Novel Decentralized Voltage-Centered EV Charging Control Algorithm Using DSRC System in Low Voltage Distribution Networks

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This work was supported by a publications grant of the TUIASI, project number GI/P19/2021.

ABSTRACT Currently, all major Vehicle Manufacturers agree that the future of mobility is electric. All of them have started selling Electric Vehicles (EVs). It is clear that these types of vehicles will require charging, which in turn will have an impact over the power distribution systems. All the studies show that the impact over the power systems will be significant and may be disastrous in case there will be no investments. Unmanaged EVs charging can lead to a huge increase in energy costs due to an increased level of investments in energy infrastructure. This paper proposes a Decentralized EV Charging Control (DEV-CC) system that can be executed by the existing on-board Electronic Control Units (ECU) and uses Dedicated Short-Range Communication (DSRC) to establish communication between EVs. The proposed DEV-CC, adapts the EV charging power depending on the Low Voltage Distribution Networks (LVDN) voltage levels measured by EVs themselves. The main purpose of the proposed DEV-CC is to charge all EVs connected to the LVDN without allowing the voltage to drop below the imposed limit. As the results will show, the proposed DEV-CC manages to charge all EVs while keeping the voltage levels within the LVDN above the allowable limits. The proposed DEV-CC does not require any investments from the Distribution System Operator (DSO), can be implemented on EVs with minimal costs and is a viable solution to the expensive Smart Grid systems.

INDEX TERMS Decentralized EV Charging Control System; Charging Power Control; Dedicated Short-Range Communication; Low Voltage Distribution Networks; Electric Vehicles, Voltage Control.

I. INTRODUCTION

The increasing emissions constraints have put a great pressure on Vehicle Original Equipment Manufacturers (VOEM). As a result, to reduce the global and local pollution, VOEMs have introduced Electric Vehicles (EVs) to the market.

The worldwide number of Electric Vehicles on the road has passed the verge of 5 million in 2018 [1]. On the other hand, the sales of EVs are not slowing down, with 564,000 EVs sold in 2019 in Europe alone [2]. Energy consumption for driving purpose only for an EV range from 0.16 kWh/km to 0.35 kWh/km [3],[4]. If medium driving distance in EU of 40 km/day at a medium energy consumption of 0.25 kWh/km is considered, daily worldwide energy consumption produced by EVs is around 50 GWh. Perhaps, 50 GWh worldwide energy consumption is small, but if it is considered that 77% (i.e., about 40 GWh) of energy necessary for EVs is delivered in home networks [5], this number becomes huge. The main problem is that 40 GWh of electricity, need to be delivered in Low Voltage Distribution Networks (LVDN), and the numbers are increasing daily. It needs to be mentioned that the high number of charging events happening in home networks are a direct result of a very cost cautious behavior shown by EV owners [5]; they want to have a cheap option to satisfy their mobility needs.

Technical and economic assessment studies on the impact of an increasing number of EVs over distribution networks [6],[7],[8],[9] show that unmanaged EV charging will have negative impacts over the correct and efficient operation of the Distribution Networks (DN). Further studies point out that the entire energy sector will be in trouble if EV charging is unmanaged or mismanaged [9],[10],[11],[12],[13],[14];
transmission networks and power generation will also be impacted. The problems that can be encountered in the energy sector are long known, however an applied solution doesn’t exist, due to reduced EV adoption.

The amount of energy that needs to be delivered in LVDN will increase dramatically in the near future. But in authors opinion, the amount of energy necessary for EV is only a secondary problem; the biggest problem will be the amount of power necessary for EV charging. EV charging at home is happening at low and very low power [5]; in European networks the power delivery will be especially challenging as a result of two factors: on one hand, the increasing number of EVs will require huge amounts of power; on the other hand, European households usually have access to multiple energy sources, so the LVDNs are sized according to their power consumption. Basically, European LVDNs are not sized to handle high-power processes like EV charging or heating. If EV charging is not correctly managed, investments in LVDN to increase cable cross-sections will have to be performed, and of course, these will have an impact over the energy rates.

With regard to EV charging management, the literature identifies two types of approaches, namely centralized control and decentralized control. A typical centralized approach is presented in [15], where all EVs are connected to a single centralized control unit. However, the system proposed suffers from two major disadvantages: first, the system requires performant data acquisition communication networks, and second, EV needs, as an energy consumer and a mobility device, are not taken into consideration.

Paper [16] presents a decentralized approach to EV charging. Besides the need for a performant communication network, this approach requires that all EVs are connected to high performance charging stations. The charging stations capable of performing these tasks are very expensive. A system that requires high costs to be supported by any party is unlikely to be implemented.

Multiple parties within the scientific community consider that fast charging solutions will be used for EV charging. In [17] economic optimizations are made for high-power charging stations, by introduction of an algorithm that controls EVs charging, EVs admission, pricing and scheduling. The algorithm has a sole purpose of charging station profit maximization. In authors’ opinion, investments in charging infrastructure should be focused on keeping the energy rates low, because low energy rates are often linked to high level of society welfare.

Strategy based on time-of-use price and system load have been introduced [18]. This strategy tries to balance the benefits of EV owners (saving costs) and system operator (relieving loads) by creating mutually beneficial arrangements. However, EVs aren’t treated individually, so their individual needs might not be satisfied. Moreover, even if the purpose of marginal cost reduction is achieved, it is unclear if local constraints are taken into account. Even further, the entire Demand-Response approaches are being questioned when it comes to EV charging management [19].

Aggregators are for profit entities that are capable of exerting control over the charging process over a considerable number of EVs. They act as intermediary between EVs, energy markets and Distribution System Operator (DSO). Aggregators usually own the Smart Charging infrastructure and have contractual obligations with EV owners to deliver the necessary energy.

To make a profit, aggregators need to understand well the user behavior, because this has a direct impact over the profits they can make [20]. In [20], it is shown that certain aspects of user behavior have a quadratic relationship with the associated energy costs. However, aggregators need to manage their relationship with the EV owners very carefully, because imposing constraints on when EVs are charged might influence owner perception, or even EV adoption. The presented study doesn’t take into account machine learning techniques that can be applied to understand user behavior [21]. In [21], the EV departure time is predicted using Machine Learning algorithms based solely on the historical data collected from these. After the Machine Learning is trained the computation time is very small and it is suitable for real-time application. The results show that considerable errors are obtained based only on historical data alone.

There are multiple strategies that bring substantial benefits to EV aggregators. EV charging load-shifting technique [22] is the easiest to implement and can ensure good profits. In [22], a new algorithm is proposed that treats EVs individually and manages to charge these to the targeted State of Charge (SOC). Even if the authors state that the convergence rate of the proposed algorithm is faster than the existing commercial solvers, the execution time is still very long and economic benefits are not estimated.

Controlled EV charging, or Smart charging, can be used for the benefit of the LVDN in mitigating problems like: accelerated equipment aging [23], power quality problems like voltage drop control [24], [25], [26] reactive power compensation [20], frequency control [27] distribution networks phase balancing [28], and others.

In [23], the financial benefits of implementing Smart Charging in DN are presented. It is shown that Smart Charging based on electricity price can bring great financial benefits to EV owners (reduced rates) and DSO (reduced equipment aging and investment deferring). However, it is still unclear how long will EV owners benefit from reduced energy rates [19].

In [24], use of a four-quadrant charger is proposed to increase the voltage level within a DN. However, the proposed charger is a theoretical one. Moreover, it is not clear how the proposed charger is integrated within the voltage regulation system. Additionally, it is assumed that all EVs have the same battery capacity.

In [20], a charger with a constant 0.95 capacitive power factor is used to increase the global power factor across a real
It is shown that operating costs of the DN remain the same and reinforcement investments are deferred. However, the charging power of EVs is considered either 0% or 100%, and EV internal power losses and EV on-board power consumption is ignored.

When a group of EVs participates in a market designed to ensure reliable transmission of energy, the EV group is offering ancillary services. In [27], the possibilities of EVs reducing their charging power and even switching to Vehicle to Grid (V2G) mode for Network frequency support is analyzed. It is shown that even small number of EVs are capable of significantly improving the frequency in the network after a disturbance. However, an exact topology of the simulated grid nor control system architecture are presented.

In [26], a centralized Smart Charging system is presented, that allows managing the voltage levels and thermal stress within a DN. However, EVs are discriminated solely on their SOC level and all simulated EVs have the same battery storage capacities.

In [28], a relatively simple algorithm is proposed to control the phase from which the EVs are charging with the purpose of balancing a three-phase LVDN. The results show that voltage unbalance factor is improved, however it is unclear how EV mobility and characteristics are modeled.

Providing ancillary services can bring financial benefits to EV owners however, these benefits are not significant [29]. Additionally, EVs could provide uncertainties and a significant infrastructure investment is necessary, to make possible EV participation in the ancillary services market.

