OPTIMAL CONNECTION PHASE SELECTION FOR SINGLE-PHASE ELECTRICAL VEHICLE CHARGERS

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ABSTRACT

The electric vehicle (EV) market is flourishing, thus the number of EVs connected to residential electricity networks is increasing. This presents many challenges to distribution system operators (DSOs). EV connection points and size are two of the main factors driving DSO costs. However, these factors are beyond the DSO's reach. Hence, this paper presents a method to lower the operational costs, and to increase the network hosting capacity for EVs, by finding the best connection phases for EV chargers. The method is designed as a simple and practical tool for DSOs and it provides tangible actions to lower the costs with minimum effort. The results obtained on a case study based on a Belgian low-voltage (LV) distribution network show how this simple optimal decision can help DSOs to decrease their operational costs.

I. INTRODUCTION

With the European Union Directive encouraging electrical vehicle (EV) purchase [1], the electricity distribution network has faced a 168% increase in new EV owners in the first half of 2021 compared to 2020 [2]. This increase in load due to new EVs may impact the level of imbalance in low-voltage distribution networks and may considerably contribute to network losses and under-voltages experienced by network consumers (residential, commercial, etc.). If these issues are not mitigated, they may considerably influence the operational costs for distribution system operators (DSOs) and limit the network hosting capacity for new EVs.

Network issues such as under-voltage and phase imbalance, and, hence, increased loss, are already encountered by DSOs in their current networks. However, the increased connections of new EVs may worsen these problems. Since the connection point and size are usually factors beyond the DSOs reach, several studies have been conducted to mitigate these network issues. Two types of solution are proposed: managing the charging of EVs, or strategies to control the network. Studies managing the charging of EVs rely on the potential flexibility of the charging time as well as the possibility to charge an EV at a different location. Papers [3]-[5] present methods to rebalance the network by controlling either the location and/or the time of EV charging. Paper [4] uses the battery flexibility of EVs to counter network imbalance. The network control strategies focus mainly on automatic switches [6]-[10].

The optimal selection of the connection phase of EV chargers is, however, a less-investigated solution, yet it is the technique which requires the least effort from the DSO's point of view and might provide the most practical solution with the available infrastructure.

This paper proposes a practical framework for identification of the optimal connection phase of new single-phase personal EV chargers. The proposed framework is composed of two main building blocks: I. a module which calculates a defined cost for a given set of connection phases of network single-phase EV chargers, II. a derivative-free optimizer that finds the optimal connection phase of network single-phase EV chargers in conjunction with the module. The methodology is examined through simulation studies on a low-voltage (LV) distribution network based on a real-life Belgian network.

The rest of the paper is organized as follows. Section II presents the proposed methodology building blocks including the cost calculation module. The simulation results are presented in Section III to showcase the application of the approach proposed. Finally, Section IV concludes the paper.

II. METHODOLOGY

This study considers an unbalanced three-phase LV network. The network topology is represented by a tree graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, where $\mathcal{N}$ is the set of nodes and $\mathcal{E}$ designates the set of edges linking the nodes. The study horizon $\mathcal{T}$ is the set of all time steps denoted t. The complex load time-series of each node, $S_{n\in\mathcal{N}, t\in\mathcal{T}, p\in\mathcal{P}}$, are considered as inputs as well as the edge impedances. The

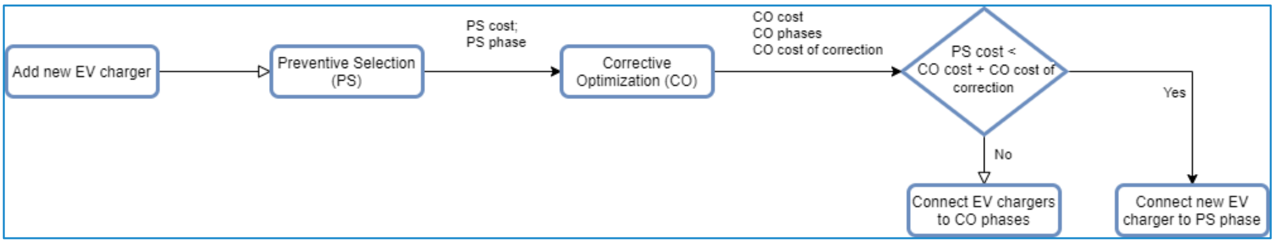


Figure 1 Proposed methodology general flow.

