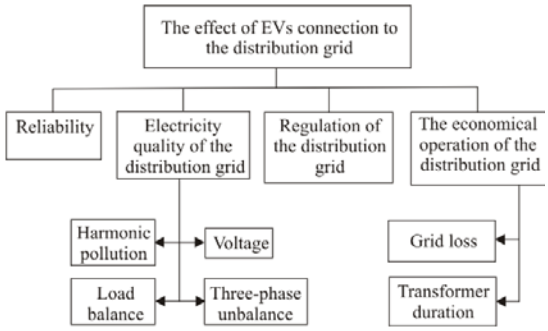


Fig. 1: The impact factors of EVs to the distribution grid.

A mathematical problem is formulated to find the best strategy for EV charging stations in a distribution network by considering both charging (G2V) and discharging (V2G) the electrical vehicles, in terms of electricity price, voltage level and power losses. The optimized strategy will result in shifting the load mainly because of the electricity price [22].

Note that charging can be performed in various ways: EVs can use an on-board or off-board charger, or use inductive charging while parked, thanks to Inductive Power Transmission (IPT) technology. The ultimate experience of IPT is charging while in motion, of which a prototype named On-Line Electric Vehicle (OLEV) has been designed in the Korea Advanced Institute of Science & Technology. Those cases being rare, we can consider in this paper that the charging is done via a physical connection with an on-board plug.

The coordination of the EVs charging/discharging management and intermittent energy sources (such as wind power, solar power) can enhance the grid absorbing ability for the intermittent energy sources. The wind power and the fluctuation of EV charging power have obviously correlation. In V2G system, one EV or assembled EVs can be controlled via control center from the grid for automatic charging and discharging, thus achieving participation in grid operation for a more intelligent grid.

EV charging involves many Smart Grid actors, whose goals are sometimes different: the EV owners want to store the necessary energy in the battery as quickly as possible, eventually at the lowest cost, without considering the impact on the generation costs or on the network operation. The electricity producers and retailers are mainly driven by net benefits, while the network operators generally aim to ensure the most efficient use of resources and to maintain the supply-demand balance.

The algorithm performs the management of the electric charging stations, considering that the connection between vehicles and grid is bidirectional. The bidirectional mode of operation allows the vehicles fleet to operate as a load, distributed storage or standalone energy source.

The objective function is:

$$\left[MIN\right]Cost = \sum_{i \in A}\sum_{j \in B} P_{ch/dsch,ij} \cdot \Delta t \cdot p_{el,i} \tag{1}$$

where $P_{ch/dsch,ij}$ is the control variable of the objective function and represents the charge/discharge power at the time instant i for the j^{th} EV;

– Δt represents the sampling period of time;
– $p_{el,i}$ is the price of electricity at time i, in €/kWh;
– A is the set of time intervals, $A = [T_{arriv}; T_{dep}]$;
– T_{arriv} is the arrival time on an EV;
– T_{dep} is the departure time of an EV;
– B is the number of vehicles present in the parking, with $B = 1 \ldots n$;

subject to:

*a) **Power constraints***

This category of restrictions is divided into two subcategories:

– *Global power*, which refers to the maximum power absorbed/injected by the charging station from the electrical grid at a specific instant of time;

– *Individual power*, which refers to the maximum power absorbed/injected by an EV at a specific instant of time.

Global power:

$$P_{\min-global} \leq \sum_{j \in B} P_{ch/dsch,ij} \leq P_{\max-global} \;, \; \forall i \in A \quad (2)$$

where $P_{\min/\max\text{-}global}$ is the maximum absorbed/injected power by the charging station; these limits can be imposed within the specific agreements between the consumer and the energy supplier in terms of the network loading, voltage levels, protection settings, etc.

Individual power:

$$P_{\min-ind} \leq P_{ch/dsch,ij} \leq P_{\max-ind} \;, \; \forall i \in A; \forall j \in B \quad (3)$$

where $P_{\min\text{-}ind}$ and $P_{\max\text{-}ind}$ are the minimum and maximum powers for the discharging process. The minimum power is just a sign convention as the charging power is positive and the discharge power is negative.

*b) **State of charge (SOC) constraints***

The SOC constraints are also divided into two subcategories:

– *Evolution and limits of state of charge*; this constraint refers to the variation in time of SOC and its technical limits;

– *State of charge for departure time (final SOC)* – this constraint expresses the state of charge of battery at the time of departure (SOC_{final}).