As it can be seen, the proposed EV smart charging systems rely on communication networks in their decision process. The existing wireless communication protocols should be able to handle the necessary data. The importance of sampling interval is verified in [30], and the conclusion is reached that a faster sampling rate reduce the errors in V2G operation, however the oscillations are removed only when the granularity is increased. IEEE 802.11 communication protocol is modelled, tested and proves to be reliable in supporting EV smart charging [31]. The [31] research is extended and machine learning techniques are added, to replace the information exchange loss or delays [32]. The results show that artificial neural networks can be successfully used to counteract the effects of communication network congestions.

In this paper a novel Decentralized EV Charge Control (DEV-CC) system is proposed. In comparison with the above presented systems, the proposed DEV-CC doesn’t require any investments from the DSO or from EV owners. DEV-CC system has been designed specifically so that it could be run on the on-board Electronic Control Units (ECUs) and doesn’t require any interventions on EV design from hardware point of view. The proposed DEV-CC system, uses the Dedicated Short-Range Communication (DSRC) system to establish communication between EVs.

Through the DSRC system, the value of a single coefficient called Global Charging Coefficient is exchanged between vehicles. Based on these values (own value and received values from other EVs), each EV increases or decreases its charging power. As a result, the proposed DEV-CC system will keep the voltage level across the entire network, above the imposed minimum limit, and as long as the network is capable of delivering the necessary power, DEV-CC will charge all EVs to their desired SOC. A very important aspect of the proposed DEV-CC system, is that embedding it on-board of nowadays EVs will require only software adaptations. In automotive manufacturing one of the cheapest components of any vehicle is the software due to sheer number of vehicles sold.

The main contributions of this paper are:

1. The introduction of a novel Decentralized EV Charging Control (DEV-CC) system, based on a simple methodology which reunites the interests of both EV owners (desired SOC) and DSO (voltage profiles).

2. To satisfy these interests, DEV-CC uses DSRC communication with a different purpose than the ones it has been designed for and used until now, to the best knowledge of the authors.

The rest of this paper is organized as follows. In Section II the on-board charging system architecture and its operation are presented. Section III, presents the EV simulation model and the proposed DEV-CC system. Chapter IV presents the case study and the data used for the case study. In chapter V, the results of the simulations are presented, with subsections treating each aspect from both LVDN and EVs points of view. Chapter VI presents the conclusions.

II. DEVELOPMENT IN VEHICLE MANUFACTURING

Recent worldwide trends to reduce the emissions both locally and globally have put a great pressure on VOEM. At the same time, governments around the world are continuing to impose harsh emission constraints, and some of them took a step further announcing the date at which all the cars sold on their territory need to be Zero Emissions.

A. EV ARCHITECTURE

Even if EVs are not a novelty, their architecture is still not standardized. In this paper the main interest is focused on the architectures EVs; more than this, the architecture of the 400 V Direct Current (DC) on-board network is the main topic.

Development of EVs is still ongoing, and VOEMs are changing technologies and equipment at a very high pace. When it comes to charging, a generally used system can be identified, as presented in Fig. 1. The DSRC unit in Fig. 1 is not used in existing EVs, but the authors consider it in this paper as the main communication device in controlling the charging process of EVs.
EVs have a very high power factor during the charging process [33]. Papers [20, 34] show that during charging, EVs could compensate the power factor within the LVDN which will result in voltage level increase. For an easier modelling, in this paper it is considered that EV are not performing any power factor corrections and their consumption power factor is 1. So EVs will be modeled as a purely resistive load.

B. DEDICATED SHORT RANGE COMMUNICATION

All the VOEMs agree that the future of mobility is electric and autonomous. An autonomous vehicle is a vehicle that is capable of self-driving, requiring no intervention from the driver. One of the most important developments for autonomous driving are related to DSRC communication.

This paper focuses around the topic of voltage level control in LVDN during EVs charging. In this context, the authors did not intend a detailed approach to the DSRC system, using the DSRC concept only as a communication system between EVs. However, some general details of the DSRC system as a vehicular communication protocol will be presented.

DSRC system allows establishment of wireless communication between vehicles and between vehicles and systems from the road-side infrastructure. The DSRC band uses the 5.850-5.925 GHz frequency range for short and medium distance communication between vehicles, ensuring a high-speed communication at low latency, below 100ms [35]. The entire communication band is split into 7 channels of 10 MHz each; the channels are numbered from 172 to 184 using only even numbers. From functional point of view, the channel 172 is the control channel that is used exclusively for network management and safety; the other six channels are available for services [36]. Even if the main functionalities for DSRC are referring to vehicle safety and driver experience, it seems that DSRC has also triggered the interest of other applications; these applications will have a lower priority than vehicle safety, but these will be allowed [37].

On the other hand, the messages transmitted within this system respect the following structure: Application Identifier, Message Identifier, Message Expiration Date, Message Length, Error Detect Code and Message Body [38]. The first 5 data fields, are reserved for message header and have a total length of 5 Bytes, whereas the actual message can reach up to 255 bytes. The communication principle between EVs, using this system is presented in Fig. 2.

In our study, the actual communication within the DiGSILENT Power Factory software script is not simulated. All the Global coefficients are computed by the script and stored in a vector variable, which is accessible to all simulated EVs.

A closer look at Fig. 1 will show the two ways of charging for EVs. The main interest in this paper is EV charging at home which is executed mainly with the ON-Board Charger (ONBC).

When charging through ONBC, the power is delivered from the LVDN through an Alternating Current (AC) measurement and protection unit to the ONBC. The charger transforms the energy from AC to DC and supplies the on-board High Voltage (HV) network. Here the energy at 400 V DC is distributed to all the on-board consumers and the remaining energy is stored electrochemically inside the High Voltage Battery (HVB).

ONBC is the base equipment of any EV that allows low-speed charging at any available socket. It usually delivers a charging power of up to 5 kW. Because this type of charger delivers low power, this requires that EV is stationary for long periods.

All vehicles require some sort of cabin preconditioning. In case of EVs cooling and heating is produced using a Heat Pump (HP). For EVs it is crucial to ensure a high efficiency equipment, as it can extend the maximum travel range of the vehicle without an increase of HVB storage capacity. Cooling/heating system is taken into account during charging as an EV on-board power consumption.

Every time the charging process is started the target SOC at which the charging will be stopped is 100%. Many EVs are capable of scheduled charging, where the owner, when he leaves the car, is setting up the time at which he wants to start charging or when charging needs to be finished. But this is still not smart charging from others’ point of view, which considers that smart charging is a process that needs to be able to adapt to the conditions existing in the network.
desired SOC or $SOC_{des}(i)$ will be established for each vehicle taking into consideration not a theoretical value (100%), but a practical one that satisfies the next day traveling needs of the EV’s owner. Thus, each EV calculates the travelling needs of its owner as an average trip distance, based on historical data.

So, all EVs will arrive at $T_{arr}(i)$, with an existing $SOC_{ind}(i)$; to satisfy daily mobility needs of their owners EVs will depart at $T_{dep}(i)$, with a current SOC of at least $SOC_{des}(i)$. The initial SOC was generated randomly in the range of 40% to 90%.

From LVDN point of view, an EV is in one of two states, specifically: it is either present and in need of charging, or it is absent when EV is in use. So, in this paper EV mobility is modelled as an amount of energy that is consumed from the battery by EVs, combined with a period of absence from LVDN when the EV is in use. The maximum possible value of $SOC_{des}(i)$ is limited to 100%, by the BMS. However, charging the HVB to 100%, produces additional HVB degrading. That is why, the values of $SOC_{des}(i)$, have been generated randomly within the range of 85% to 95%.

Technically speaking, from the LVDN point of view the main challenges consist in the increased energy demand of EVs that is overlapping with the domestic energy demand of households, such as the one shown in Fig. 3 [40]. As known, the household consumption is varying during the day. The arrival time of EVs considered in this paper (between 4 PM and 6 PM) is at the beginning of the evening peak load of households, and since DSO does not know about the EVs’ additional power consumption, the increased power consumption can lead to high voltage drops in LVDN.

FIGURE 3. General hourly load profiles for households.

To avoid this situation, the proposed charging control system described in this section can be implemented as a solution.

1) HVB STORAGE CAPACITY

Presently, all EVs’ designers are choosing EV’s charging system characteristics based on drivers’ experience, without considering power system’s infrastructures in any way. Of
course, this is a harsh statement to make, but the position is understandable, since VOEMs are competing to sell vehicles and not energy.

The most important characteristics that have impact over the charging process are the HVB storage capacity and the rated power of the ONBC. Usually, these two characteristics are correlated; none of the VOEMs want to sell an EV that has a high HVB storage capacity and a low-power ONBC, because these EVs would have to be stationary long periods of time for charging; on the other hand, a combination of low HVB storage capacity and a high-power ONBC makes no sense.