power consumption of EVs $P^{EV}_{n\in\mathcal{N},t\in\mathcal{T},n_p}$ is also considered as an input, where n_p is the EV connection phase which is assumed to be the same as the node load connection phase. Both complex voltages ($V_{n\in\mathcal{N},t\in\mathcal{T},p\in\mathcal{P}}$) and currents ($I_{n\in\mathcal{N},t\in\mathcal{T},p\in\mathcal{P}}$) are obtained through solving power flow equations.

This study assumes that the DSO is aware of EV charger connections to the network. The method has a preventive selection and a corrective optimization. After installation of a new EV charger at a random location, preventive selection finds the optimal connection phase of the EV charger that leads to the lowest operational costs in the future. Corrective optimization will search for the optimal connection phase of all the EV chargers connected to the network, including the new one, to minimize the cost. As shown in Fig.1, whenever the corrective optimization cost plus the cost of correction (the labour cost) is less than the minimum preventive selection cost, rephasing all the network EV chargers according to the corrective optimization output is justifiable. Otherwise, only the latest added EV charger will be connected to the optimal phase selected by the preventive selection.

In this paper, for any given set of connection phases, the cost is calculated by a module presented in the next subsection. However, the proposed methodology above is not limited to the network management strategy and the cost terms considered in the module. When notification of a new installation is received, preventive selection evaluates each possible connection phase {a, b, c} using the cost calculation module. The output of preventive selection is the connection phase with the lowest cost. Then, corrective optimization solves a minimization problem. The objective function of the minimization problem minimizes the cost outputted by the module. The variables of this objective function, and thus the inputs of the module, are sets of all EV connection phases. To solve this optimization problem a derivative-free optimization algorithm can be used. In this paper, a genetic algorithm is used [11]. The output of the corrective optimization is the cost associated with the optimal set of all network EVs connection phases. However, rephasing all the EVs also has a labour cost that accounts for the cost of physically rephasing the EV charger connection nodes. If the sum of the corrective cost and the labour cost is smaller than the preventive cost, the connection phases of both the EV chargers and their associated nodes are rephased according to the best set of all EV connection phases obtained through corrective optimization. In the other case, if the preventive selection cost is lower, then the new EV charger and the node associated to it are connected to the connection phase outputted by preventive selection.

Cost Calculation module

The module computes a cost in terms of euros to represent a DSO's operational cost in a study horizon $\mathcal{T}$ that could be passed on to customers. Two main parts are considered for the cost:

$$\sum_{t\in\mathcal{T}} C^{NL}_t + C^{EV}_t .$$

The network loss cost (C^{NL}) which is calculated from the network's active power loss (P^{NL}). The network's active power loss is defined as the difference between the power that is inputted in the network and the power that loads extract from the network:

$$P^{NL} = \sum_{t\in\mathcal{T},\, p\in\mathcal{P}} P^{input}_{t,p} - P^{loads}_{t,p}$$

where:

$$P^{input}_{t,p} = \mathbb{R}\left(V^{root}_{t,p} \cdot I^{root*}_{t,p}\right).$$

The considered loads include the added EV consumption:

$$P^{loads}_{t,p} = \sum_{n\in\mathcal{N}} P_{n,\,t,\,p} + \left(P^{EV}_{n,\,t,\,p} - P^{EV,\,c}_{n,\,t,\,p}\right).$$

The right subtraction updates the EV consumption time-series $P^{EV}_{n\in\mathcal{N},t\in\mathcal{T},n_p}$ following a chosen curtailment policy. The curtailed EV power is denoted by $P^{EV,\,c}_{n\in\mathcal{N},t\in\mathcal{T},\,n_p}$. Curtailment is a strategy that is not foreseen to be applied in the near future for such customers by Belgian DSOs.