Evolution and limits of the state of charge:

$$SOC_{\min} \leq SOC_{ij} \leq SOC_{\max} \;, \; \forall i \in A; \forall j \in B \quad (4)$$

where SOC_{ij} represents the state of charge at the time instant i for the j^{th} EV; whereas $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper limits of SOC, respectively.

State of charge for departure time – final SOC:

At the instant $i = T_{dep}$, the state of charge of battery must coincide with SOC_{final}, which is set by the owner of EV when it arrives at the charging station:

$$SOC_{ij} = SOC_{final,j} \;, \; i = T_{dep} \;, \; \forall j \in B \quad (5)$$

where $SOC_{final,j}$ represents state of charge at the time of departure for the j^{th} EV.

4. Case Study

The simulations are performed on a test electrical distribution network consisting of two radial branches, supplying five MV/LV secondary transformers (ST) (20/0.4kV) from one source/substation (Figure 2). The secondary transformers are equipped with transformers of 630 kVA rating.

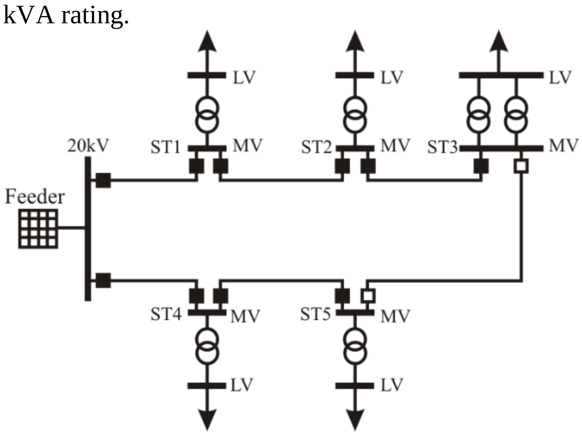


Fig. 2: The test distribution network.

We assume that the studied network supplies 960 subscribers (consumers), including multi-family houses, single family houses, schools, kindergartens, a medical clinic, office buildings, supermarkets, public lighting which are located in the same area. Figure 3 shows the aggregated load curve.

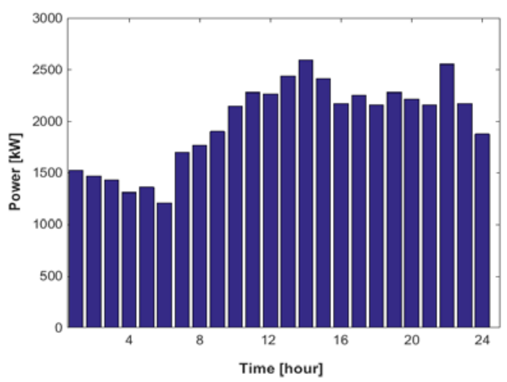


Fig. 3: Load curve of distribution network.

In this study, we consider the coordinated charging control of the charging station, and the optimization is based on electricity price variation. The electricity price profile is taken from the ELIX platform (European Electricity Index) for 13/07/2016 (fig. 4). It is easy to see that the electricity price profile is similar to the load curve, which means that during peak load hours the electricity price is high, while during load valley the electricity price is lower.

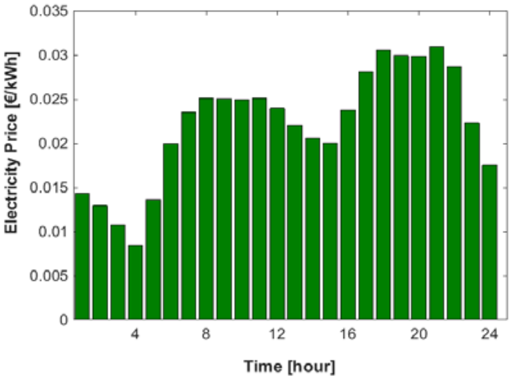


Fig. 4: Electricity price profile.

The following general assumptions are considered:

- ✓ each secondary transformer accommodates one charging station;
- ✓ number of vehicles in each charging station: *10 vehicles*;
- ✓ constraints:

$$\begin{cases} P_{\min/\max-global} = 150 \text{ kW}; \\ P_{\min/\max-ind} = 22 \text{ kW (400V, 32A)}; \\ SOC_{\min} = 30\,\%; \\ SOC_{\max} = 100\,\% \end{cases}$$

Additionally, the input data for the 10 EVs at the charging stations ST 1 are given in Table 1. The characteristics of the other charging stations are slightly different by the ST1.