The available literature for EVs mentions a total energy storage capacity within the range of 6 kWh to 100 kWh; with the low limit for cheaper EVs, like Renault Twizy, and the high limit for expensive EVs, like Tesla Model S/X. Considering these limits, the storage capacity of EVs used in this study was randomly generated between 20 kWh and 80 kWh. By reducing the range in which the total HVB energy storage capacity was generated, the authors intended to eliminate the rare vehicles, at the boundaries of the original range.

2) ONBC CHARGING CHARACTERISTICS

In this study, a particular case is considered, the one when any EV should be able to fully charge with the ONBC functioning at its maximum rated power \((P_{\text{max}}(i))\) in 8 hours. Therefore, by simple division of the HVB storage capacity by 8 hours and rounding towards the upper limit the rated ONBC charging power is determined.

Some of the EVs have a higher HVB storage capacity, which will result in higher ONBC rated power. In Romanian law, the maximum recommended power for single-phase LVDN connections is around 11 kVA [41]. Based on this recommendation and taking into account additional household consumption, the authors opted for a threshold charging power of the ONBC equal to 9 kW. As a result, all the vehicles that have ONBC rated power higher than 9 kW, will be considered to use a 3-phase connection to the LVDN. The rest of EVs, with ONBC rated power lower than 9 kW, are considered to use single-phase connection to the LVDN. It is considered that ONBCs have a power regulation capability to keep the power balance within the on-board HV network. In this paper, it is considered that EVs are capable of controlling their charging power in the range 0 to 100%, with a resolution of 5%.

An additional functionality of the ONBC required by the proposed charging control algorithm is the capability of measuring of the LVDN AC terminal voltage level.

3) ZAM

ZAM is a functionality that activates whenever the EV is connected to an electricity source but the EV is not actually charging the HVB; during ZAM, ECUs and HVAC unit, and it’s both components (i.e., circulation pump and HP) are supplied.

In automotive, ECUs are designed to be very energy efficient devices. Moreover, ECUs have a sleep mode that is activated whenever the ECU does not participate in the process it is designed for. While in sleep mode the ECUs’ energy consumption is negligible, so taking into account the purpose of this paper the energy consumption of sleeping ECUs is ignored. Modern EVs have tens of ECUs on-board, however during charging only six ECUs are functioning in nominal mode (Fig. 1).

Hence, to model ZAM in a simple way, the following assumptions are made:

1. Each active ECU consumes constantly a power of 10 W supplied by the on-board LV network.
2. Constant power consumption of 20 W for the circulation pump (notation \(C_{\text{CP}}\) will be used further).
3. A variable power consumption of the HP equal to 2% from the power consumed from the LVDN, \(P_{\text{PN}}(i,t)\), denoted \(P_{\text{HP}}(i,t)\).

B. EV MODEL DURING CHARGING.

To build the mathematical model of EVs during charging, the power flow from LVDN to the HVB must be considered. For this, the charging system architecture in Fig. 1 is simplified by removing the on-board communication system and drawing the power flow on the diagram (blue arrows). The simplified charging system architecture and the power flow are presented in Fig. 4 and Fig. 5.
in HVN ($\Delta P_{\text{Cab}}$). Finally, $P_{\text{DC/DC}}$ is composed of the power consumed by ECUs ($P_{\text{ECU}}$), the HVAC unit ($P_{\text{HVAC}}$) and internal losses ($\Delta P_{\text{DC/DC}}$). A simplified power flow is presented in Figure 4.

\[
P_{\text{N}}(i,t) = \frac{P_{\text{CH}(i,t)}}{\eta_{\text{Cab}} \cdot \eta_{\text{ONBC}}} + \frac{P_{\text{HVAC}(i,t)} + P_{\text{ECU}}}{\eta_{\text{Cab}} \cdot \eta_{\text{ONBC}} \cdot \eta_{\text{DC/DC}}} \tag{1}
\]

In (1) and further, index $i$ refers to the vehicle, and index $t$ refers to the time moment.

1) POWER CONSUMPTION OF THE HVAC UNIT

To make a correct estimation of the actual power stored within the HVB, $P_{\text{HVAC}(i,t)}$ needs to be estimated. HVAC power consumption is dependent on the amount of heat/cooling needed on-board. $P_{\text{HVAC}(i,t)}$ can be estimated using (2):

\[
P_{\text{HVAC}(i,t)} = P_{\text{CP}}(i,t) + P_{\text{HP}}(i,t) \tag{2}
\]

where: $P_{\text{CP}}$ – the power consumed by the circulation pump; $P_{\text{HP}}$ – the power consumed by the HP.

The exact power consumption of the circulation pump and the HP is varying based on the electronics temperature, external temperature, fluid temperature and on other design parameters. It is expected that some components are different from one manufacturer to another, so the power consumption of these two components must be considered as being specific to each vehicle. However, in this paper a constant power consumption is assumed ($C_{\text{CP}} = 20$ W, as mentioned in Subsection III.B.3.). When it comes to the HP, the power consumed depends on the cooling necessities for the high-power equipment. Since the amount of power losses within the high-power components increases naturally with the increased power circulating through these, based on [42], the power consumption of the HP is considered linearly dependent on the power consumed from the network $P_{\text{N}}(i,t)$. Consequently, a 2 % quota of the power consumed from the network was considered. Hence, equation (2), becomes (3):

\[
P_{\text{HVAC}(i,t)} = C_{\text{CP}} + 0.02 \cdot P_{\text{N}}(i,t) \tag{3}
\]

2) POWER LOSSES WITHIN THE EV

Besides the power consumption of the ECUs and the heating/cooling installation, power losses naturally occur across the charging network and in the equipment on-board. For the purpose of this paper, it is considered that all on-board equipment is operating at constant efficiency, with the following values:

- DC/DC converter efficiency, $\eta_{\text{DC/DC}} = 92\%$, as in [43];
- ONBC efficiency, $\eta_{\text{ONBC}} = 95\%$, as in [44];
- Battery efficiency, $\eta_{\text{HB}} = 99\%$, as in [44];
- Cable efficiency, $\eta_{\text{Cab}} = 99.5\%$.

3) EV CHARGING POWER

As previously mentioned, there are two EV operating modes considered in this paper, namely ZAM mode and charging mode.

If an EV is operating in ZAM mode (i.e. $P_{\text{CH}(i,t)} = 0$), the only power consumption on-board is the power supplied to the ECU. On the other hand, ECUs are designed to function properly in any conditions, including high temperatures, without requiring cooling (i.e. $P_{\text{HVAC}(i,t)} = 0$). So, equation (4) becomes (5):

\[
P_{\text{N}}(i,t) = \frac{P_{\text{ECU}}}{\eta_{\text{Cab}} \cdot \eta_{\text{ONBC}} \cdot \eta_{\text{DC/DC}}} \tag{4}
\]

For the charging mode, using (1) the charging power $P_{\text{CH}(i,t)}$ can be determined as a function of $P_{\text{N}}(i,t)$ and the on-board consumption and power losses, as in (5).

\[
P_{\text{CH}(i,t)} = P_{\text{N}}(i,t) - \frac{P_{\text{ECU}}}{\eta_{\text{Cab}} \cdot \eta_{\text{ONBC}} \cdot \eta_{\text{DC/DC}}} - \frac{C_{\text{CP}} + 0.02 \cdot P_{\text{N}}(i,t)}{\eta_{\text{ONBC}} \cdot \eta_{\text{Cab}}} \cdot \eta_{\text{ONBC}} \cdot \eta_{\text{Cab}} \tag{5}
\]

4) HVB SOC ASSESSMENT

Up until now, the mathematical model was focused on EVs internal power consumption and the equipment efficiency. This is actually necessary for assessing the EV’s SOC. During the charging process, the SOC changes based on the charging power delivered to the HVB, i.e. $P_{\text{CH}(i,t)}$, cumulated as the amount of electric energy stored by the HVB system, as in (6):

\[
SOC_{\text{act}}(i,t) = SOC_{\text{act}}(i,t - 1) + W_{\text{CH}(i,t)} \cdot \eta_{\text{BAT}} \cdot \frac{W_{\text{CH}(i,t)}}{Cap(i)} \cdot 100 \tag{6}
\]

where:
- $i$ – the EV identification number, with values from 1 to 40;
- $SOC_{\text{act}}$ – the actual SOC, at moment $t$, in %;
- $Cap$ – total HVB storage capacity, in kWh;
- $W_{\text{CH}}$ – the amount of energy in kWh, stored within the HVB between moments $t-1$ and $t$. $W_{\text{CH}}$ is calculated using (7).

\[
W_{\text{CH}}(i,t) = P_{\text{CH}}(i,t - 1) \cdot \eta_{\text{BAT}} \cdot [t - (t - 1)]/NS = P_{\text{CH}}(i,t - 1) \cdot \eta_{\text{BAT}} / NS \tag{7}
\]

where $NS$ is the number of samples per hour (e.g. if the sampling time interval is equal to 10 minutes, then $NS=60$ min./10 min.=6 samples/hour).

