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SMART CHARGING OF MULTIPLE EVS IN SMART GRID RADIAL LOW VOLTAGE DISTRIBUTION NETWORKS

BY

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Abstract. The harsh emissions constraints have pushed the Automotive industry to introduce Electric Vehicles (EV). Since the beginning of this millennia the numbers of EVs have increased from thousands to millions nowadays. The impact of EVs charging, over the Electrical networks has been studied in many publications, and everybody reached the same conclusion: if EV’s charging is not managed, the energy industry will suffer; increased investments, new energy production facilities will lead to increased energy prices. The concept of managing the EV’s charging process is connected to Smart Grid concept, and many publications are stating that a single centralized entity should regulate the chargingprocess. As such, in this paper a similar centralized EV charging control algorithm in low voltage distribution networks (LVDN) is proposed. The proposed algorithm, is regulating the EV charging power, while considering the LVDN network constraints. Specifically, the voltage constraints are taken into account, because the voltage levels within the network are a power supply quality indicator.

Keywords: EV charging; LVDN; Smart Grid; EV Smart Charging.

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1. Introduction

The increasing emissions constraints, have pushed the Vehicles Original Equipment Manufacturers (VOEM) to introduce electrified powertrains. In EU the VOEMs have to respect not only the single Vehicles emissions constraints but also the newly introduced Corporate Average Fuel Economy (CAFE) coefficient (Wikipedia). This coefficient is calculated as a harmonic mean of fuel consumptions, for the vehicles that are sold by a VOEM in a certain year. For the calculation of CAFE coefficient, the EVs sold are taken as zero when it comes to Fuel Consumption; this means that every EV sold reduces the CAFE for that VOEM.

A very high level of attention has been given to Toyota Prius and Tesla, who managed to raise the public awareness during a period in which fuel costs were high. The trend has been picked up by many VOEMs and now almost every Manufacturer has some versions of electrified powertrains nowadays.

The performance of Electric Vehicles has increased, many manufacturers are coming up with new models and reduced prices. This resulted in increase of EV sales, which have been increasing exponentially. In 2019 according to Bloomberg the EV sales have been at around 2.2 million vehicles (insideevs.com, 2019). Nowadays, many manufacturers have reached the conclusion that the future of mobility is electric, which resulted in increased diversity of EVs to meet the clients demands and wishes. So, if at the beginning the EVs have been seen only as compact personal cars to be used within cities, nowadays there are electric SUVs, and even sports cars being produced (The Guardian, 2019). Since EVs can satisfy all the customer needs and wishes, in the future the EV sales will only go higher.

Increasing EV numbers will increase the challenges when it comes to power supply. The energy consumed by an EV for driving itself, based on the medium energy consumption of 0.25 kWh/km and the medium driving distance of a personal car in EU of around 40 km/day results in a medium energy consumption of around 10 kWh/day.

As shown in (Kriukov, 2014), the most difficult situation for power supply will be seen in suburban energy distribution networks, where the energy consumption will be higher due to longer driving distance and where due to lower energy consumption density, Distribution System Operators (DSO) are opting for radial structure of the network.

Studies are showing that, if not carefully managed the energy consumed by EVs during charging will create huge problems in energy distribution networks (Clement-Nyns *et al*., 2010). Other studies have also shown that even the High Voltage Transmission Networks (HVTN) will suffer (Scott, 2007).

In (Jin *et al*., 2013) a dynamic EV charging control algorithm is presented based on Lyapunov optimization. The presented algorithm schedules EV charging to minimize energy prices taking into account the renewable energy generation and real-time electricity price. Even though the results are promising, the mean travelling range for the simulated EVs is 3.22 miles, which is very low. At the same time, it is unclear if the generated State Of Charge (SOC) are connected somehow to the travelled distance.

A strategy based on system load and time-of-use price have been introduced in (Moon, 2017). This strategy balances the benefits of EV owners (saving costs) versus system operator (relieving loads) by creating mutually beneficial arrangements. However, EVs are treated only as a group, and even if, marginal cost reduction is achieved, it is unclear if local constraints are taken into account. Even further, the Demand-Response approaches are under discussion when it comes to EV charging management (Kühnbach, 2021).