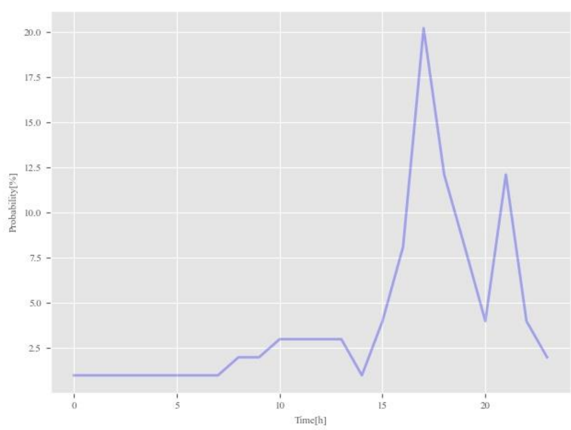


Figure 2 EVs charging probability in percent by hours.

Table 1 Cost results, per unit, obtained for adding up to four new EV chargers starting with six initially. The selected connection phase is in bold.

Total number of installations	PS Phase A Cost	PS phase B cost	PS phase C cost	CO cost	CO total cost (number of nodes that should be rephased)
7	4.09	4.79	**1.07**	0.96	1.18 (5)
8	**1.14**	1.14	1.15	0.95	1.21 (6)
9	3.66	**1.30**	2.20	1.22	1.44 (5)
10	1.38	**1.36**	1.38	1.29	1.64 (8)

However, it remains a practical and easy-to-use criterion to determine a cost and assess our methodology. Several curtailment policies can be considered. For the sake of simplicity, as the study of the best curtailment policy is out of the scope of this paper, for each time step, the considered curtailment policy curtails all the consuming EVs if under-voltage is detected. The under-voltage threshold is set to -5% of the nominal voltage.

To ease the computation of a cost in euros, both the curtailment and the network loss costs are obtained by considering the Belgian average electricity price of 2020. It is important to note that this curtailment price is a default value that is set only for the purpose of assessing our methodology. Such a cost and, more generally, load management policies will have to be carefully designed by regulators.