As it can be easily deduced, the energy $W_{\text{CH}(i,t)}$ is a simple integration between time intervals $t-1$ and $t$, of the average power $P_{\text{CH}(i,t)}$ and an efficiency $\eta_{\text{BAT}}$. 

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During functioning in ZAM mode, SOC of the HVB onboard of EVs stays constant.

C. CHARGING CONTROL ALGORITHM

The authors had in mind from the very beginning to propose an easy to implement methodology, that can be simply deployed on any modern EV. Thus, the proposed DEV-CC, doesn’t require any new hardware installation, or hardware design review, or smart charging stations to control EV charging power.

The main novelties of the proposed methodology are:

- It is used a minimum amount of information, specifically the voltage level in LVDN buses, measured by ONBC devices.
- The power charging control algorithm for EVs is simple and original, based on the calculation of Global Charging Coefficient that directly reflects the voltage level in the entire electrical distribution network.
- Use of the DSRC system as a means of communication between EVs.

The charging system architecture in Fig. 1 shows that the MSS is the only charging system component connected to all the ECUs that can influence the charging process. Additionally, the MSS is designed to control high complexity and ultra-fast processes like airbag deployment, AEBS, torque control and others. Therefore, the MSS is an ECU powerful enough to run a real-time control process. Generally speaking, the software that is running on the MSS has multiple functionalities that are active or inactive depending on vehicle status; during charging most of these functionalities are idle, so running an additional algorithm for charging control will not overload the MSS’s existing resources.

When EVs are connected to the LVDN the voltage level across the network will be greatly influenced by the charging power of each EV. This dependence (charging power-voltage level) is the central element that underlies the development of the algorithm proposed in this paper for EV charging management. The algorithm seeks to ensure that all EVs connected to the LVDN are charging, while the voltage level in maintained within the allowable limits.

It is assumed, that DSRC has the capability to share among EVs their Global Charging Coefficients \(GC_{ch}(i,t)\), with real values. The Global Charging Coefficient is calculated as a function of nine coefficients as in (8):

\[
GC_{ch}(i,t) = a(i,t) \cdot b(i,t) \cdot c(i,t) \cdot d(i,t) \cdot f(i,t) \cdot \sqrt{1-p(i,t)} \cdot T_{ch}(i,t) / T_{cr}(i,t) + w(i,t)
\]

The nine coefficients are described below:

- \(a(i,t)\) is a Boolean coefficient, which indicates whether the voltage level constraints are violated or not. In this way, \(b(i,t) = 1\) if \(u_{m} > u_{cr}\), and 0 otherwise. The minimum voltage level allowed within the LVDN by the Romanian standards is 0.9 p.u.; in the LVDN analyzed in this paper, not all end-buses in the network contain an EV connected to it; so, a margin coefficient equal to 1.02 is considered, and the critical voltage results as \(u_{cr} = 0.9 \cdot 1.02 = 0.918\) p.u. Here, \(u_{m}\) is the voltage level within the LVDN measured by ONBC and \(u_{cr}\) is the minimum allowable threshold value.
- \(c(i,t)\) is a coefficient with real values, which is equal to the measured voltage \(u_{m}\), in p.u.
- \(d(i,t)\) is a coefficient with real values, that represents the power needed by the EV (in p.u. with respect to \(P_{med}(i)\)). \(d(i,t)\) is calculated using (9).

\[
d(i,t) = \frac{P_{med}(i,t)}{P_{max}(i)}
\]

\(P_{med}(i,t)\) is the average charging power, which ensures that the desired SOC\(_{med}(i)\) is reached, at the departure time \(T_{dep}(i)\); at every moment of time, \(P_{med}(i,t)\) is calculated using (10).

\[
P_{med}(i,t) = \frac{[SOC_{med}(i) - SOC_{act}(i)][Cap(i)]}{100[T_{dep}(i) - t]}
\]

The coefficient \(d(i,t)\) varies with time following \(P_{med}(i,t)\), as \(P_{med}(i)\) is constant. High values of \(d(i,t)\) show that an EV is approaching \(P_{med}(i)\), the situation where the global SOC reduction procedure will be triggered. By introducing \(d(i,t)\) in the calculus of \(GC_{ch}(i,t)\), the EVs that require higher average charging powers are encouraged to charge earlier.

- \(f(i,t)\) is a coefficient with real values that is used to assign higher values for coefficient \(GC_{ch}(i,t)\) to those EVs with higher voltage levels at their LVDN bus. In this paper, \(f(i,t)\) will be equal to 1.2 when the voltage level at the connection bus is higher than 0.98 p.u., and 1 otherwise.

\(-1-p(i,t)\) is a self-penalty factor, used to reduce the coefficient \(GC_{ch}(i,t)\) for EVs that are already charging. In this way, an EV that is charging at moment \(t\) will have a lower value of \(GC_{ch}(i,t)\) at the moment \(t + 1\).

\(p(i,t)\) is the actual charging power in p.u. \(p(i,t)\) is calculated by a simple division of the actual charging power to the maximum charging power of the ONBC, \(P_{max}(i)\).

\(w(i,t)\) is a factor used to distinguish the situations in which voltage levels decrease below the imposed threshold \((b(i,t)=0)\) and the situation in which an EV is charging at \(P_{max}(i)\) (the situation when \(-1-p(i,t)\) is zeroed). For all EVs charging at \(P_{max}(i)\), \(w(i,t)\) will take the value of \(\varepsilon\), and will be equal to 0 otherwise. \(\varepsilon\) is a constant equal to an infinitely small positive value.

\(T_{ch}(i,t)\) is the time elapsed since the EV has connected to the LVDN for charging.

\(T_{cr}(i,t)\) is the critical moment of time calculated using (11).

\[
T_{cr}(i,t) = T_{dep} - \frac{[SOC_{act}(i) - SOC_{act}(i)][Cap(i)]}{100P_{max}(i)} - \Delta T
\]
where $\Delta T$ is a time margin, used to ensure an earlier detection of critical time; in this paper the value of $\Delta T$ has been set to 10 minutes. As it is described, $T_{cr}(i,t)$ will increase for EVs that are charging and remain constant for EVs that are not charging.

The pseudocode of the charging control algorithm that uses these Global Charging Coefficients $GC_{ch}(i,t)$, is presented below.

**DEV-CC Algorithm pseudocode.**

Detect if EV in connected to LVDN;

Calculate coefficients $a(i,t)$, $b(i,t)$, $c(i,t)$, $d(i,t)$, $f(i,t)$, $p(i,t)$, $w(i,t)$, $T_{ch}(i,t)$ and $T_{cr}(i,t)$;

If $a(i,t)=0$ then $P_N(i,t)=0$; {EV charged; 0$^*$};

Else {Calculate $GC_{ch}(i,t)$; 1$^*$;

Transmit $GC_{ch}(i,t)$ and Receive $GC_{ch}(j,t)$;

If ($GC_{ch}(k,t)>0$) then

\
\begin{align*}
&\{y=\max (GC_{ch}(k,t)); A^* \\
&\text{If } (y=GC_{ch}(i,t)); \\
&\quad P_N(i,t+1)=P_N(i,t)+0.05*P_{max}(i);\}
\end{align*}

Else if ($P_N(i,t)=0$) then wait; $B^*$;

Else $P_N(i,t+1)=P_N(i,t)-0.2*P_{max}(i);$

If (t=$T_{cr}(i,t)$) then {Launch Global SOC Reduction procedure;}

Transmit Global SOC reduction signal by DSRC;}

where:

- $i$ - refers to the EV performing the calculation;
- $j$ - refers to the other EV besides $i$;
- $k$ - refers to all EVs.

As it can be seen in pseudocode, after detecting that EV is connected to the LVDN, the DEV-CC algorithm is activated. In the first step, all coefficients used to compute $GC_{ch}(i,t)$ – equation (8) – are determined. Based on the value of $a(i,t)$ the algorithm splits in two branches: the case $a(i,t)=1$ (Branch 1$^*$), when the power control side is activated, and otherwise, when EV charging is stopped, because the EV is fully charged (Branch 0$^*$).

On Branch 0$^*$, it makes no sense for EV to participate in the charging control algorithm, so that the calculation of $GC_{ch}(i,t)$ is not executed and no information is exchanged with other EVs. When $a(i,t)=0$ and $SOC_{def}(i)\geq SOC_{def}(i)$, the EV doesn’t require charging anymore, so the power consumed from the network $P_N(i,t)$ is set to 0.