Table 1: Input Data – Charging station

Input Data	***Vehicle***				
	EV 1	**EV2**	**EV3**	**EV4**	**EV5**
SOC init [%]	30	45	30	50	32
SOC final [%]	100	100	100	100	100
Battery capacity [kWh]	22	27	36	70	24
Arrival Time [hour]	18:30	14:20	4:10	23:00	9:10
Departure Time [hour]	7:30	23:40	9:00	8:20	11:50
Input Data	***Vehicle***				
	EV6	**EV7**	**EV8**	**EV9**	**EV10**
SOC initial [%]	45	50	43	37	70
SOC final [%]	100	100	100	100	100
Battery capacity [kWh]	17	36	24	35	50
Arrival Time [hour]	14:30	19:50	16:20	23:00	1:10
Departure Time [hour]	1:00	6:40	5:30	8:30	10:50

Using the price profile shown in Figure 4, the behavior of all EVs during the 24 hours interval is achieved. As shown in Figure 5, the EVs are mostly charged during periods of lower price and intensive traffic, while during high price periods and peak loads the EVs are injecting power back to the grid.

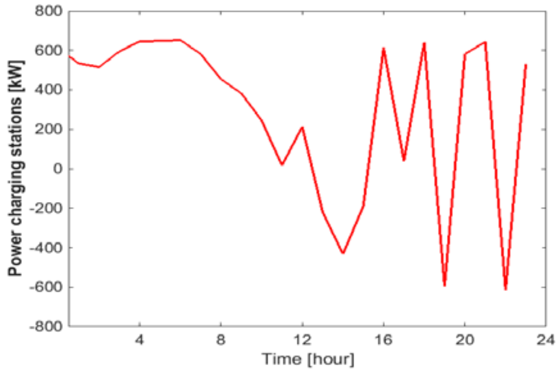


Fig. 5: Total load curve at the charging stations.

Figure 6 illustrates the total load in the grid for three scenarios: i) reference / base case load; ii) optimized EVs charging; iii) un-optimized EVs charging. In the un-optimized scenario, the electrical vehicles are charged instantaneously when they are plugged-in and the batteries will be fully recharged as fast as possible without considering the daily electricity price or other constraints. It is obvious that when optimization is applied, the load curve (dashed line) is smoothed as compared to the other two cases. This is a reaction in accordance with the price profile which is similar to the load profile. The load curve shape resulted for the scenario iii) is similar to the initial case but with the additional load from the electrical vehicles.

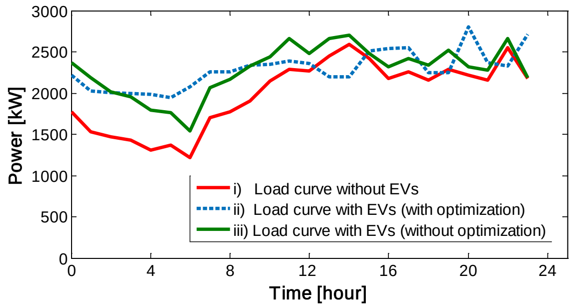


Fig. 6: The total load curve for three scenarios.

By inserting charging stations into the distribution network, the maximum peak load achieved initially at 2 p.m. (2593.96 kW) moves at 9 p.m. (2800.76 kW) for the case with optimized charging, and 3 p.m. (2704.24 kW) for the case without charging optimization. An increase in the electricity consumption during the night hours is observed, which corresponds to low electricity price. This means that a more optimal use of the energy sources is achieved, leading to reduced investments in the distribution network.

a. Power losses

Analyzing the active power losses, the most favorable scenario is the case with optimized charging, where the power losses are minimum, that is 892.5 kW (18% higher than the reference scenario, case in which power losses are 752.69 kW).

