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Is It Necessary to Fully Charge Your Electric Vehicle?

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ABSTRACT The transition of the transportation sector from internal combustion engine vehicles to battery electric vehicles (EVs) will heavily increase the energy demand on the network, causing severe techno-economic problems. To solve these issues, advanced charging strategies were proposed to reduce the EVs' charging impact on the network. The problem arises when all EV-owners decide to fully charge their EVs at night even if they might not use the total charged energy the next day. Hence, even with the presence of advanced charging and control strategies, the problem of high penetration level of EVs might not be completely solved without the positive participation of the EV-owners. Some questions can be asked and need answers. Is it necessary to fully charge all EVs at night? What happens if fully charging the EVs is delayed to the next day? To answer these questions, this paper studies the impact of charging EVs to different State of Charge (SOC) levels on the network. Since controlling the charging of all EVs is difficult, a three-level charging strategy is developed that suggests the SOC threshold-limit for each EV, which guarantees the network's operation within its maximum limits even with a 100% penetration level of EVs charging simultaneously.

INDEX TERMS Electric vehicle, state of charge, power quality, distribution systems, charging strategy.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Climate change and global warming become the main reasons to accelerate the transition from a fossil fuel-based to a renewable energy-based world [1]. Electric Vehicles (EVs) play the main role in this transition since the transportation sector emits almost 27% of the global CO2 worldwide, according to IEA report released in 2020 [2]. The future of fully battery-driven EVs is very promising since they use 100% of electricity [3], [4], and they can be charged from renewable energy sources (RES). There is a move worldwide to shift completely to RES [5]. The future of the RES (such as solar, wind, geothermal or hydroelectricity) is very prominent, although some researchers still believe in nuclear fusion, which might pose risks for nuclear weapon proliferation [6], [7]. Despite the advantages of EVs, they can also cause problems on the distribution network since they consume a considerable amount of energy during a short period of time [8]–[10]. Since most of the EVs are owned by householders, they are mostly fully charged at homes or in buildings at night [11], [12]. The problem arises when all EVs fully charge at the same time, which might increase the stress on the network and the distribution transformers. However, is it necessary to fully charge EVs at night? Is it possible to charge, e.g., 80% at night and continue charging the remaining 20% the next day when the car owners arrive at their work or on their way? What happens in both scenarios if EV owners decide to fully charge or not fully charge their EVs at night? Is there an easy way to tell the EV owners what the limit is to charge their EVs in a certain period of time? These questions should be addressed since it is important to know whether fully charging a high penetration level of EVs can affect the network or not, even if energy management and optimization algorithms are used.

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B. LITERATURE REVIEW

In the literature, there are many papers on the optimization of EV charging in parking lots [13]–[16], homes [17], [18], buildings [19], [20], and charging stations [21]–[23]. There are four main control strategies that can be used to schedule the charging of EVs, which are centralized, decentralized, hierarchical, and distributed [22], [24], [25]. The first one uses a centralized control architecture, such as a parking lot, in which one central controller schedules the charging of all EVs in the parking [26]. This controller has some advantages, such as obtaining a globally optimal solution, while the main disadvantage is that the optimization problem becomes more complicated by the increment of plugged-in EVs [27]. In addition, this strategy is not possible to be implemented on the distribution network level for its complexity. The second control strategy uses a decentralized control architecture, such as at home, in which each user (e.g., householder) schedules the charging of his EV independently from other end-users, even neighbors on the same distribution transformer [28]. This kind of strategy provides local optimal solutions, while it might not be efficient on a larger scale, such as a network. The third strategy uses a hierarchical control architecture, which is a kind of combination between centralized and decentralized [27], [29], [30]. There is a central controller (e.g., distribution system operator) that communicates with local controllers (e.g., homes) in order to reach a globally optimal solution. This control strategy could be considered the best for the case of a distribution network. However, it has some drawbacks, such as the complexity of the system, the high cost, and the high simulation time. The fourth strategy uses a distributed control architecture [31], [32], in which each end-user communicates with its neighbors without the existence of a central controller as in the multi-agent control architecture. On the other hand, some papers, such as [33] proposed a two-step optimization model based on an effective hybridization of centralized and decentralized scheduling methods to manage a large-scale EV fleet microgrid. In the first step, prediction-based day-ahead optimal scheduling of EVs was used, and in the second step, online coordination was deployed using a scoring system to encourage drivers to follow the first step. Despite that authors were able to reduce the simulation time by reducing the number of decision variables, authors did not consider the network's constraints and maximum limits in their model. Therefore, it was not clear how many EVs can be charged simultaneously for specific periods and what the maximum energy demand limit was that should not be exceeded while charging EVs. Despite the advantages of the chosen control strategy, the scheduling of all EVs on the network becomes a difficult task, especially when the behavior of the end-users is highly stochastic. Moreover, the optimization process can diverge in case one or more constraints are violated when scheduling the charging of EVs. Hence, controlling all EVs on the distribution network needs a new way of thinking, and simple algorithms are required to simplify the complexity of charging EVs.

C. CONTRIBUTIONS

To answer the questions and find a solution to the mentioned problem, it is important to study the impact of charging EVs to different state of charge (SOC) levels on the network, which is done in this paper. Briefly, the contributions of this paper can be summarized as follows:

- To the best of the authors' knowledge, this is the first paper that studies the impact on the network of charging EVs to different SOC levels. This study is important since it shows that energy management systems might not be enough to solve the problem on the network under extreme conditions without the cooperation of the end-users,
- This paper proposes a SOC threshold limit for each charging EV on the network. The proposed limit should not be exceeded in order to maintain a good operation of the network while respecting its constraints and maximum limits,
- A simple and novel three-level control strategy algorithm is proposed that suggests the SOC threshold limit (final SOC) to the EV owners, which they have to consider while charging their EVs.

II. PROBLEM FORMULATION

A. DEFINITION OF THE EXISTING PROBLEM

Nowadays, energy management is considered one of the best methods to schedule the electrical loads at the end-users level or even on the distribution network [34]. Energy management uses defined optimization algorithms with objective functions and constraints, which are dependent on the end-users needs. Since the end-users' behavior is highly stochastic, sometimes the constraints can be violated or unexpectedly changed, which may affect the optimal solution; thus, it affects the stability of the network.

For example, suppose that an EV-owner arrives home in the evening and decides to fully charge his EV at night for the next day. Since the charging process occurs at night for a relatively long period (between 8 and 12 hours), charging many EVs with small battery capacities (or a small difference between the initial and final SOCs) might not cause any problem to the distribution network. Therefore, energy management systems work perfectly by scheduling the charging of EVs and minimizing both the charging cost and the impact on the network. However, if the battery sizes of all EVs are large (e.g., 100kWh), and the energy demand for charging EVs is high (difference between the initial and final SOCs), fully charging all EVs on the same distribution transformer (or even on the same network) at night might increase the peak demand drastically even if sophisticated optimization algorithms and demand response programs are used. Therefore, severe voltage drops and power losses might happen, and the power demand might exceed the power limits of the transformers and power lines, which may put the network at risk of failure and can cause a brownout or blackout. From this place, the problem is caused by the collective behavior of all end-users rather than the type of optimization technique or demand response program (DRP) that are used. In another meaning, EV-owners should ask themselves if it is urgent to fully charge their EVs at night or not. Do they accept to charge their EVs to a certain SOC level (e.g., 80%), and continue charging the remaining SOC in the next day at the destination or on their way? **FIGURE 1** shows an example of the total power profiles on a distribution transformer where many homes with EVs are connected. EVs are charged to different SOC levels (40%, 60%, 80%, and 100%) and for three different objective functions. In **FIGURE 1.a** a fixed electricity cost is considered (dashed green curve), in which the charging power of the EV is almost constant. It can be remarked that charging all EVs simultaneously might exceed the transformer's nameplate rating even for a SOC = 80%. In **FIGURE 1.b**, the main objective is to minimize the power losses on the distribution transformer, in which the charging fills the valley and flatten the total power demand. Despite the effort in reducing the peak demand compared to **FIGURE 1.a**, a SOC greater than 85% can always exceed the transformer's nameplate rating because of the high energy demand during this period. Moreover, it is not known whether the EV-owners really need to fully charge their EVs at this critical period or not. In **FIGURE 1.c**, a day-ahead time-varying electricity price is applied in which EVs are mostly charged when the electricity price is low. Consequently, peak load on the transformer is created even when EVs are charged for a SOC of less than 60%. This is due to the fact that EV-owners try to benefit from the low electricity price to fully charge their EVs even if they do not really need the additional charged energy, which make the problems worsen on the distribution transformer and the network. It can be remarked from **FIGURE 1** that the SOC level has a high impact on the power profile on the distribution transformer and may cause peak demand on the network even if sophisticated optimization algorithms and DRPs are used. Therefore, it is important for the end-users to know exactly their energy needs and to which SOC level they should charge their EVs in a way to minimize the negative impact on the network. From this place, a question arises, is it possible to determine a threshold limit of the SOC in which EVs should not exceed during the charging process in order to respect the networks' limits? This question is answered in the next section.