On Branch 1$^*$, the power control branch is activated. Here, $GC_{ch}(i,t)$ is computed and exchanged with other EVs. At this stage, $GC_{ch}(i,t)$ can be equal to 0 only when the voltage conditions in the LVDN are violated ($u_{nLVDN}(i)<u_{crit}$). Thus, if all the EVs have positive $GC_{ch}(i,t)$ (LVDN voltage levels are within allowable limits), the algorithm increases the charging power (Branch A) and otherwise, when at least one $GC_{ch}(i,t)$ is equal to 0, the charging power is decreased (Branch B).

On Branch A$^*$, each EV check if its $GC_{ch}(i,t)$ has the maximum value among all vehicles, and if it does, the charging power is increased. Under these circumstances, at each moment $t$, only one EV (the one with the maximum $GC_{ch}(i,t)$ coefficient) will increase its charging power. As mentioned previously, the charging power can be modified with a resolution of 5%, and the maximum power consumed by an EV from the LVDN is limited to $P_{max}(i)$.

On Branch B$^*$, a decrease in the charging power becomes necessary. All EVs that are charging will decrease their charging power. To guarantee a faster response to the voltage drop in LVDN, the algorithm uses a step of charging power decrease of 20%. Of course, the minimum charging power for all EVs is limited to 0, to avoid V2G mode.

At each moment of time $t$, all the EVs are verifying whether their critical moment of time $T_{cr}(i,t)$ has been reached or not. If $T_{cr}(i,t)$ has been reached for at least one of the EVs, that EV will trigger a procedure for global SOC reduction (Branch 1$^*$). At this stage all the EVs will reduce their total needed energy (from the beginning of the charging process) by a fixed amount $\Delta W_{SO}=200$ Wh. This value represents 1% of the lower value of the range in which HVB storage capacities have been generated. This process is called *global SOC reduction*.

The algorithm is designed so that the global SOC reduction procedure will be triggered only if voltage levels within the LVDN are low, which in turn means that the LVDN is not capable of delivering the needed power and energy.

When EVs are charging, their power consumption from the network $P_N(i,t)$, and the voltage levels in LVDN are changing continuously. The feedback from the LVDN is obtained by a new voltage measurement by the ONBC and repeating the loop for the next moment of time $t+1$.

**D. CHARGING CONTROL SYSTEM**

As it was mentioned earlier, the proposed charging control system uses only functions that can be embedded onto the on-board ECUs. In the following, a short explanation on how the proposed system works is provided.

1. The ONBC is the system component which executes 2 functions:
   a. LVDN voltage level measurement and transmission to MSS;
   b. Receiving the charging power set point from MSS, and control the power consumed from the network, $P_N(i,t)$.
2. The BMS calculates the SOC and all the needed information for the charging process, and sends this information to the MSS.
3. The MSS is responsible with executing the following functions:
   a. Receiving LVDN voltage level, and calculate $GC_{ch}(i,t)$;
   b. Transmission of own $GC_{ch}(i,t)$ and receiving of $GC_{ch}(j,t)$ from other EVs using the DSRC protocol;
c. Executing the proposed charging control algorithm, and identifying the moments of time when the charging power needs to be increased/decreased.

d. Sending the charging power set point to the ONBC.

4. The DSRC is responsible with information exchange between EVs.

IV. CASE STUDY

The purpose of this section is to test the proposed algorithm and to prove the feasibility of the method using a simple but realistic and relevant distribution LV test feeder.

With this aim in mind, the authors have chosen to prepare a study case test system consisting in a 37 bus LV distribution feeder. The topology of the feeder (Fig. 6) was inspired by the IEEE 37 bus test system, but the network parameters (conductor cross-section, resistance, reactance, line sections length etc) and consumer characteristics were chosen to reflect the usual practices in Romanian LV distribution networks.

The following paragraphs describe the necessary details for this case study.

A. BUILDING THE LV NETWORK.

The test LVDN was built based on the following assumptions:

1. The test network is considered to operate at low voltage European standard, 400/230 V. The transformer at bus 799 has been eliminated, and bus 799 is considered as the LV terminal of the MV/LV substation. At the same time, the transformer in the original diagram, between buses 709 and 775, was eliminated and replaced with a LV line, as can be seen in Fig. 6 and Table I.

2. The slack bus is considered at bus 799.

3. The distance between two adjacent buses is equal to 40 m. This is the usual distance between poles for overhead LVDNs in Romania.

4. The topology of the network in Fig. 6 is resumed in Table I, where for each line section the source node, end node and the type of conductor are indicated. The characteristics of the four types of conductors used, can be found in Table II: conductor cross-section, and the electrical parameters.

5. The LVDN supplies with electricity 84 household loads. The allocation of each load to the buses is presented in
Table III. For each bus, the field “# of loads” in Table III shows the number of supplied household consumers. The “Load type” field shows the typical load profile type of the household, based on their annual energy consumption. The application of the load profiling methodology for modelling residential consumers is presented in Appendix A.

6. The allocation of EV to their buses is presented in Table III. The household consumers in Table III to which EVs are allocated are marked with letter “e”.

7. Due to the limited range of communication of DSRC, to check the possibility of establishing communication between two vehicles, geometric coordinates were assigned for each EV. These coordinates are shown in Table IV.

8. For a closer simulation of the European policy for distributed generation integration in LVDN, a power source has been introduced at Bus 730. This power source is meant to analyze the local impact of distributed generation over EV charging. However, this study does not consider such an influence, and hence, the power source is considered injecting a constant power of 10kW, at a power factor equal to 1.

### TABLE IV. EVS CHARACTERISTICS

| EV no. | HVB storage capacity [kWh] | Tpwr | Tdrop | SOC init [%] | SOC des [%] | Energy needed [kW] | ONBC rated Power [kW] | Phase | X | Y | BUS |
|--------|-----------------------------|------|-------|-------------|------------|-------------------|------------------------|-------|---|---|-----|
| 1      | 68 5:10 8:30 12.33 9 B 48.5 83.6 722 |
| 2      | 24 5:30 9:00 5.35 3 A 3.4 139.3 724 |
| 3      | 56 4:10 7:10 8.18 8 A 105.8 132.3 706 |
| 4      | 34 4:50 7:20 8.84 4 A 163.1 89.4 718 |
| 5      | 77 4:00 7:50 14.66 11 C 203.5 38.8 731 |
| 6      | 26 4:40 8:20 2.1 3 A 99.3 22 713 |
| 7      | 77 4:30 8:40 5.11 11 C 186.3 46.8 731 |
| 8      | 67 4:50 7:10 21.89 9 C 306.3 67.4 741 |
| 9      | 43 4:20 9:10 5.48 6 A 311 91.2 741 |
| 10     | 67 4:10 8:10 21.57 9 C 264.3 55.1 740 |
| 11     | 58 4:00 9:00 3.59 8 C 302.3 63.7 735 |
| 12     | 70 4:10 8:0 36.57 10 C 332.9 63.6 735 |
| 13     | 59 4:50 9:30 7.67 8 A 139.5 134.8 729 |
| 14     | 64 4:20 7:20 2.7 9 C 70.5 61.2 742 |
| 15     | 58 5:10 7:20 19.66 8 A 26.7 51.6 712 |
| 16     | 61 4:40 8:20 21.39 8 B 306.8 16.4 738 |
| 17     | 34 4:30 7:20 1.89 4 A 301.2 1.6 738 |
| 18     | 22 4:50 7:10 8.89 3 B 257.8 8.8 775 |
| 19     | 60 5:00 8:20 31 8 C 197.5 48.5 708 |
| 20     | 77 4:40 7:20 14.3 11 C 73 41.8 705 |
| 21     | 44 4:30 8:0 10.12 6 A 58.9 2.8 701 |
| 22     | 65 5:50 9:30 1.04 9 A 154.6 5.4 730 |
| 23     | 28 4:30 8:0 2.09 4 C 170 8.6 730 |
| 24     | 45 4:10 7:30 3.98 6 C 134.6 53.9 727 |
| 25     | 61 5:20 8:10 18.45 8 C 200.9 40.2 708 |
| 26     | 34 5:30 7:30 4.62 4 B 266.1 41.7 734 |
| 27     | 58 4:40 8:40 7.64 8 B 42.2 21.8 712 |
| 28     | 24 5:50 9:00 2.63 3 A 120.5 117.7 729 |
| 29     | 77 4:50 7:50 11.92 11 C 205.9 47.3 731 |
| 30     | 53 5:40 9:10 9.58 7 A 65.2 59 713 |
| 31     | 64 5:40 8:30 11.93 9 B 228.4 -64 736 |
| 32     | 48 5:50 8:30 9.59 6 A 318 -24.8 737 |
| 33     | 73 4:20 7:50 17.88 10 A 333.1 -27.4 711 |
| 34     | 51 5:40 7:30 5.17 7 A 63.6 -78.1 742 |
| 35     | 26 4:30 8:10 1.09 3 C 204.5 -72.4 732 |
| 36     | 70 4:50 7:50 12.23 10 C 95 125.7 724 |
| 37     | 68 4:50 7:20 3.63 9 B 61.1 39.5 713 |
| 38     | 75 5:10 7:40 5.89 10 C 144.4 74.2 718 |
| 39     | 29 4:30 7:20 7.97 4 B 166.7 133.9 725 |
| 40     | 55 4:50 8:20 4.23 7 B 42.1 16.1 701 |

### B. VEHICLE CHARACTERISTICS

In this paper multiple EV characteristics are taken into account, like HVB storage capacity, SOC at arrival and departure, time of arrival and departure, and others. All are described in Subsection III.B. with arguments on how these parameters were generated. Data for these parameters are shown in Table IV.