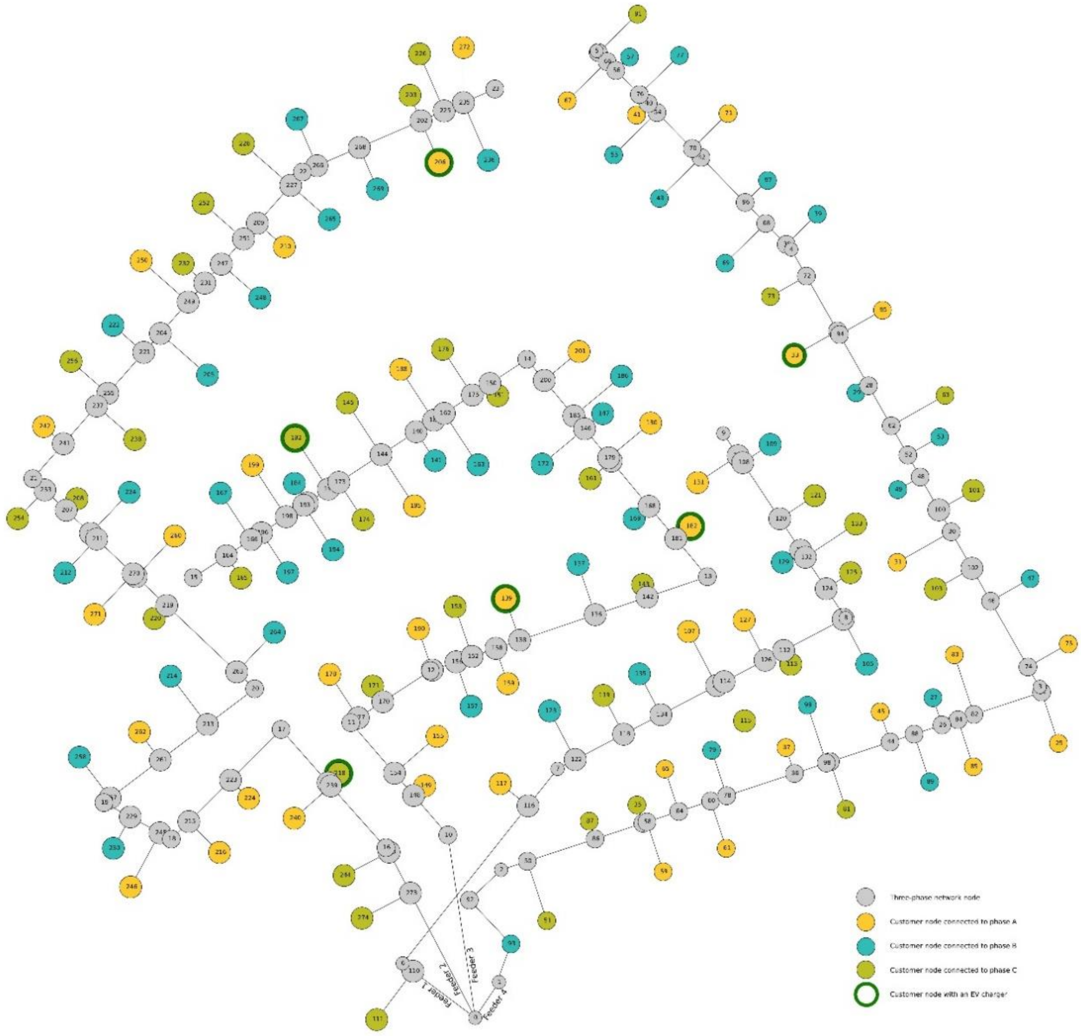


Figure 3 Network case study.

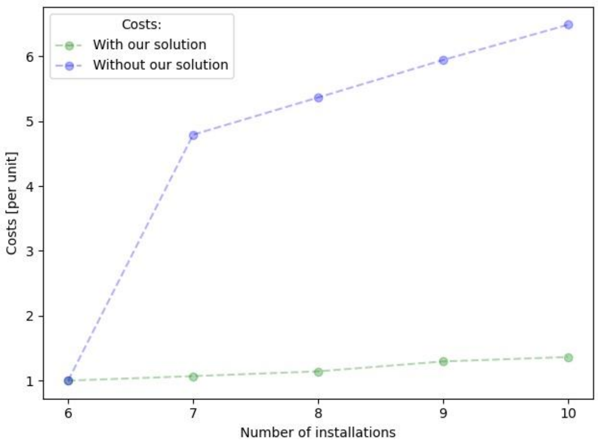


Figure 4 Variation of cost, per unit, by adding new EV chargers staring from six initial installations.

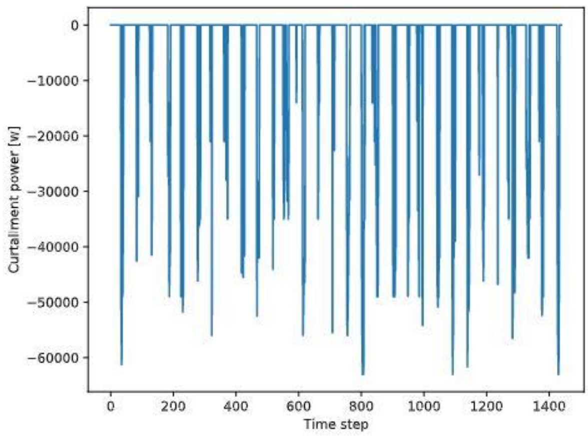
III. CASE STUDY

This section presents the results obtained while applying the methodology to a test system inspired by an existing Belgian three-phase LV distribution network. The network has 128 customer nodes spread on four feeders and these nodes are possible EV charger locations. The EV chargers are assumed to be connected to the customer load phase. The EV charging time-series are generated from charging probabilities depicted in Fig. 2 [12]. The nominal power of EV chargers considered is 7kW. The costs are shown in per unit (pu) of the sixth installation's cost.