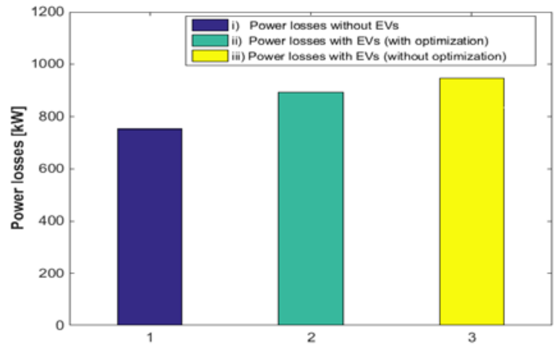


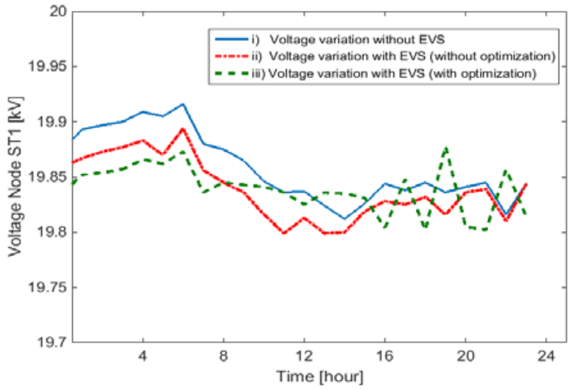
Fig. 7: The active power losses for all three scenarios.

For the case with uncoordinated charging, the power losses are bigger, that is 945.85 kW (with 26% higher than the reference scenario).

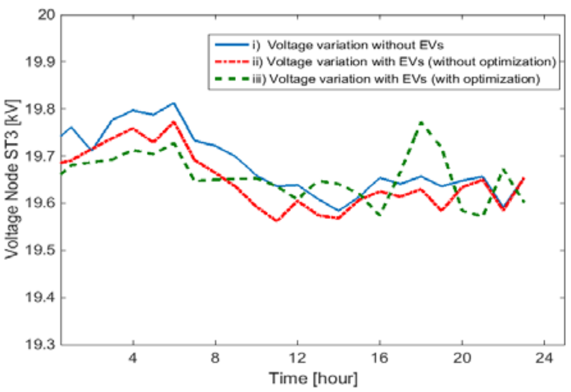
The results obtained for the power losses are presented in Figure 7.

b. Voltage profile

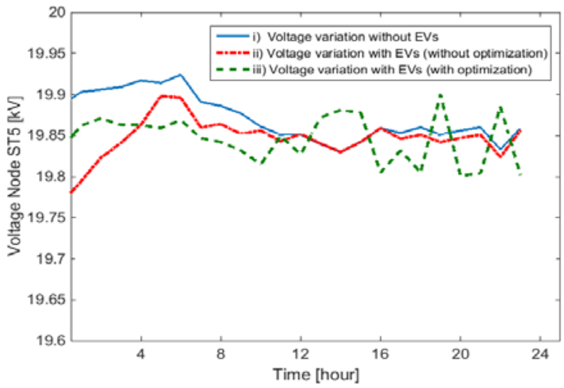
Figure 6 shows the voltage variation at three random secondary transformers (ST) for each case considered in the charging strategy.



a) Voltage at bus ST 1



c) Voltage at bus ST 3



e) Voltage at bus ST 5

Fig. 8. Voltage variation in nodes of electrical distribution network.

The simulations performed have revealed that the voltage may differ from one secondary transformer / charging station to another, depending on the initial load and the additional EV load.

In both cases with electrical vehicles the voltage decreases because of the additional load. However, the coordinated / optimized EV charging allows achieving a smoothed voltage profile for the 24-hour horizon, eventually with small variations around certain values. This is a result also of the load shift from midday to night hours.

A particularity of the optimized strategy is observed when the electrical vehicles are allowed to inject power into the grid. The change of the EVs from charging mode (power absorbed from the grid) to discharging mode (power injected into the grid) will result in sudden voltage variations, as observed for the time interval from 16:00 to 24:00. This problems may not necessary appear when considering a larger number of vehicles with greater diversity in the state of charge. Also, if the simulation time would be divided into smaller intervals, e.g. 15 minutes down to 5 minutes, a smoother voltage profile would result; however, this is conditioned by appropriate legislation and metering/ communication infrastructure.

5. Conclusions

This paper presents a linear programming based mathematical problem employed for optimizing the EV charging, while considering mainly the electricity price and the technical and operations characteristics of the vehicles.

The optimization algorithm helps achieving the best solution for EV charging aiming to minimize the total electricity cost, for both reference load and EVs, for the 24-hour time horizon. The algorithm allows the EVs to inject power back to the grid when the price is too high, but this is subjected to maintaining at appropriate hours the required state of charge.

As the electricity price is highly dependent on the load profile at the national level, the proposed optimization strategy for the total load (reference load and EVs load) results in better exploitation of the power grid, leading to reduced power losses, smaller financial expenses, and, is additional wiring is required, minimized investments in network expansion.

The charging behavior of large-scale electric vehicles will bring a critical effect on the power grid but the storage characteristics of EVs will provide new opportunities for the power grid security and economical operation as well.

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