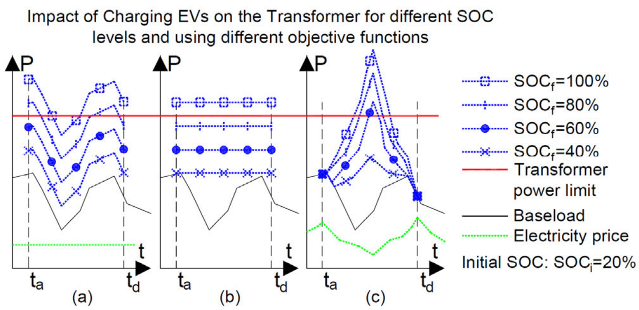


FIGURE 1. Example of the Impact of charging EVs to different SOC levels on a distribution transformer under different objective functions.

B. PROPOSED ALGORITHM TO CALCULATE THE SOC THRESHOLD LIMIT FOR EV-OWNERS

To reduce the impact of the fully charged EVs with high penetration levels, we propose an algorithm that works on three levels on the network, as presented in **FIGURE 2**. The main goal of this algorithm is to calculate the SOC threshold limit that should not be exceeded while charging all EVs on the network. Respecting this limit guarantees the good operation of the distribution network within its maximum limits even with a 100% penetration level of EVs. The algorithm works in 6 steps, as will be explained hereafter.

Step 1:

The Home Energy Management System (HEMS) predicts the average active ($P_{n,h}^{BLavg}$) and reactive ($Q_{n,h}^{BLavg}$) power demand of the baseload at home h on the node n, as in Equations (1) and (2). Where, T is the period of the study (e.g., at night), $P_{n,h,t}^{BL}$ and $Q_{n,h,t}^{BL}$ are the active and reactive power demand of the baseload at instant t. In this paper, a baseload is an electrical load at home which is not considered in our optimization model. The HEMS also predicts the average power demand of the EV ($P_{n,h}^{EVavg}$) as in (3). Where, $P_{n,h,t}^{EV}$ is the predicted power demand of the EV at instant t, $E_{n,h}^{EVB}$ is the EV battery capacity for the home h at node n, $SOC_{n,h}^{i}$ and $SOC_{n,h}^{f}$ are the initial and final SOCs of the EV.

$$P_{n,h}^{BLavg} = \frac{1}{T}\int_{t\in T} P_{n,h,t}^{BL} dt \quad (1)$$

$$Q_{n,h}^{BLavg} = \frac{1}{T}\int_{t\in T} Q_{n,h,t}^{BL} dt \quad (2)$$

$$P_{n,h}^{EVavg} = \frac{1}{T}\int_{t\in T} P_{n,h,t}^{EV} dt = \frac{E_{n,h}^{EVB}\left(SOC_{n,h}^{f} - SOC_{n,h}^{i}\right)}{T} \quad (3)$$

Step 2:

The Smart Distribution Transformer (SDT), the aggregator in our case, receives $P_{n,h}^{BLavg}$, $Q_{n,h}^{BLavg}$ and $P_{n,h}^{EVavg}$ from homes, then, SDT calculates its average total active (P_{n}^{Tavg}) and reactive (Q_{n}^{Tavg}) power demands, as in Eq. (4).

$$\begin{cases} P_{n}^{Tavg} = \sum_{h=1}^{H}\left(P_{n,h}^{BLavg} + P_{n,h}^{EVavg}\right) & (a) \\ Q_{n}^{Tavg} = \sum_{h=1}^{H}\left(Q_{n,h}^{BLavg}\right) & (b) \end{cases} \quad (4)$$

Step 3:

Each SDT sends its data P_{n}^{Tavg}, Q_{n}^{Tavg} to the distribution system operator (DSO), with its node number and location. A central controller receives the data and starts to do the power flow analysis of the network based on the received data. Where, $\Delta P_{\%}$ represents the step power in percentage

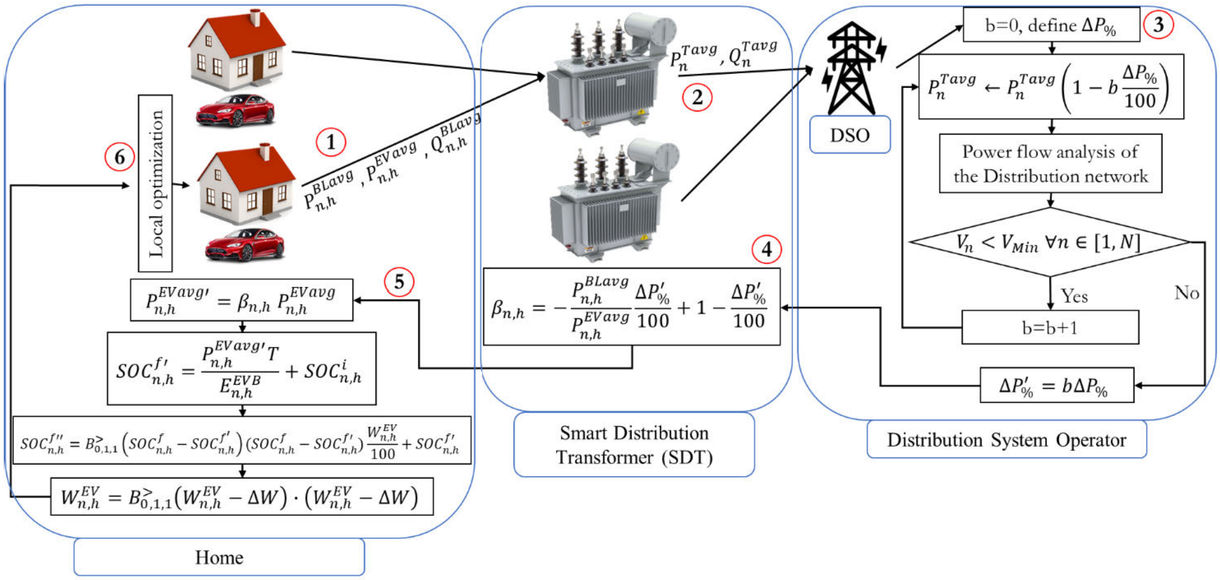


FIGURE 2. Proposed algorithm to control the final SOC level of the end-users.