### C. SIMULATION SCENARIOS

As it can be easily deduced, the DEV-CC algorithm proposed in this paper is highly dependent on the voltage levels measured in the LVDN. Hence, the main difference between scenarios considered in this study is the voltage level at the slack bus.
The base voltage level profile at the slack bus is presented in Fig. 7. The voltage profile in Fig. 7 follows the pattern often encountered in distribution networks for residential areas power supply. As one can see, the base voltage profile is varying within the range 0.99 p.u. - 1.035 p.u. The lowest voltage level is encountered at 7:30 PM, which corresponds to household evening peak-load consumption. The voltage levels are also very low, during the morning peak-load consumption, between hours 8:30 AM and 9:30 AM. At the same time, the voltage level is often higher than 1 p.u., which corresponds to DSO voltage regulation strategies, to reduce energy losses in distribution networks and to ensure a good voltage level at consumers.

**FIGURE 7.** The base voltage level profile at the slack bus.

In the purpose of highlighting certain moments of time, a vertical line has been placed in the graph and a tag has been applied to that moment of time. In Fig. 7 the authors intended to highlight the moment of time T1, that occurs at 7:20 PM, when the lowest voltage level is encountered. Other moments of time will also be highlighted in this way when the results of the simulation will be presented.

The proposed scenarios use the same voltage profile, presented in Fig. 7, multiplied with a voltage level factor. The voltage level factor has been chosen to simulate the 0/+1/-1 (a voltage level factor of 1.000 p.u.).

Two other scenarios, S1’ and S1”’, will be used to illustrate some particular aspects, such as the evolution of SOC, with or without the application of the global SOC reduction procedure:

- Scenario S1’: presence of EVs and a voltage level factor of 0.980 p.u.
- Scenario S1’”: presence of EVs and a voltage level factor of 0.985 p.u.

**D. IMPLEMENTATION DETAILS**

The proposed model of EVs together with the test LVDN have been implemented in the DIgSILENT Power Factory software [45]. Power Factory is a powerful simulation environment. The methodology presented in Section III, was implemented using exclusively the DIgSILENT Power Factory software application. Indeed, this application is specialized for calculating the steady state and dynamic operating conditions of the electric transmission and distribution networks. It also allows the development of user defined functions, using for this purpose the DPL (DIgSILENT Programming Language) component [45]. Thus, the authors have developed their own DPL functions that implement the entire calculation methodology presented in section III (EVs model, DSRC implementation and DEV-CC algorithm), to which are added the genuine DIgSILENT functions for the power flow calculation in the LVDN (Timesweep for load profile modelling and power flow calculation).

The simulation is run for 24 consecutive hours with a sampling of 10 minutes. Since the goal of the paper is to analyze the charging process of the EVs and its impact over the network during the night, while EVs are parked at households, the results are presented starting from 12:00 PM until 12:00 PM the next day. In this way, the charging process is analyzed continuously and the results can be understood easier.

**V. RESULTS**

Before presenting the results, a short introduction on the expected behavior is presented below.

At the beginning, when $r$ has values near $T_{aref}(i)$, there are only few EVs arrived at the households and start charging. The expected behavior here is that the first EVs to arrive, will have a higher charging power for a short period, until other EVs arrive or the household consumption increases significantly. Consequently, the voltage across the LVDN will tend to decrease, and it will tend to get below the threshold value at some buses. This is when the proposed DEV-CC algorithm will reduce the power consumed by EVs and the voltage levels will stabilize at values within the allowable limits.
As the time passes, the number of EVs will increase, but the power consumed by EVs from the network will still be low, because the household power consumption is still high during peak-load. As the household peak-load consumption passes, EVs will begin to increase their charging power. During this period of time, EVs with high values of $GC_{des}(i,t)$ will be selected. EVs that require higher amounts of energy and relatively low rated power of ONBC will be prioritized.

In scenario S1, as the time passes and $T_{cr}(i,t)$ begins to approach $T_{cr}(i,t)$, the EVs with the smallest critical time will get selected for charging. As mentioned previously, EVs that are selected for charging will increase their $T_{cr}(i,t)$. Here the trigger of Global SOC reduction procedure is needed, only when EVs do not manage to charge with high-enough power, and there are multiple EVs that have similar $T_{cr}(i,t)$. This behavior is expected in scenarios S1 due to lower voltage levels in the network. On the other hand, in scenarios S2 and S3, due to higher voltage levels, the importance of $T_{cr}(i,t)$ is lower, and the Global SOC reduction procedure is not triggered.

As the time passes, EVs that started their charging earlier will satisfy their energy needs and will stop charging, leaving other EVs, hopefully enough time to fully charge to $SOC_{des}(i)$ by the time of departure. Depending on voltage level at the slack bus and on household power consumption, all EVs or only a part of them will be able to charge to their $SOC_{des}(i)$ by the time of departure. EVs will adapt their charging power to household power consumption continuously during the simulation. At moments when household consumption is high the EV consumption will be low, and vice-versa.

As a theoretical concept, if the LVDN is properly sized and the electricity consumption for purposes other than charging EVs is not excessive, the DEV-CC algorithm can ensure the complete charging of all EVs. However, in real life, when the network is not properly sized and/or the load is high, using DEV-CC will not guarantee that all EVs will charge to their $SOC_{des}(i)$. Nevertheless, this was never the purpose of DEV-CC algorithm. In fact, the DEV-CC algorithm is proposed as a cheap method (for both DSO and EV owners) to manage the negative impacts that can occur within the LVDN and/or the households, while multiple EVs are charging.

A. SOC AT DEPARTURE

The main interest in this paper, is to manage EV charging to reach their $SOC_{des}(i)$, as long as the LVDN is able to deliver the needed amount of energy and power. To be able to draw some conclusions, the SOC results are presented graphically in Fig. 8-9 for the three main charging scenarios.

As one can see, in scenarios S2 and S3 (Fig. 9) all EVs succeed to charge up to the $SOC_{des}(i)$ before departure; however, in scenario S1 (Fig. 8) most of the EVs don’t. In fact, only a single EV, namely EV15 succeeds; the rest of the EVs charge partially, at values lower than $SOC_{des}(i)$. The reason for this behavior in scenario S1 is the low voltage level in the network (the voltage level factor is 0.975 p.u.).

To better emphasize this influence, in addition to scenario S1, two other auxiliary scenarios were considered (S1’ and S1’’), both with low values of the voltage level factor (0.980 p.u., respectively 0.985 p.u.). For scenarios S1’ and S1’’, the SOC graphs are shown in Fig. 10 and 11. Comparing Figs. 8, 10 and 11, one can easily observe that when the voltage at the slack bus increases (from 0.975 to 0.980 and then to 0.985 p.u.), $SOC_{dep}(i)$ increases for all EVs, and so does the number of fully charged EVs.

In scenario S1 only a single vehicle (EV15) has managed to fully charge; in scenario S1’, four EVs have reached their $SOC_{des}(i)$, specifically EV2, EV3, EV4, and EV15; finally, in scenario S1’’, eleven EVs reached their $SOC_{des}(i)$, specifically: EV2, EV3, EV4, EV8, EV14, EV15, EV17, EV18, EV20, EV22 and EV34. On the other hand, one can observe that the EV that fully charged in scenario S1 is also fully charged in scenarios S1’ and S1’’. Moreover, the EVs that fully charged in scenario S1’ are also fully charged in...
scenario S1”’. This shows that the DEV-CC algorithm applies similar discriminations between different scenarios, and these discriminations are based on the EVs’ needs and the voltage level across the LVDN.

The behavior described above shows that the voltage level at the slack bus (LV terminal of the MV/LV substation) has a direct impact over the execution steps of the DEV-CC algorithm that control the EVs’ charging process. Also, this highlights that to allow the increase in the charging power for EVs during certain period of time, the DSO can simply increase the voltage level at the main power source.