A new algorithm is proposed that treats EVs individually and manages to charge these to the targeted State of Charge (SOC) in (Xing, 2017). However, the algorithm execution time is long and economic benefits are not estimated; even though, the authors state that convergence rate of the algorithm is faster when compared to existing solvers.

A similar simulation to the one presented in this paper can be seen in (Richardson, 2012). In (Richardson, 2012) EVs are charging under an objective function that seeks to maximize the EV charging power under the minimum voltage constraints at the customer point of connection. Even though the simulation results look promising, the test network is insufficiently described, all EVs have the same charger rated power and the EV charging control system architecture is not described.

In this paper an “EV charging at home” scenario is presented and a novel EV charging control algorithm is proposed. The aim of the algorithm is to ensure the desired final SOC for each EV while keeping the voltage levels across the DN above the minimum allowable level. If voltage level below the allowable limit occurs, the algorithm reduces the desired SOC of EVs, keeping at the same time the voltage levels above the allowable limit. The proposed charging algorithm is executed partially on EVs’ electronic control units, and a part on a centralized control unit. This reduces the amount of data that needs to be exchanged between EV and the central control unit.

The rest of the paper is structured as follows. In section 2, the case study data are presented, together with the rational considered behind the data generation. Section 3 presents the EV charging control algorithm. Section 4 presents the results and discusses these; Section 5 presents the conclusions.

2. Case Study

2.1. Grid

To avoid a very long explanation regarding the grid, we are going to use the IEEE 37 bus grid, adapted to function as a LVDN. A more detailed information can be found in (Kriukov, 2014). To highlight the relevance of this research, same load profiles for the households have been used as in (Kriukov, 2014).

In our case study, we are going to consider that the EV owners are charging the EVs in the households' network. Since the household has already a power supply from the LVDN, we are going to consider that the DSO doesn't know about the appearance of the EVs and the extra power and energy demand in the network.

Even if the DSO knew about the appearance of EVs in the LVDN we are going to consider that corporate strategy for developing the distribution network is focused on implementation of Smart Grid technologies in their networks rather than replacing the cross-section of the conductor wires.

2.2. EV Charging

Nowadays, the storage capacity of EVs is measured in kWh, due to a high-level storage capacity of batteries. EVs are usually sold with 2 charging devices, one on-board of vehicle and one as an external charger.

The on-board charger has a low charging power, with a power of maximum 7kW. However, the 7 kW on-board chargers are rare and usually these come along with EVs with a very high battery capacity. The on-board chargers are capable of charging the battery from 0 to 100% State of Charge (SOC) in about 5 to 10 hours. These slow chargers allow the EV to charge from a normal socket no matter where these have a grid connection.

In our case study we can consider that the vehicle is charging at what we can call Home Network. Charging in the Home Network will happen every time the vehicle arrives at home. Nowadays vehicles, are capable of establishing an information exchange with the owner's smartphone, which knows exactly the GPS coordinates of the household locations so the identification of Home network is not a problem.

2.2.1. Battery Capacity

The battery capacity of EVs varies greatly based on the type of usage of the EV. City EVs has a lower battery capacity starting with 7 kWh up to 20 kWh, but recently the EVs started increasing their battery capacity with some batteries reaching over 80kWh. In our study case we are analyzing the impact of EVs charging over a LVDN located in residential suburban areas. This means that these EVs will be adapted to travel longer distances on a single charge. For our study case we decided to eliminate from our analysis the EVs that cannot travel a distance of at least 120 km. The battery capacity of the EVs has been randomly generated between 22 and 77 kWh.

2.2.2. EV Charging Power

The maximum charging power has been calculated based on the battery capacity. To emulate real life behavior, we considered that the on-board charger is capable of fully charging the battery in 8 hours. So, based on battery capacity, we calculated the maximum charging power (P_{max}) by simple division of battery capacity by 8 hours and rounded the value obtained.

Taking into account that some of the vehicles have a higher battery capacity which results in higher charging power, we considered that all the vehicles with a charging power higher than 9 kW have a 3-phase charger. For all the other EVs, we considered single-phase chargers and we randomly generated the phase on which this EV is connected to the LVDN.