(e.g., $\Delta P_{\%} = 1\%$), b is the iteration number to reach the optimal solution (e.g., 20 iterations). Then, the central controller checks the average voltages on all nodes as in Eq. (5). If one node has an average voltage drop below or above the recommended limits (V_n^{Min}, and V_n^{Max}), the power flow analysis is repeated with a new value of P_n^{Tavg} as in Eq. (6). Once all nodes are within the recommended voltage limits ($V_n^{Min} \leq V_n^{avg} \leq V_n^{Max}$), the DSO sends the new value of $\Delta P'_{\%}$ to all SDTs asking them to reduce their average power demand by $\Delta P'_{\%}$ (e.g., $\Delta P'_{\%} = 7\%$).

$$V_n^{Min} \leq V_n^{avg} \leq V_n^{Max} \quad \forall n \in [1, N] \tag{5}$$

$$P_{n,new\ value}^{Tavg} = P_{n,old\ value}^{Tavg} \left(1 - b \overbrace{\frac{\Delta P_{\%}}{100}}^{\Delta P'_{\%}} \right) \tag{6}$$

Step 4:

Each SDT receives the new value of $\Delta P'_{\%}$ and calculates how much power should be reduced for each home according to Eq. (7) where $P_{n,h}^{BLavg}$ and $P_{n,h}^{EVavg}$ are already known values, (e.g., $P_{n,h}^{BLavg} = 3kW$, $P_{n,h}^{EVavg} = 5kW$, $\Rightarrow \beta_{n,h} = -\frac{3}{5}\frac{7}{100} + 1 - \frac{7}{100} = 0.888$). The value of $\beta_{n,h}$ is in per unit and it is sent to each home connected to the same SDT.

$$\beta_{n,h} = -\frac{P_{n,h}^{BLavg}}{P_{n,h}^{EVavg}} \frac{\Delta P'_{\%}}{100} + 1 - \frac{\Delta P'_{\%}}{100} \tag{7}$$

Step 5:

Since only the EV is considered the main element to be controlled at home in this paper, the average charging power rate of the EV is determined by Eq. (8), (e.g., $P_{n,h}^{EVavg'} = 0.888 \cdot 5kW = 4.44kW$). Then, it is possible to determine the SOC level that should be respected by the end-user to maintain the stability on the network as in Eq. (9). However, the end-user may not be satisfied by this new value of the SOC (e.g., $SOC_{n,h}^{f'} = 80\%$), since he might need to charge his EV to a higher SOC level (e.g., SOC = 90%) for an urgent trip. For this reason, we propose an urgency factor $W_{n,h}^{EV}$ for urgent charging of the EV, where $W_{n,h}^{EV} \in [0, 100]$. A value $W_{n,h}^{EV} = 0$, means that it is not urgent for the end-user to fully charge his EV for the next day, which gives the DSO great flexibility to control the SOC level of the end-user in order to maintain the stability on the network. A value $W_{n,h}^{EV} = 100$ means that it is very urgent for the end-user to charge his EV to the desired SOC level (e.g., 90% instead of 80%). Therefore, the charging of his EV is of high priority, and it becomes a little bit difficult for the DSO to control the SOC level of this end-user. The new final SOC value is determined in Eq. (10), considering the urgency factor set by the end-user. If $W_{n,h}^{EV} = 100$, $SOC_{n,h}^{f''} = SOC_{n,h}^{f}$ which is the SOC determined by the end-user (e.g., 90%). If $W_{n,h}^{EV} = 0$, $SOC_{n,h}^{f''} = SOC_{n,h}^{f'}$ which is the SOC determined by the DSO (e.g., 80%). $SOC_{n,h}^{f''}$ is the SOC threshold limit that should not be exceeded in order to guarantee a good operation of the distribution network within its recommended limits.

$$P_{n,h}^{EVavg'} = \beta_{n,h} P_{n,h}^{EVavg} \tag{8}$$

$$SOC_{n,h}^{f'} = \frac{P_{n,h}^{EVavg'} T}{E_{n,h}^{EVB}} + SOC_{n,h}^{i} \tag{9}$$

$$\begin{aligned} SOC_{n,h}^{f''} &= B_{0,1,1}^{>}\left(SOC_{n,h}^{f} - SOC_{n,h}^{f'}\right) \\ &\quad \cdot \left(SOC_{n,h}^{f} - SOC_{n,h}^{f'}\right) \frac{W_{n,h}^{EV}}{100} + SOC_{n,h}^{f'} \end{aligned} \tag{10}$$

$$\begin{aligned} &B_{0,1,1}^{>}\left(SOC_{n,h}^{f} - SOC_{n,h}^{f'}\right) \\ &\quad = \begin{cases} 1 & if\ SOC_{n,h}^{f} \geq SOC_{n,h}^{f'} \\ 0 & if\ SOC_{n,h}^{f} < SOC_{n,h}^{f'} \end{cases} \end{aligned} \tag{11}$$

where, $B^{>}_{a,b,c}(\cdot)$ and $B^{<}_{a,b,c}(\cdot)$ are the Bayeh step functions proposed in this paper and defined in Equations (12) and (13). They are the general case of step functions in which they can take three values (a, b, and c), where $b \in [a, c]$.

$$B^{>}_{a,b,c}(x - x_0) = \begin{cases} a & if\ x < x_0 \\ b & if\ x = x_0 \\ c & if\ x > x_0, \quad where\ b \in [a, c] \end{cases} \tag{12}$$

$$B^{<}_{a,b,c}(x - x_0) = \begin{cases} a & if\ x > x_0 \\ b & if\ x = x_0 \\ c & if\ x < x_0, \quad where\ b \in [a, c] \end{cases} \tag{13}$$

What happens if all end-users decided to put the urgency factor ($W^{EV}_{n,h}$) equal to 100%? It means that all of them want to fully charge their EV urgently for the next day. Hence, this might not solve the problem of energy congestion and might not help the DSO to control the charging limit of the end-users. To solve the problem, Eq. (14) is proposed in which we intend to reduce the urgency factor $W^{EV}_{n,h}$ by a value of ΔW (e.g., $\Delta W = 1\%$) in each iteration done by the algorithm. It means that in case the stability issue is not solved on the network with the new suggested SOC value ($SOC^{f'}_{n,h}$) in Eq. (9), the DSO is obliged to reduce $W^{EV}_{n,h}$ for all end-users by ΔW and the new $W^{EV}_{n,h}$ value becomes $W^{EV}_{n,h} = W^{EV}_{n,h} - \Delta W$ as in Eq. (14) and (15), (e.g., $W^{EV}_{n,h} = 100 - 1 = 99\%$). Therefore, end-users who put their urgency factor $W^{EV}_{n,h} = 100\%$ in the first iteration, will receive a new value $W^{EV}_{n,h} = W^{EV}_{n,h} - \Delta W = 99\%$ in the next iteration. Also, end-users who put a $W^{EV}_{n,h} = 80\%$ will receive a new value $W^{EV}_{n,h} = W^{EV}_{n,h} - \Delta W = 79\%$, and so on so forth.

$$W^{EV}_{n,h} = B^{>}_{0,1,1}\left(W^{EV}_{n,h} - \Delta W\right) \cdot \left(W^{EV}_{n,h} - \Delta W\right) \tag{14}$$

$$B^{>}_{0,1,1}\left(W^{EV}_{n,h} - \Delta W\right) = \begin{cases} 1 & if\ W^{EV}_{n,h} \geq \Delta W \\ 0 & if\ W^{EV}_{n,h} < \Delta W \end{cases} \tag{15}$$

Step 6:

After determining the new SOC threshold limit ($SOC^{f''}_{n,h}$) that should be respected by the end-users, the HEMS starts to optimize and schedule the charging of the EV considering the limits imposed by the DSO and the end-users. In this paper, a convex optimization problem for a home with a single EV is described in the following equations. Where Eqs. (16) and (17) present the objective function and Eqs. (18) to (23) represent the constraints. The main goal of the objective function is to minimize the electricity cost at home, considering the baseload ($P^{BL}_{n,h,t}$) and the EV ($P^{EV}_{n,h,t}$). Where C^V_t and C^F_t are the time-varying electricity price (e.g., RTP, TOU), and the fixed electricity price (e.g., 0.7\$/kWh), respectively. Δt is the step time interval (i.e., $\Delta t = 0.5$ *hours*). $\min\left(V^{avg}_{n,in}\right)$ represents the minimum voltage drop on any nodes of the distribution network. V^{Min} is the minimum required voltage drop limit (e.g., 0.95 pu). If $\min\left(V^{avg}_{n,in}\right) < V^{Min}$, it means that there is at least one node on the network in which its voltage is less than the recommended limit (e.g., $\min\left(V^{avg}_{n,in}\right) = 0.93 < 0.95$). Therefore, in this case $\left(B^{>}_{0,1,1}\left(\min(V^{avg}_{n,in}) - V^{Min}\right) - 1\right) = -1$, and the objective function becomes $OF = Min\Big(\sum_{t\in T}\left(C^V_t P^{BL}_{n,h,t} + C^F_t P^{EV}_{n,h,t}\right)\Delta t\Big)$. In another meaning, the electricity price to charge the EV becomes fixed, which helps the EV-owner to reduce the charging cost of his EV and to spread the charging for the whole period T. Hence, the stress on the network is reduced. If $\min\left(V^{avg}_{n,in}\right) \geq V^{Min}$, it means that all nodes on the network have a voltage higher than the minimum limit (e.g., $\min\left(V^{avg}_{n,in}\right) = 0.98 \geq 0.95$). Hence, there is no problem for charging EVs during night even with high power demand. In this case $\left(B^{>}_{0,1,1}\left(\min(V^{avg}_{n,in}) - V^{Min}\right) - 1\right) = 0$, and the objective function becomes $OF = Min\left(\sum_{t\in T} C^V_t (P^{BL}_{n,h,t} + P^{EV}_{n,h,t})\Delta t\right)$. In another meaning, the electricity price to charge the EV becomes variable (e.g., RTP), which helps the householder to minimize his electricity cost and to charge his car during low electricity price while respecting the voltage limit on the network. For both cases, the householder and the DSO are satisfied even for a very high penetration level of EVs.

The optimization problem in this paper is linear and can be solved with linear programming since only one EV is considered at each home with unidirectional power flow. However, more electrical loads can be added, and bidirectional power flow can be considered, which might transform the optimization model into a more complex problem which might become nonlinear.

$$OF = Min\left(\begin{array}{c} \sum\limits_{t\in T}\left(C^V_t\left(P^{BL}_{n,h,t} + P^{EV}_{n,h,t}\right)\Delta t\right) \\ +\left(B^{>}_{0,1,1}\left(\min(V^{avg}_{n,in}) - V^{Min}\right) - 1\right) \\ \times \sum\limits_{t\in T}\left(P^{EV}_{n,h,t}\left(C^V_t - C^F_t\right)\Delta t\right) \end{array}\right) \tag{16}$$

where,

$$B^{>}_{0,1,1}\left(\min\left(V^{avg}_{n,in}\right) - V^{Min}\right) = \begin{cases} 1 & if\ \min\left(V^{avg}_{n,in}\right) \geq V^{Min} \\ 0 & if\ \min\left(V^{avg}_{n,in}\right) < V^{Min} \end{cases} \tag{17}$$

The constraints are stated in equations (18) to (23). Where Eq. (18) represents the maximum power limit ($P^{Max}_{n,h,t}$) at home including the baseload ($P^{BL}_{n,h,t}$) and the charging rate of the EV ($P^{EV}_{n,h,t}$). $\eta^c_{n,h}$ is the charging efficiency of the battery. $P^{Max}_{n,h,t}$ is described in Eq. (19); where $P^{MCB}_{n,h}$ is the main circuit breaker capacity (e.g., 10kW); $P^{RL}_{n,h,t}$ is the reference limit calculated by the DSO or the aggregator in order to maintain the stability on the network (e.g., $P^{RL}_{n,h,t} = 8kW$ at t = 3h, and $P^{RL}_{n,h,t} = 9kW$ at t = 5h). $P^{RL}_{n,h,t}$ is used to reduce or increase the load demand at home depending on the needs of the DSO. For example, if there is an overload on the SDT, the DSO may reduce $P^{RL}_{n,h,t}$ in order to reduce the load of all consumers in a certain period. However, if the demand is low, the DSO may increase $P^{RL}_{n,h,t}$ in order to encourage the users to consume more electricity for a specific period of time. Eqs. (20) and (21) show the energy limit of the battery for the minimum ($SOC^{Min}_{n,h}$) and maximum ($SOC^{Max}_{n,h}$) SOCs, respectively. $E^{EVB}_{n,h}$ is the battery capacity (e.g., $E^{EVB}_{n,h} = 100kWh$). $SOC^{f''}_{n,h}$ is the SOC threshold limit imposed by the DSO as in Eq. (10). Eq. (22) represents the energy limit of the demand at home for a certain period $T_i \in T$. E^{Min}_{n,h,T_i} and E^{Max}_{n,h,T_i} are the minimum and maximum energy limits at home for the period T_i. Finally, Eq. (23) presents the minimum and maximum charging and discharging limits of the EV at instant t. If $\min\left(V^{avg}_{n,in}\right) < V^{Min}$, then $B^{>}_{0,1,1}\left(\min(V^{avg}_{n,in}) - V^{Min}\right) = 0$, and the maximum charging limit becomes $P^{EV}_{n,h,t} \leq E^{EVB}_{n,h}\left(SOC^{f''}_{n,h} - SOC^{i}_{n,h}\right)/T$. In another meaning, the charging power is limited in order to reduce the impact on the network when the total load demand is higher than the maximum capacity of the network. If $\min\left(V^{avg}_{n,in}\right) \geq V^{Min}$, then, $B^{>}_{0,1,1}\left(\min(V^{avg}_{n,in}) - V^{Min}\right) = 1$, and the maximum charging limit becomes $P^{EV}_{n,h,t} \leq P^{MaxCh}_{n,h,t}$. In another meaning, the charging power is limited to the maximum charging level of the EV (e.g., AC Level 2 at home up to 19.2kW according to SAE J1772). Hence, the impact on the network is reduced even with a very high penetration level of EVs. The algorithm in **FIGURE 2** finds the optimal value of the charging limit in Eq. (23), which guarantees that the voltage drops on any nodes of the network will never become lower than the recommended limit (e.g., 0.95 p.u.).

$$P^{BL}_{n,h,t} + \frac{P^{EV}_{n,h,t}}{\eta^{c}_{n,h}} \leq P^{Max}_{n,h,t} \tag{18}$$

$$P^{Max}_{n,h,t} = \min\left(P^{MCB}_{n,h}, P^{RL}_{n,h,t}\right) \tag{19}$$

$$\sum_{t\in T} P^{EV}_{n,h,t}\Delta t = E^{EVB}_{n,h}\left(SOC^{f''}_{n,h} - SOC^{i}_{n,h}\right) \tag{20}$$

$$E^{EVB}_{n,h} SOC^{Min}_{n,h} \leq \sum_{t\in T} P^{EV}_{n,h,t}\Delta t \leq E^{EVB}_{n,h} SOC^{Max}_{n,h} \tag{21}$$

$$E^{Min}_{n,h,T_i} \leq \sum_{t\in T_i}\left(P^{BL}_{n,h,t} + P^{EV}_{n,h,t}\right)\Delta t \leq E^{Max}_{n,h,T_i} \tag{22}$$

$$P^{EV}_{n,h,t}\begin{cases} \leq \min\left(\begin{array}{l} P^{MaxCh}_{n,h,t}\cdot B^{>}_{0,1,1}\left(\min\left(V^{avg}_{n,in}\right) - V^{Min}\right) \\ +\left(1 - B^{>}_{0,1,1}\left(\min\left(V^{avg}_{n,in}\right) - V^{Min}\right)\right) \\ \times \frac{E^{EVB}_{n,h}\left(SOC^{f''}_{n,h} - SOC^{i}_{n,h}\right)}{T} \end{array}\right) \\ \geq P^{MinDisch}_{n,h,t} \end{cases} \tag{23}$$