B. EV ARRIVAL AND CHARGING

The results presented up to this point are true for the final moment, at the departure time. The next paragraphs will present and analyze the behavior during the entire simulation interval. To have a clear visualization of the behavior within the test LVDN, the number of EVs present at any moment in the LVDN (in charging or waiting mode) is given in Fig. 12. The information in Fig. 12, is similar to the information provided in Table 5 (\( T_{arr(i)} \) and \( T_{dep(i)} \)); it is only presented graphically for a better understanding. As it was mentioned in subsection III.B, the modelled EV are EVs used with a sole purpose of work/home commuting so, in Fig. 12, the EVs begin to arrive to their households at 4:00 PM and all EVs will depart by 9:30 AM next day. Between 5:50 PM and 7:10 AM next day all EVs are present and connected to the LVDN for charging.

The proposed DEV-CC system discriminates EVs based on their \( GC_{des}(i,t) \), which in turn means that not all EVs that are connected to the LVDN are charging at a given moment of time \( t \). The number of EVs that are actually charging, without specifying the exact power consumed from LVDN, in scenarios S1 to S3 are presented in Fig. 13.

On the other hand, between 4:00 PM and 4:40 PM, immediately after the first EVs arrived at the households, the number of EVs that are charging is the same in all 3 scenarios. This behavior is to be expected, as described in the beginning of this chapter.

The profiles in Fig. 13 also show that, during simulation, the number of EVs that are charging differs greatly between the three scenarios. For scenario S1, with the lowest voltage level, the number of EVs simultaneously charging is the lowest (with a maximum value of 26 vehicles), while for Scenario S3, with the highest voltage level, it reaches up to 34 vehicles. Hence, the lower the voltage levels, the less EVs are simultaneously charging, and vice-versa.

In Fig. 13 the moment when charging is completely stopped for different scenarios can be easily seen: scenario S1 – 8:30 AM; scenario S2 – 6:00 AM; scenario S3 – 3:00 AM. Once again, this sequence of EVs finishing their charging is determined by the voltage level at the slack bus. The higher the voltage level, the faster the charging. On the other hand, all EVs charging process is currently stopped when they reach the \( SOC_{des}(i) \). However, the values of \( SOC_{des}(i) \) can be impacted by the global SOC reduction procedure, as described below.

The influence of voltage level at the slack bus over the charging process can also be seen in the application of Global SOC reduction procedure. Once again, for comparison reasons, the auxiliary scenarios S1’ and S1” will be used together with scenario S1. As can be seen in Figs. 8, 10 and 11, in all three scenarios, the charging is stopped before all EVs have reached their \( SOC_{des}(i) \). This happens because the Global SOC reduction procedure has been triggered. In scenario S1 for 24 times; in scenario S1’ for 16 times; in scenario S1” for 5 times. Each time the Global SOC reduction procedure is triggered all EVs are reducing their \( SOC_{des}(i) \). The new value of the \( SOC_{des}(i) \) that results after the Global SOC reduction procedure will be referred to as \( new\_SOC_{des}(i) \).

\( SOC_{des}(i) \), \( new\_SOC_{des}(i) \) and \( SOC_{dep}(i) \), in scenarios S1, S1’ and S1” are presented in Figs. 14, 15 and 16, respectively. There is a clear correspondence between the voltage level at
FIGURE 14. SOCdes, new_SOCdes and SOCdep in scenario S1 (u=0.975 p.u.).

FIGURE 15. SOCdes, new_SOCdes and SOCdep in scenario S1’ (u=0.980 p.u.).

FIGURE 16. SOCdes, new_SOCdes and SOCdep in scenario S1” (u=0.985 p.u.).

the slack bus and the values of the new_SOCdes(i) that result from the number of times the Global SOC reduction procedure was triggered. The higher the voltage level, the higher new_SOCdes(i) and the lower the number of triggered Global SOC reductions.

To understand the behavior of EVs as a group, Fig. 17 presents the EVs charging power profiles for the main charging scenarios, namely S1, S2 and S3. As one can see, the charging power profiles in Fig. 17 present a similar pattern to that of the number of charging EVs profiles in Fig. 13. Thus, the charging power increases from S1 to S3, following the voltage trend (from 0.975 p.u. to 1.025 p.u.). At the same time, charging ends the faster, the higher the voltage level.

FIGURE 17. EVs’ charging power.

On the other hand, the variation of the charging power profiles in Fig. 17, in conjunction with the variation of the voltage at the slack bus from Fig. 7, reflects, among others, the response of the DEV-CC algorithm to voltage variations. A good example is the voltage drop at moment T1. At that moment, the voltage at the slack bus has a steep drop. This sudden change in voltage causes a response from the DEV-CC algorithm that determines a reduction, to a greater or lesser extent, in the charging power of EVs. Thus, in scenario S1 the charging power is rapidly reduced to 0, the remaining power being the ZAM mode consumption. For scenario S2, at T1, the voltage dip is smaller and the charging power is reduced to 0 only for 2 EVs. Finally, in the S3 scenario, when the voltage dip is the smallest, there is only a reduction in the charging power of all EVs, without stopping their charging. This means that DEV-CC algorithm manages to adapt the EV charging power continuously to the voltage levels across the LVDN.

Worth mentioning that, comparing the profiles in Figs. 7 and 17, one can observe that the active power profiles have a similar variation pattern to that of the voltage profile. This is more obvious for scenario S1, where the voltage level factor is the lowest (0.975 p.u.).

C. VOLTAGE LEVELS ACROSS THE LVDN

As shown in Fig. 17, EV charging power increases with the voltage level at the slack bus; however, this is not the main target of the DEV-CC algorithm proposed here. DEV-CC system allows EV charging while keeping the voltage levels across the LVDN above the imposed minimum allowable value. This subsection will present and discuss the voltage levels across the LVDN.

The minimum limit considered in this paper is 0.9 p.u., and it will be used within all the voltage level graphs that follow as the scale lowest value. For reasons of space, the authors chose to present the voltage variation only for three nodes, considered representative, namely:

-- Bus 712 has been chosen as an end-node closer to the slack bus. EV15, the only vehicle that is fully charged in scenario S1 is powered from this bus
-- Bus 725 has been chosen because it is an end-node at a median, reasonable distance from the slack bus, and because it is on a different branch from the main axis.
Bus 741 has been chosen because it is the end-node with the longest electrical power supply path, the farthest from the source. Because EVs use mostly single-phase chargers, the voltage profiles for the selected nodes are presented separately for each phase of the three-phase system.

Figures 18, 19 and 20 present the voltage profiles at bus 712 for the three main charging scenarios. The voltage levels vary within 0.95 p.u. and 1.06 p.u. range, well above the imposed minimum limit of 0.9 p.u. Moreover, the voltage level profiles follow the general pattern of the slack bus voltage profile in Fig 7. This is natural, because bus 712 is very close to the slack bus. A simple visual analysis shows that the voltage levels on the three phases are quasi-balanced, with a few specific exceptions.

The voltage profiles on phases A, B and C at bus 725 for the main charging scenarios are presented in Figures 21, 22 and 23. As one can see, the voltage profiles in these figures never fall below the limit of 0.92 p.u. and never exceed the values of 1.06 p.u. Since bus 725 is further away from the slack bus and it is not located on the main axis, it is expected that the voltage levels here are lower compared to the voltage profiles at bus 712 (Figures 18 to 20). There are some similarities between the voltage patterns of the buses 712 and 725, however the voltage variations are more prominent in the case of bus 725. A good example can be seen in Figs. 20 and 23, between 6:00 PM and 10:00 PM, when four voltage fluctuations can be easily observed in Fig. 23. On the other hand, Fig. 20 contains similar voltage fluctuations, but their amplitude is much lower. The voltage unbalance level between phases is higher for bus 725 as compared to bus 712, but presents a similar pattern.
Figures 24, 25 and 26 present the voltage profiles for bus 741. In this case, the voltage levels vary within the range of 0.91 p.u. to 1.06 p.u.; again, the voltage levels are above the minimum threshold of 0.9 p.u. As it can be seen, the voltage levels at bus 741 have the lowest values compared to buses 712 and 725. This is expected, because bus 741 is electrically the furthest away from the source node. Unlike nodes 712 and 725, in this case the voltage distribution on the three phases shows a high degree of unbalance, obvious for phase C. Thus, the patterns of the voltage profiles on phases A and B at bus 741 are in a certain extent similar to those for buses 712 and 725. However, the voltage profiles on phase C present a completely different pattern than the other profiles.

The shape of the voltage profiles in Figs. 18 to 26 allows the relatively simple identification of the period in which EVs are present in the LVDN and are charging. Thus, the profiles present a sharp voltage decrease when EVs begin charging and a sharp increase when they have finished charging. The longer the electrical supply path to the network bus, the more visible the charging period is.