In this case study, we are also going to consider that EVs can control their charging power in steps of 10%, with a range from 0% to 100%.

2.2.3. Vehicle's Arrival and Departure

To simulate a similar to real life behavior with respect to the vehicles arriving and connecting to the LVDN, we decided to randomly generate the moment of home arrival. In this matter we considered that a good behavior would be to arrive between the hours of 4 PM and 6 PM; similar we considered that a good behavior would be departure between 7 AM and 9:30 AM. In this way, we simulate EVs used for work travelling.

One of the most important things that needs to be known is the moment the vehicle can no longer charge from the network. For this, we are going to consider that every vehicle knows it's approximate time of departure either by learning the owner's behaviour in vehicle use or simply by asking him to input an estimated departure moment of time. In this way, the vehicles can calculate the critical moment of charging and reach the desired SOC at the moment of departure. In our study, the Critical moment of charging, is considered to be the last moment of time at which the EV needs to force charging at Pmax to reach the desired SOC. To keep the simulation relevant and consistent to our previous research we used the same arrival and departure times as in (Kriukov, 2014).

SOC at arrival (SOC_{arr}) and departure (SOC_{des}) moment of time, have been randomly generated based on the EVs battery capacity and distance travelled.

2.2.4. Additional Data for Charging Process

As we explained in previous research (Kriukov, 2019), the global efficiency of the charging process is influenced by multiple factors, like battery temperature, external temperature, battery State of Health (SOH), vehicle's power supply architecture and data exchange architecture, EV's owner behaviour and others. The efficiency of an EV during charging is difficult to calculate, so in this paper we ignored the influence of efficiency and considered a constant efficiency of 98%.

3. EV Charging Intelligence

All the EVs are connected to the same LVDN equipped with Smart Grid technologies. These technologies offer the possibility to EVs to exchange information between EVs themselves and with a central unit. When it comes to Smart grid approach, some manufacturers like ABB or Hitachi (Rys, 2021) recommend to use a single central unit that regulates the power consumption of consumers based on the information acquired from them. Hence, in this paper we considered a similar centralized approach.

The control procedure we propose for the EVs charging process is described forward.

1) Each EV calculates in real time it's Global Charging coefficient (GC_{ch}) by using (1):

$$GC_{ch}(i,t) = a(i,t) \cdot b(i,t) \cdot c(i,t) \cdot d(i,t) \quad (1)$$

where: *a*(*i*,*t*), *b*(*i*,*t*), *c*(*i*,*t*), *d*(*i*,*t*) - are also coefficients calculated as explained below. In Eq. (1) *i* is the identification number of the EV, and *t* is the moment of time.

To calculate coefficient *a*(*i*,*t*), we first calculate P_{med} by using (2):

$$P_{med}(i,t) = \frac{[SOC_{des}(i) - SOC_{act}(i,t)] \cdot Cap(i)}{T_{dep}(i) - t} \quad (2)$$

where: P_{med} – medium charging power needed by the EV number *i* to reach the desired SOC_{des} at the departure time T_{dep}; SOC_{act} – actual SOC for the EV number *i* at time *t*; *Cap* – storage capacity of the battery for the EV number *i*.

The boolean coefficient *a*(*i*,*t*) is meant to indicate the EVs that can no longer participate in power consumption control, and instead need to start charging at P_{max}. So, in case $P_{med}<0.95 \cdot P_{max}$, coefficient *a*(*i*,*t*) will be 1, and otherwise 0.

Coefficient *b*(*i*,*t*) for an EV, will take the value 1 if $u_m>1.02 \cdot u_{crit}$, and 0 otherwise. The coefficient 1.02 was chosen so as to ensure a reserve to avoid situations when the vehicle would continue charging when the voltage is very close to u_{crit}, without exceeding it, thus causing the voltage to pass below the allowable limit. The symbols used above are: u_m –the voltage measured by the EV's charger, in p.u. u_{crit} –the minimum allowable voltage level in the LVDN, in p.u.