III. RESULTS AND DISCUSSION

A. ASSUMPTIONS

To answer the open question "Is it necessary to fully charge your EV?" it is important to put this study in a context by considering some assumptions as follows:

- IEEE 123 Node test feeder is considered as a case study, as in **FIGURE 3**,
- The black dots in **FIGURE 3** represent the nodes that have homes with EVs,
- The initial data are presented as follows. Where, $P^{BLavg}_{n,h}$ is the average power demand at home; $SOC^{i,avg}_{n,h}$ is the average initial state of charge of the EV before the charging process; T is the period of charging; $P^{MaxCh}_{n,h,t}$ is the maximum charging power of the EV at home; $E^{EVavg}_{n,h}$ is the average EV battery capacity; N^{Grid}_{home} is the number of homes on the distribution network;

$$P^{BLavg}_{n,h} = 1.4kW \qquad P^{MaxCh}_{n,h,t} = 6kW$$
$$E^{EVavg}_{n,h} = 63kWh \qquad SOC^{i,avg}_{n,h} = 0.6$$
$$\text{Number of EVs at home} = 1 \qquad N^{Grid}_{home} = 2505$$
$$T = 10h$$

- Five different case scenarios are considered in this study:
  - Scenario 1: Baseload at homes without EVs
  - Scenario 2: Homes with EVs and $SOC^{f}_{n,h} = 0.778$,
  - Scenario 3: Homes with EVs and $SOC^{f}_{n,h} = 0.867$,
  - Scenario 4: Homes with EVs and $SOC^{f}_{n,h} = 0.955$,
  - Scenario 5: Homes with EVs and $SOC^{f}_{n,h} = 1$.
- OpenDSS 9.1.3.3 is considered to calculate the power flow of the IEEE 123 node test feeder network. The used data for each case scenario are presented in Table 1. Eq. (24) can be used for approximation purposes in order to calculate the average power demand on each node,

$$P^{Avg}_{Node} = \begin{cases} N_{n,h}\left(P^{BLavg}_{n,h} + \frac{E^{EVavg}_{n,h}\left(SOC^{f}_{n} - SOC^{i,avg}_{n,h}\right)}{T}\right) & (a) \\ P^{BLavg}_{n} + \frac{P^{BLavg}_{n}}{P^{BLavg}_{n,h}}\frac{E^{EVavg}_{n,h}\left(SOC^{f}_{n} - SOC^{i,avg}_{n,h}\right)}{T} & (b) \end{cases} \tag{24}$$

- Voltage drops, and power losses, are studied for each case,

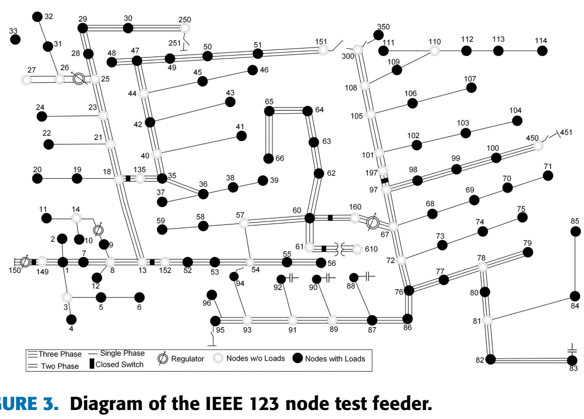


FIGURE 3. Diagram of the IEEE 123 node test feeder.

TABLE 1. Used data to simulate the IEEE 123 node test feeder.

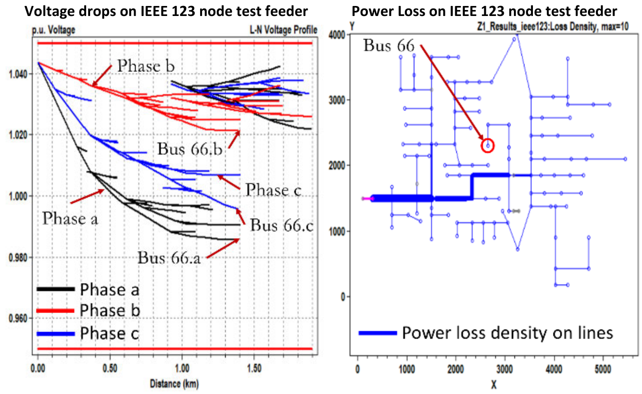
Total Power demand on the Nodes for Scenario 1 ($P_n^{BL\,avg}$), [kW]	Number of Nodes for each value	Number of homes on each node ($N_{n,h}$)	Total Power demand on the Node for Scenario 2 (P_{Node}^{Avg}), [kW]	Total Power demand on the Node for Scenario 3 (P_{Node}^{Avg}), [kW]	Total Power demand on the Node for Scenario 4 (P_{Node}^{Avg}), [kW]	Total Power demand on the Node for Scenario 5 (P_{Node}^{Avg}), [kW]
20	31	14	36	44	52	56
35	4	25	63	77	91	98
40	47	29	72	88	104	112
70	4	50	126	154	182	196
75	2	54	135	165	195	210
105	2	75	189	231	273	294
210	1	150	378	462	546	588
Total	**91**	**2505**				

- MATLAB R2018b is used for programming, optimization, simulation, and for calling OpenDSS on an HP ZBook 15G6 laptop, with a processor Intel® Core^{TM} i7-9850H CPU @2.6GHz, and 64GB RAM,
- The optimization model at homes in Eqs. (16) to (23) is convex and can be solved using linear programming.

B. IMPACT OF CONSIDERING DIFFERENT FINAL SOC LEVELS ON THE DISTRIBUTION NETWORK

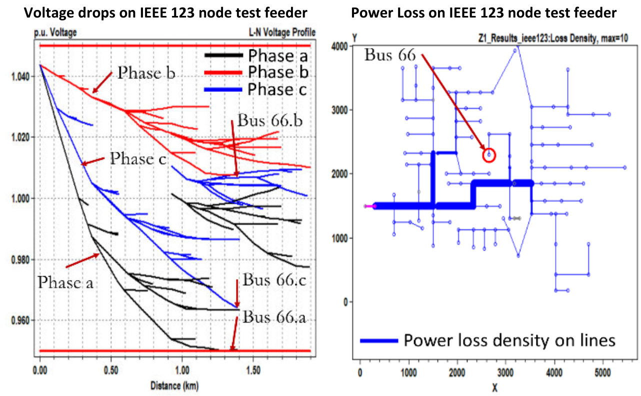
To the best of the authors' knowledge, this is the first study that compares the impact of charging EVs to different SOC levels on the distribution network. The importance of this study is to show that HEMSs and DRPs may not be enough to solve the high penetration level of EVs without the help of the end-users. Therefore, it is important to collaborate between the DSO and the end-users to attain a win-win situation for both parties. The main objective of the DSO is to minimize the operation cost of the network and reduce the techno-economic losses, while the main objective of the end-users is to reduce their electricity cost. In this subsection, the impact of the five previously mentioned scenarios on the network is studied. **FIGURE 4** to **FIGURE 8** present the average voltage drops and power losses at night for different charging scenarios.