A particular aspect is highlighted in Fig. 26, where the voltage decreases sharply to near the minimal allowable value of 0.9 p.u. At this point, we recall that the principle of DEV-CC algorithm aims to maintain the supply voltage above this value. As a safety measure, however, the implementation of the algorithm limits the voltage decrease to the critical value $u_{crit} = 1.02 \times 0.9 = 0.918$ p.u.

Next, the particular shape of the voltage profiles in Fig. 26 is explained. There is no single argument that by itself could explain the pattern of phase C voltage profiles in Fig. 26. However, the grouping of the voltage profiles on phase C in the 3 scenarios, while the EVs are charging, is justified by the operating mode of the DEV-CC system: in all scenarios EVs connected on phase C are charging at high power, which determines an abrupt voltage decrease, beyond $u_{crit}$. At this point, the DEV-CC intervenes and reduces the charging power, followed by oscillations of the charging power and the voltage around the critical values. These voltage oscillations around the critical value remain in the same range for all three scenarios.

D. EV CHARGING POWER

The results presented above consider EVs rather as a group than individually. Next, individual EV charging profiles will be presented. From the 40 EVs considered in this study, only four, deemed as most relevant, have been chosen, namely:
FIGURE 28. Charging power for EV15.

-- EV15, since it is the only EV that fully charged during scenario S1, connected to bus 712;

-- EV27, is the second EV connected to bus 712, that partially charged during scenario S1;

-- EV37, is the EV with the highest energy needs, or the lowest SOC;

-- EV13 is the last to depart, and has medium energy needs.

The following graphical representations show the evolution in time of the EVs’ charging power in the three main scenarios. Also, for the assessment of the charging power, parameter $P_{\text{max}}$ is marked in the upper part of these graphs, with a thick dashed line, which indicates the maximum charging power available.

Figs. 28 and 29 present the charging power profiles of EV15 and EV27 respectively. Both EV15 and EV27 are connected to the same bus (bus 712), but on different phases: A and B, respectively. However, one can observe that EV15 is selected earlier for charging by the DEV-CC algorithm than EV27. As was mentioned in Subsection V.A, EV15 manages to fully charge in all scenarios, including S1, while EV27 does not reach $SOC_{\text{des}}$ in scenario S1. The early selection of EV15 over EV27 is due to the higher energy needed in the case of EV15. Analyzing the EVs data presented in Table 5, one can notice that EV15 needs 19.7 kWh, while EV27, only 7.6 kWh. This shows that the most important discrimination coefficient in the calculation of $GC_{ch}(i,t)$ is $d(i,t)$, introduced in Subsection III.D.

In Fig. 30 the charging profiles of EV37 are presented. In all scenarios, as soon as EV37 arrives, it starts charging at a very high power, due to high value of its needed energy; EV37 requires 36.3 kWh up to $SOC_{\text{des}}$. Thus, the charging profile of EV37 shows best the evolution in time of $d(i,t)$ and its’ implicit $GC_{ch}(i,t)$.

FIGURE 30. Charging power for EV37.

$GC_{ch}(i,t)$ implicitly; specifically, an EV that needs high amounts of energy is selected to charge earlier and at relatively high power; due to this, the value of its $d(i,t)$ coefficient reduces, which results in relatively reduced charging power later in time.

FIGURE 31. Charging power for EV13.

Besides providing additional data that the discrimination performed by DEV-CC is made in the same way, the profile in scenario S1 shows that EVs that are departing later, are also starting their charging later. Thus, EV13 starts charging at 7:50 AM, with a rapidly increasing charging power and finishes charging at 8:30 AM. At 8:30 AM, in scenario S1 EV13 is charged at its $SOC_{\text{des}}$, however at that time the value of its desired SOC has been reduced, by triggering the Global SOC reduction procedure. For instance, the initial value of $SOC_{\text{des}}$ for EV13 was 96% and after the repeated triggering of the Global SOC reduction procedure the final $SOC_{\text{des}}$ was set to only 84%. The departure time of EV13 is 9:30 AM, which in turn means that this EV could and probably would charge to higher SOC, but it stops charging at the new value of $SOC_{\text{des}}$.

E. NIGHTTIME HIGH-MOBILITY SCENARIO

The results presented so far considered a special case for EVs travelling scenarios, namely the case of a fixed number of 40
EVs, used for home-work commuting exclusively. Basically, each EV which arrives at home remains at this location until the morning of the next day. This could be referred as “Nighttime Zero-Mobility scenario” (NZM). This is the reason for a flattened appearance of the profile for the number of EVs present at home in Fig.12.

To take into consideration a different hypothesis concerning EVs behavior during nighttime, an additional scenario based on higher level of mobility of EVs was considered. This is the so called “Nighttime High-Mobility scenario” (NHM). Thus, a part of EVs is leaving homes earlier, while other EVs arrive, during night.

Of the three basic scenarios presented above (S1, S2 and S3), for the NHM case only S2 scenario is considered, the one with an intermediate value of the voltage in the slack bus (\(u = 1.00\) p.u.). The departures of present EVs and the arrival of new ones were generated randomly using a normal distribution, with a mean value corresponding to 12:00 PM (departures) or 2:35 AM (arrivals) and a standard deviation of 2:40 (2 hours and 40 minutes), for both cases (departures and arrivals). The resulting time limits were: 6:40 PM and 7:10 AM. The variation of the number of vehicles present in the households for the NHM case is presented in Fig. XX. Compared to the graph in Fig. 12 which shows the variation of the number of EVs present in LVDN, for the NZM case, when throughout the night the number of EVs was constant, this time there is a permanent variation of EVs number.

The results presented, show that the DEV-CC system proposed in this paper performs EV charging power control without allowing the voltage to drop below the minimum allowable threshold. For implementation, DEV-CC requires only EV software adaptations which in automotive field are considered to be cheap solutions. The DEV-CC system uses the on-board DSRC system and does not require any other communications network or any other smart devices, so it can be implemented basically anywhere with almost no costs for EV owners and the DSO.

Future research will analyze the economic benefits after implementation of DEV-CC for both DSO and EV owners. Also, the DEV-CC system proposed in this paper is at its first review, so in authors opinion, there are still multiple different functionalities that can be added, namely: LVDN balancing, LVDN optimization and others. The proposed DEV-CC algorithm can be implemented for any electrical network, so other network topologies will also be tested.

**APPENDIX**

For consumers’ modeling, typical load profiles (TPLs) for residential consumers taken from a Romanian DSO were used. The TLPs are modeled as load profiles with 24 hourly levels of residential consumers, differentiated by the annual level of consumption, as follows:

- C1: between 0 and 400 kWh/year;
- C2: between 401 and 1000 kWh/year;
- C3: between 1001 and 2500 kWh/year;
- C4: between 2501 and 3500 kWh/year;
- C5: over 3500 kWh/year.

When it comes to the variation of the consumed powers for domestic consumption and for charging, a complementarity can be observed. This evolution is normal, considering the fact that during household consumption peak hours the charging power for EVs must decrease to maintain the voltage level, while during off-peak hours the EVs charging power is increased by DEV-CC.

**VI. CONCLUSIONS**

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It should be noted that, according to the methodology presented on the DSO website [46], the TLPs are generated daily, automatically, using online monitoring with smart meters of a sample of consumers in each category. The actual consumption profile $P(t)$ associated with a consumer can be modeled using the following information: consumption category in which the respective consumer falls ($c = C1 \div C5$); the TLP associated with that category ($PT$) and the consumer’s annual electricity consumption ($W_{year}$):

$$P(t) = PT_c \cdot \frac{W_{year}}{365} \quad (12)$$

where: $t$ - is the time moment with a 10 minutes sampling.

For the 84 residential consumers in the test network in Fig. 34 the following distribution between the 5 categories of consumption was considered: C1 - 8 consumers; C2 - 34 consumers; C3 - 26 consumers; C4 - 11 consumers and C5 - 5 consumers.

Using the simple procedure described above and the statistical data on annual energy consumption provided by DSO on the 84 consumers simulated in the test network, daily load profiles were generated for each of the 84 consumers in the test network. For illustration, Fig. 35 shows the load profiles thus generated for 5 consumers, 1 consumer for each of the 5 consumption categories.

Unlike the examples in Figures 34 and 35 and (12), which use hourly sampling, a 10-minute sampling is used in the case study presented in this paper.

**FIGURE 34. Typical Load Profiles for residential consumers.**

**FIGURE 35. Load profiles for 5 residential consumers: C1(385 kWh/year); C2(840 kWh/year); C3(2122 kWh/year); C4(2875 kWh/year); C5(3823 kWh/year).**

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