Coefficient $c(i,t)$ for an EV, will be always equal to the measured voltage, u_m.

Coefficient $d(i,t)$ is calculated by using (3).

$$d(i,t) = \frac{[SOC_{des}(i) - SOC_{act}(i,t)] \cdot Cap(i)}{P_{max}(i) \cdot [T_{dep}(i) - t]} \tag{3}$$

Coefficient $d(i,t)$ represents the need of the EVs for high power charging. So, an EV which will require charging at a higher power will have a higher value for $d(i,t)$ coefficient.

2) Each EV sends its GC_{ch} valueto a central unit in real-time. The central unit is receiving the GC_{ch} from all the EVs and makes discrimination based on these coefficients as depicted in the Fig. 1.

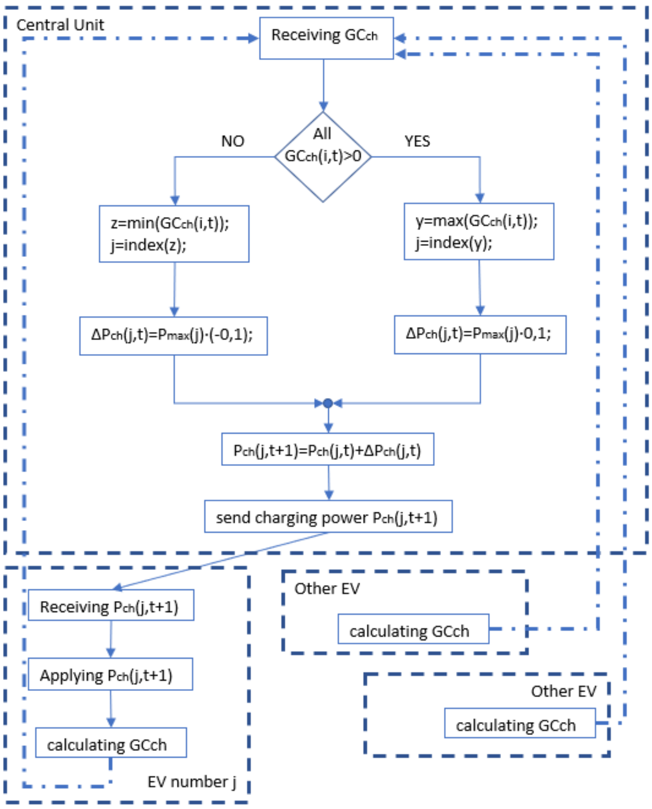

Fig. 1 – Charging control algorithm.

When regulating the charging power of an EV, the central unit exchanges information only with the impacted EV. Once an EV is applying its new P_{ch}, the power flow in the LVDN changes, which inevitably leads to changes in GC_{ch} for all the EVs. If the algorithm is run in real-time the charging power of EVs will inevitably adapt to the voltage profile conditions in the LVDN.

4. Results

The above methodology has been implemented in DIgSILENT Power Factory program (www.digsilent.de). To implement the EVs control logic we have written a script in DPL. DPL is a programming language embedded in DIgSILENT Power Factory program, that allows control the state of all the components of the grid, and the simulation parameters of the grid components.

Since the arrival and charging of EVs to the Home Network are at the centre of this paper, we decided that the best moment to start the simulation would be 12 PM, in this way the arrival and departure of EVs can be seen as a single time interval on the graphic profiles like those in Figs. 2 to 7.

As mentioned in subsection 2.1, the network used in this simulation is the IEEE 37 bus network adapted to functioning as a LVDN. The detailed description of the network can be found in (Kriukov, 2014). Moreover, the household loads and the amount of energy required by the EVs are the same, so the results can be compared to those presented in (Kriukov, 2014). On the other hand, in this paper the Romanian standard regulation was considered, based on which the minimum voltage level for power supplied in radial networks should never fall below 90% of the nominal voltage.

In the following, for reasons of space economy, the results of the case study will be presented briefly. Thus, for the voltage profiles, the value for 2 buses, considered representative, will be indicated, namely buses 724 and 729, both being network-end buses, where the voltage is expected to reach the lowest values. On the other hand, for the variation of the EV's charging power, 4 vehicles have been chosen at random, namely EV3, EV8, EV9, EV29.