FIGURE 4 presents the impact of homes without EVs on the network regarding the voltage drop and power losses, which are considered as the reference values in the simulation. It can be remarked that all nodes are within the recommended voltage limits (0,95 and 1.05 p.u.). The power losses on the lines are equal to 95.3kW, and the total load on the network is 3526.4 kW. When EVs are plugged in, the power demand increases drastically, and the voltage profile of the network stays within the recommended limits until a final SOC = 0.778 as in **FIGURE 5.a**. In this case, the final SOC is called the "SOC threshold limit" because any additional energy demand can drop the voltage below the recommended limit (0.95 p.u.). Once the final SOC of the EVs exceeds the threshold limit, it can be remarked from **FIGURE 6** to **FIGURE 8** that the voltage drop is worsened every time the final SOC increases, and the number of nodes with a voltage below the recommended limit increases too. In other meaning, the network will not be able to support the charging of all EVs for a SOC > 0.778. Hence, all end-users will not be satisfied at the same time, and there is a need to find a solution to satisfy both end-users and the DSO.



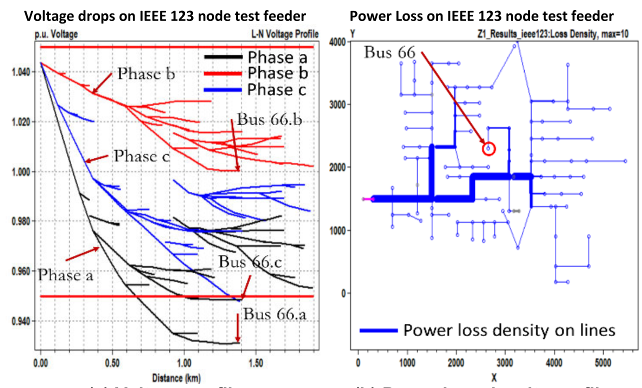
(a) Voltage profile (b) Power loss density profile

FIGURE 4. Impact of considering Scenario 1 (Homes without EVS) on the distribution network (IEEE 123 node test feeder).



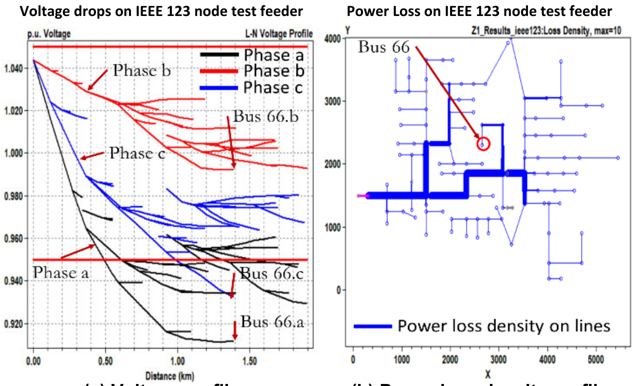
(a) Voltage profile (b) Power loss density profile

FIGURE 5. Impact of considering Scenario 2 (Homes with EVs and $SOC_f = 0.778$) on the distribution network (IEEE 123 node test feeder).



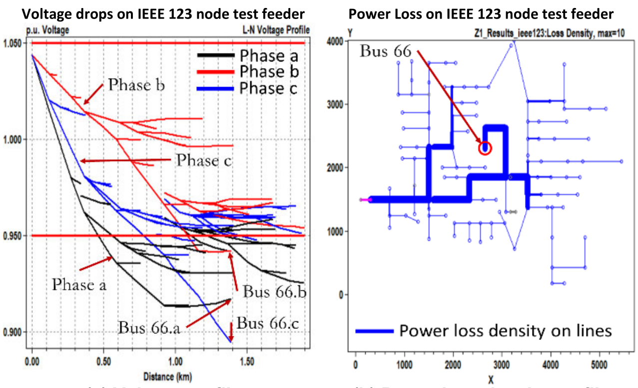
(a) Voltage profile (b) Power loss density profile

FIGURE 6. Impact of considering Scenario 3 (Homes with EVs and $SOC_f = 0.867$) on the distribution network (IEEE 123 node test feeder).



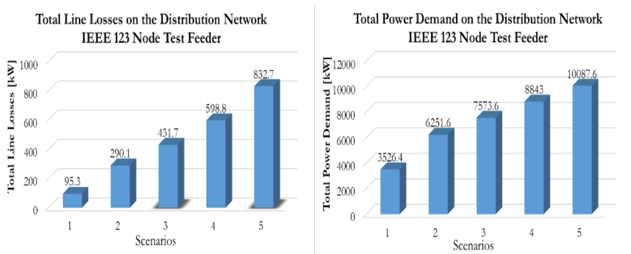
(a) Voltage profile (b) Power loss density profile

FIGURE 7. Impact of considering Scenario 4 (Homes with EVs and $SOC_f = 0.955$) on the distribution network (IEEE 123 node test feeder).



(a) Voltage profile (b) Power loss density profile

FIGURE 8. Impact of considering Scenario 5 (Homes with EVs and $SOC_f = 1$) on the distribution network (IEEE 123 node test feeder).



(a) Total Line Losses on the Distribution Network for all Scenarios. (b) Total Power Demand on the Distribution Network for all Scenarios.

FIGURE 9. Impact of charging EVs to different SOC levels on the (a) line losses, and (b) power demand of the IEEE 123 node test feeder.

FIGURE 9 presents the impact of charging EVs to different SOC levels on the line losses and power demand of the distribution network. When the energy demand increases, the line losses, and power demand increase too.

FIGURE 10 shows the total power demand on a transformer for the five mentioned scenarios considering a fixed electricity tariff (refer to **FIGURE 13**). It can be remarked that by charging EVs to a SOC greater than 0.8, the load demand starts to exceed the nameplate rating of the transformer. In **FIGURE 11**, it can be remarked that for a time-varying electricity tariff (refer to **FIGURE 13**),

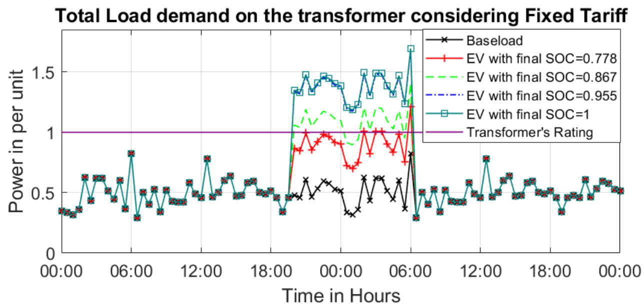


FIGURE 10. Impact of charging EVs to different SOC levels on the transformer using fixed electricity price.

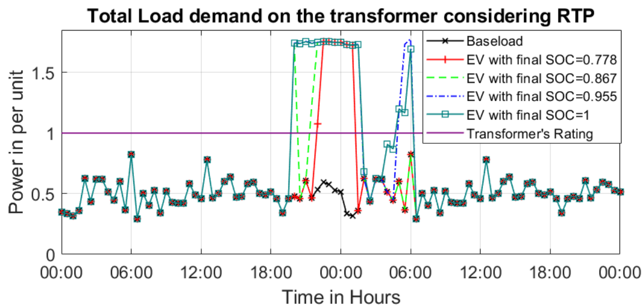


FIGURE 11. Impact of charging EVs to different SOC levels on the transformer using time-varying electricity price.