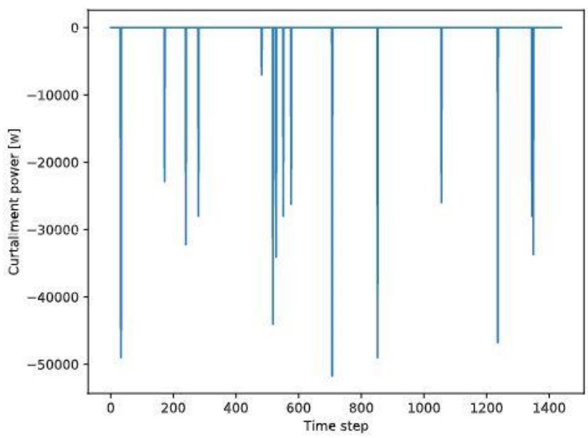
In the first considered scenario, six EV chargers are assumed to be initially connected to the network. Then, sequentially, to mimic several consecutive EV buyers, four chargers were set up according to the hosting capacity found in [12]. Table 1 shows the different costs obtained for the different number of installations. The first new installation is on feeder 4, shown in Fig. 3. On this feeder, an EV charger was initially connected to phase A and most of the customers were connected to phases A and B. For phase B, the customers were mainly at the downstream of the feeder. As expected, and as shown in Table 1, phase C is selected. As another example, the third new installation is on feeder 1. On this feeder, two initial EV chargers are connected. One of them is connected to phase A and is located at the downstream of the feeder while the other one is connected to phase C at the upper section of the feeder. The single-phase customers are almost equally distributed between phases. The new EV charger is, thus, selected to be connected to phase B. The results show that the cost varies depending on the location of the charger. For all the four new EV chargers, the CO finds a set of connection phases for all EV chargers that leads to a smaller operational cost, but the labour cost stops the rephasing from being cost effective.

Fig. 4 shows the costs evolution with our solution and without it. The cost with our solution is the one in bold shown in Table 1. The cost without our solution is the cost while installing the EV chargers at the node customer connection phase. For the first new EV charger, the connection phase without our solution would be the customer's current phase, phase B, with a cost of 4.49 pu during the considered time horizon. However, our solution proposed to connect it to phase C with a cost of 1.07 pu for the same time horizon. The difference in slop of the two lines shows that our method finds better connection phases. From this figure, the method reduced the costs by up to, on average, 78%.

To highlight the improvement in decreasing the curtailment, let us consider a second scenario, with eight initial EV chargers. In this case, the total corrective cost, including rephasing costs of five chargers, is 1.47 pu. This cost is smaller than the preventive selection cost, which is 5.94 pu. Fig. 5(a) shows the curtailment without corrective rephasing with nine installations and Fig. 5(b) shows the curtailment powers with corrective rephasing. The use of our solution can lead to a significant increase of network



(a) Curtailment powers for 9 installations without CO



(b) Curtailment powers for 9 installations with CO

Figure 5 Simulation curtailment powers for the nine installations without CO and with CO.

availability and decrease of curtailed power.

IV. CONCLUSION

With massive integration of EV chargers, DSOs may face increasing challenges such as greater voltage imbalance and decrease of power quality in frequency, both leading to higher operational costs. Optimal selection of the connection phase of EV chargers requires the least effort but is a less-investigated solution to this problem. This paper has presented a two-step method to this end. The method performs an optimal selection of the connection phase of each new EV charger, and it simultaneously checks if it is financially justifiable to modify the connection phase of all the installed network chargers to the optimal phases identified. Results obtained with a real Belgian-based LV network show that using optimal selection of the connection phase of EV chargers enables a saving up to 78% in operational cost for a given scenario. The method has a simple logic and is applicable to any distribution system. It provides actions which can be helpful for DSOs in real-world practical cases. The proposed methodology is intended as a planning study; therefore, the running time was not investigated.

This work can be extended along several lines. First, a well-thought methodology for careful selection of the study horizon, curtailment, network loss and phase switching costs could be developed, as they affect the final decision. Also, more terms can be considered in the cost function and more sophisticated curtailment strategies or more appropriated flexibility policies should be considered. Second, besides the EV chargers, the tool could take other types of installation into account, such as photovoltaics. Finally, in this study, future loads and EV charging time-series are assumed to be known. Further studies may involve the uncertainty in EV characteristics as well as charging and load forecasts. The method could, thus, be extended to be considered stochasticity.

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