Figures 2 and 3 show the voltage level for all three phases at the two representative buses (724 and 729). As one can see, the voltage levels are within the imposed limits. The lower voltage levels are encountered starting with 4 PM, when household owners start consuming energy within the household itself and additional power is consumed by EVs for charging. High level of unbalance can be also seen in the voltage profiles, but the phase balancing problem is outside the area of interest for this study. When it comes to voltage levels, in (Richardson, 2012) the voltage levels are also above the imposed minimum threshold.

As can be seen in Figs. 4 and 5, the charging power varies greatly between 0 and P_{max}. One can easily notice that the charging process is not continuous, especially for EV 3, EV 9 and EV 29. The charging power for EV 8 never reaches P_{max}, while EV 3, EV 9 and EV 29 reach maximum charging powers especially during night time, which is the off-peak hours for household consumption. During that period of time the influence of the voltage level is lower, and the main discriminant in selecting the EV under charging will be the EV's SOC. On the other hand, for EVs which do not reach P_{max}, the charging process takes longer, and level of the charging power varies in a great extent, due to the influence of network voltage level, which is the main discriminant in this case.

An EV charging power consumption shift occurs in (Richardson, 2012) in the controlled EV charging scenario. It is mentioned that the EV power consumption shift happens due to the voltage levels at the customer connection point. In this research, a similar behavior can be seen in most cases; as such, Figs. 4 and 5, three EVs (out of the four presented) start their charging much later than their arrival. However, not all EVs exhibit the same behavior. For instance, one can see that EV8 starts charging immediately at arrival. this is due to the fact that the algorithm was designed to prioritizes EVs with higher energy needs (lower actual SOC levels).

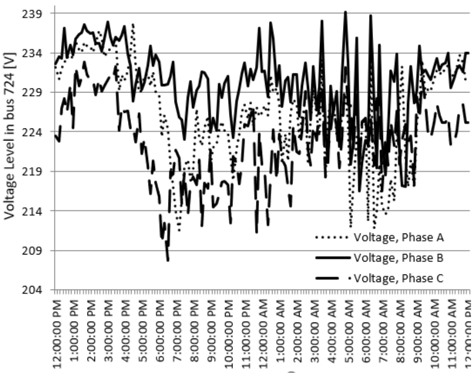

Fig. 2 – Voltage level during the simulation in busbar 724.

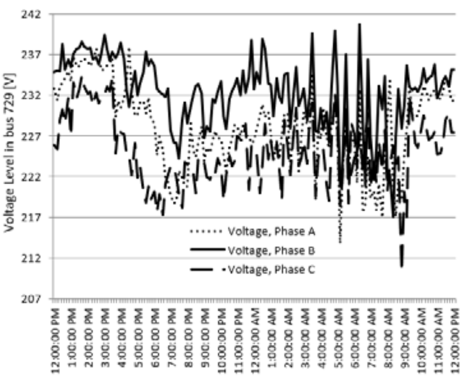

Fig. 3 – Voltage level during the simulation in busbar 729.

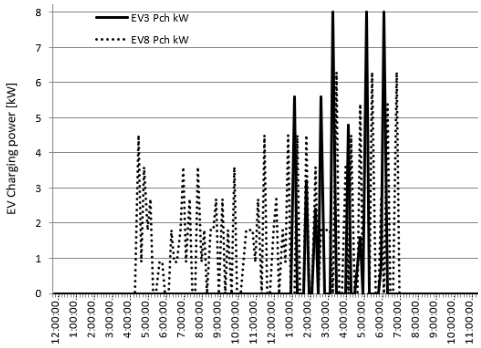

Fig. 4 – EV Charging power for EV3 (P_{max}=8 kW) and EV8 (P_{max}=10 kW).