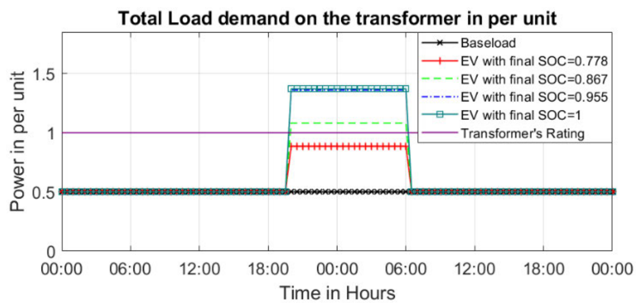


FIGURE 12. Average impact of charging EVs to different SOC levels on the transformer.

householders prefer to minimize their electricity cost by charging the EVs during low electricity prices. Hence, peak demand can be created even for a small SOC level since all EVs are charging at the same time. **FIGURE 12** depicts the average power demand on the transformer for each scenario, in which it is obvious that charging EVs to a final SOC greater than 0.8 can exceed the transformer's capacity even if sophisticated charging strategies and optimization techniques are used to reduce their impact. Therefore, the solution is to reduce the final SOC for the end-users until the average power demand respects the network's constraints, as will be discussed in the next subsection.

C. IMPACT OF THE PROPOSED ALGORITHM ON THE END-USERS AND THE DISTRIBUTION NETWORK

In the previous subsection, it was remarked that if all EVs were charged for a final SOC > 0.778 (as in **FIGURE 6** to **FIGURE 8**), the voltage drop exceeds the recommended limit, which may put the network in danger of losing its stability. On the other hand, charging EVs to a SOC lower than the desired one may not satisfy some EV owners. In this subsection, we will use our proposed algorithm to solve the problem and calculates the SOC threshold limit for each end-user. However, to encourage EV owners to follow the suggested SOC threshold limit (e.g., SOC = 0.7), the DSO offers them to charge the remaining energy the next day for a reduced tariff. Hence, the DSO is satisfied by respecting the network's limits and constraints, and EV owners are also satisfied by reducing the charging cost of their EVs the next day.

As an example, consider that the data in Table 2 are used for simulation purposes. The first column represents the average baseload of the nodes. There are in total 7 different types of nodes in IEEE 123 node test feeder. The second and third columns represent the initial and final SOC desired by the EV owners. The fourth and fifth columns represent the urgency factor ($W^{EV}_{n,h}$) and its iteration step (ΔW) to charge the EV to the desired SOC level, respectively. Finally, the last column represents the SOC threshold limit suggested by our algorithm in order to maintain the stability of the network. **FIGURE 14** shows the voltage drops of all nodes on the network for the values mentioned in Table 2. It can be observed that at iteration "0" (**FIGURE 14**.a before implementing our algorithm), there are some nodes that have a voltage below the recommended limit (0.95 p.u.) due to the high energy demand used to charge EVs. The proposed algorithm starts to find the optimal SOC threshold limit in each iteration for all EVs in order to improve the voltage

TABLE 2. Example using our proposed algorithm.

Baseload on the node [kW]	$SOC^{i}_{n,h}$	$SOC^{f}_{n,h}$	$W^{EV}_{n,h}$	ΔW	$SOC^{f'}_{n,h}$
20	0.4	0.9	0.8	0.1	0.6475
35	0.6	1	0.8	0.1	0.7822
40	0.5	0.8	0.7	0.1	0.6175
70	0.4	0.9	1	0.1	0.647
75	0.5	0.8	0.2	0.1	0.6175
105	0.4	0.9	0.5	0.1	0.647
210	0.6	0.9	0.4	0.1	0.7172

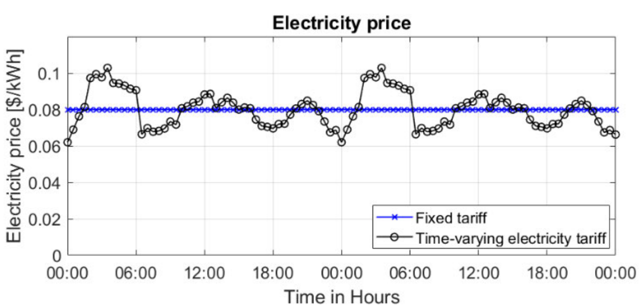


FIGURE 13. Electricity tariff used in this paper, (a) fixed price, (b) Real time-varying electricity price.

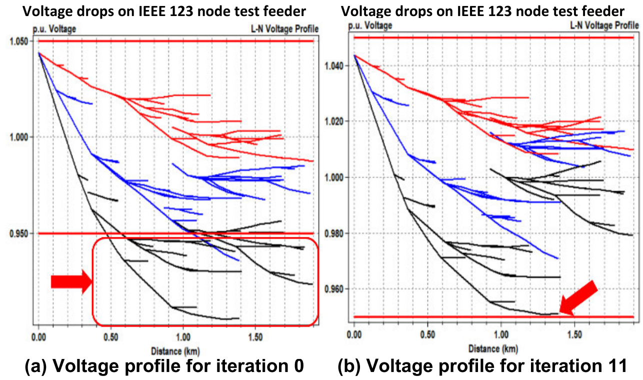


FIGURE 14. Improvement of the voltage drops on the distribution network (IEEE 123 node test feeder) by using our proposed algorithm.

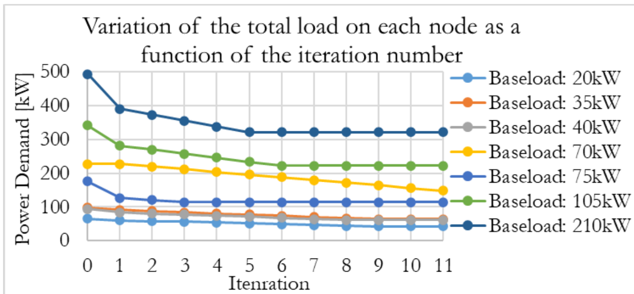


FIGURE 15. Convergence of the total load demand to the optimal threshold limits on the nodes of the network using our proposed algorithm.

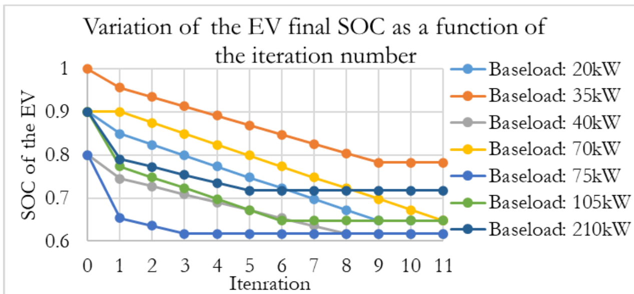


FIGURE 16. Convergence of the SOC to the optimal threshold limits on the nodes of the network using our proposed algorithm.

profile on the network. After several iterations, the voltage profile on the network is improved as shown in **FIGURE 14**.b (after 11 iterations), in which the voltage limits are met ($V > V_{Min}$). **FIGURE 15** and **FIGURE 16** present the variation of the total load demand on the network and the SOC threshold limits until they totally converge in iteration 11 for each node. It is remarked that some nodes converge to the optimal solution faster than other nodes, in which the curve becomes flat. As an example, the total load demand on the nodes that have a baseload equal to 75kW, converge in the third iteration, while the nodes with a baseload equal to 70kW converges at the 11th iteration as in **FIGURE 15**. **FIGURE 17** presents a comparison between the power losses at iterations 0 (before implementing our algorithm) and 11 (after using our algorithm), in which limiting the SOC level

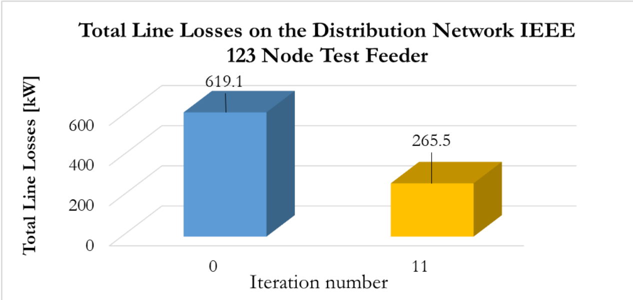


FIGURE 17. Comparing the total line losses for the iteration 0 and 11 using our algorithm.