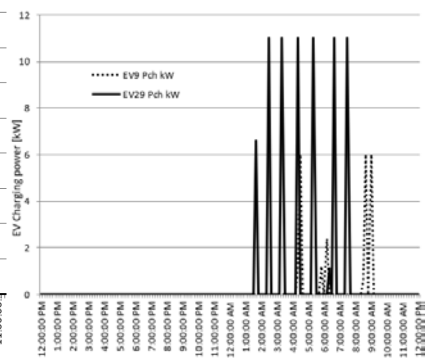

Fig. 5 – EV Charging power for EV9 (P_{max}=6 kW) and EV29 (P_{max}=11 kW).

The graphics in Figs. 2-5, and the remarks above show that the basic information available to EVs (SOC, battery capacity, P_{max} and supply voltage level) is enough to correctly discriminate the EV charging power, as in the charging control algorithm in Fig. 1.

As global information, LVDN power losses and transformer power losses can be visualized in Fig. 6. Also Fig. 7 presents the power consumption profiles for the entire LVDN. As one can see, the power losses follow the pattern of the power consumption in Fig. 7. The power consumption increases greatly, when EVs start charging, as do the power losses too. Even if the power losses are at a high level, it needs to be mentioned that none of the power losses optimization techniques have been considered in this paper.

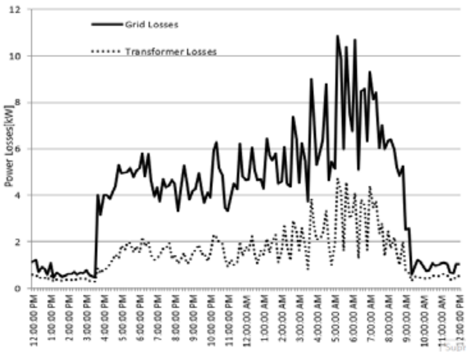

Fig. 6 – Grid power losses and transformer power losses.

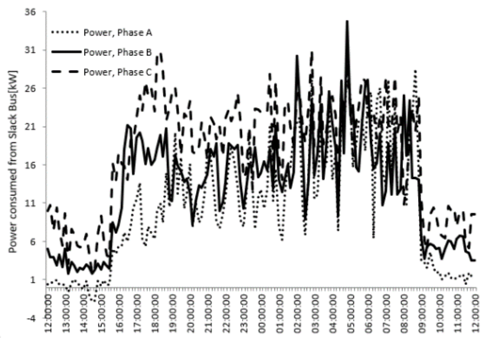

Fig. 7 – Power consumed form the slack bus.

5. Conclusions

The purpose of this paper is to present an EV charging power control algorithm that can be run in real-time and takes into account the Voltage constraints in LVDN and at the same time takes into account the EV's energy/power needs. The proposed charging control algorithm manages to deliver to EVs the necessary amount of energy and at the same time to keep the voltage levels within the imposed limits.

In future research we will focus on improving the mathematical model of the EV during charging as well as applying energy/power optimization techniques.

An additional influence has also been ignored, the LVDN voltage level measurement error. The measurement error can influence the order of the EVs during charging, but this doesn't mean that the main objective will not be satisfied. The influence of the LVDN measurements error over the proposed algorithm will be studied in future papers.

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ÎNCĂRCARE INTELIGENTĂ
A VEHICULELOR ELECTRICE ÎN REȚELE RADIALE
DE DISTRIBUȚIE SMART GRID

(Rezumat)

Impactul încărcării vehiculelor electrice asupra rețelelor electrice a fost studiat în multiple publicații, ajungându-se la aceeași concluzie: dacă încărcarea vehiculelor electrice nu este gestionată inteligent, industria energetică va avea de suferit; investițiile crescute în rețele electrice dar și în noi instalații de producere a energiei vor duce la creşterea tarifelor la energie. În prezenta lucrare este propus un algoritm de management a încărcării vehiculelor electrice, care ia în considerare necesitățile energetice ale vehiculelor dar şi constrângerile existente în rețelele de distribuție de joasă tensiune.

Algoritmul propus încarcă vehiculele punând în balanță cantitatea de energie de care acestea au nevoie și nivelul de tensiune la bornele autovehiculului. În acest sens vehiculele la bornele cărora nivelul de tensiune este ridicat vor începe încărcarea mai devreme; de asemenea, vehiculele care au nevoie de cantități ridicate de energie vor fi avantajate.