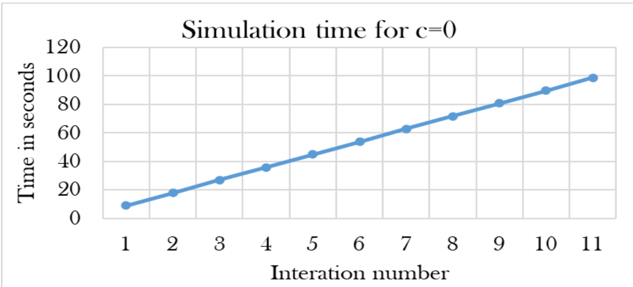


FIGURE 18. Simulation time to obtain the optimal solution using our proposed algorithm.

of the EV owners reduces the techno-economic losses on the network.

Finally, the simulation time (t_i) is presented in **FIGURE 18** in which it follows almost a linear curve and can be described by Eq. (25) where $t_{DN}^{avg} \approx 2.22s$ is the average simulation time for the distribution network on OpenDSS for one iteration, including plotting the results. $t_{home}^{avg} \approx 6.7s$ is the average simulation time at home to obtain the scheduling of the EV in MATLAB. $N_{home}^{grid} = 2505$ is the number of homes on the grid in our case. c is the configuration of the simulation and described in Eq. (26). $c = 0$ means that all homes are simulated in parallel; $c = 1$ means that all homes are simulated in series, which might increase drastically the simulation time. i is the number of iterations needed to converges to the optimal solution. It is important to mention that the simulation time depends drastically on the software, the code, the computer, and many other factors that play a crucial role in increasing or reducing the time.

$$t_i = i \cdot \left(t_{DN}^{avg} + t_{home}^{avg} \left(N_{home}^{grid} \right)^c \right) \tag{25}$$

$$c = \begin{cases} 1 & \textit{if homes are simulated in series} \\ 0 & \textit{if homes are simulated in parallel} \end{cases} \tag{26}$$

D. IMPACT ON THE ELECTRICITY COST OF THE END-USERS

In this subsection, the electricity tariff in Quebec is considered, which is a flat rate with 0.08\$/kWh. Two case scenarios are studied as follows:

- Scenario 1: all EVs are fully charged at night, which cause a problem on the network, as stated in **FIGURE 8** for a $SOC_f = 1$,
- Scenario 2: (a) Our proposed algorithm is implemented to determine the SOC threshold limit for each EV charging at night on the network, (b) and the remaining energy will be charged the next day at a reduced electricity price 0.05\$/kWh.

FIGURE 19 shows the results of the two scenarios regarding the total charging cost of EVs. Scenario 1 represents the fully charging of all EVs on the network at night, in which the total charging cost is about 6003\$. As discussed earlier, this scenario might be interesting for the end-users; however, it might be a problem for the DSO since it might create a severe voltage drop below the critical limits. Hence, scenario 2 is proposed to solve the problem. Scenario 2.a represents the cost of charging EVs to the SOC threshold limits calculated by our proposed algorithm and based on the DSO requirements. The cost of charging is about 2606.7\$ for all EVs on the network. However, for the EVs that are not fully charged due to network critical constraints and limits, the DSO offers them to continue charging their EVs the next day with a reduced electricity cost (e.g., 0.05\$/kWh instead of 0.08\$/kWh). This offer might interest the EV owners to participate in the program, and their total charging cost at night and the next day will be 4729.4\$, as presented in scenario 2.b in **FIGURE 19**. Hence, they were able to reduce their charging cost by 21% compared to the first scenario.

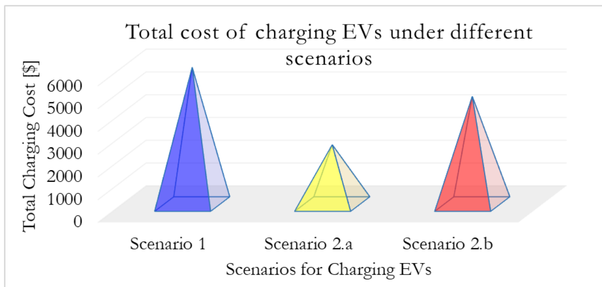


FIGURE 19. Total cost of charging EVs under different scenarios.

IV. CONCLUSION

This paper presents the impact of charging EVs to different State of Charge (SOC) levels on the distribution network. Five scenarios were considered and compared. The first scenario presents homes on the network without EVs, which is taken as a reference for comparison. The four remaining scenarios consider charging EVs at homes during the night with different SOC levels, 0.778, 0.867, 0.955, and 1, respectively. IEEE 123 node test feeder is considered as a distribution network in this paper. The network has 2505 homes, and each home has one EV. It was observed that if EVs are charged at a SOC $>$ 0.778, the voltage drops on the nodes of the network start to exceed the recommended limits, which might trigger the stability of the network. From this place, the question arises if it is necessary for end-users to fully charge their EVs at night or not. In order to satisfy both end-users and the distribution system operator (DSO), we propose an algorithm that calculates the SOC threshold limits for each EV, taking into account the constraints of the network and many other factors such as the priorities of the EV owners and their desired final SOC levels. Results show that our algorithm has maintained the voltage on the nodes of the network within the recommended limits, which will satisfy the DSO. In addition, end-users benefit from limiting their SOC level at night by continuing to charge their EVs the next day with a reduced price. Hence, it becomes more attractive for EV owners to participate in such kinds of demand response programs. Consequently, a win-win situation was reached for both end-users and the DSO. The proposed algorithm has a major benefit for the DSO especially when the total power demand on the network exceeds a certain threshold that might impact its stability and reliability.

V. FUTURE DIRECTIONS AND WORK

Based on the obtained results in this paper, it can be remarked that a high penetration level of EVs can saturate the distribution network at a certain point (as presented in **FIGURE 12**), especially when all EVs try to fully charge their batteries. Hence, the proposed algorithm suggests a SOC threshold limit for each EV in a way that the charging of all EVs on the network within the suggested limit will never exceed the network's constraints.

Despite the advancement in control strategies and optimization techniques to solve the problem of high penetration level of EVs, the distribution network is always at risk of overload and saturation. Since EVs are considered the most demanding electrical loads to date, it is necessary to minimize their energy demand and increase local energy production. Hence, the future direction in the upcoming research should focus on the following points:

- Development of self-power EVs in which renewable energy systems (i.e., photovoltaics) are integrated in the EVs to supply their batteries and increase their travel distance. In this way, EVs need less energy from the grid since they are able to self-produce a part of their energy needs from renewable energy sources,
- Manufacturing of higher efficient EVs with minimum electro-mechanical losses (i.e., aerodynamics, frictions, transmission, conversion, etc.). Minimizing the losses will also minimize the need for energy from the network,
- Increasing the local energy production at homes, buildings, parking lots, charging stations, etc., by installing renewable energy systems such as PV, wind turbines, etc.

All the above-mentioned solutions can increase the SOC threshold-limit and might allow EVs to fully charge even with a 100% penetration level. From this place, the future of EVs is very prominent and might not cause any problems if self-powered EVs and RES are widely deployed on the distribution systems besides advanced control strategies and optimization techniques.

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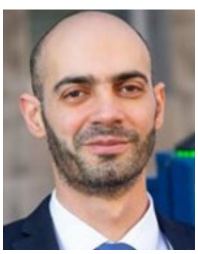

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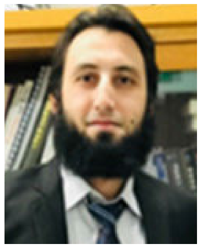

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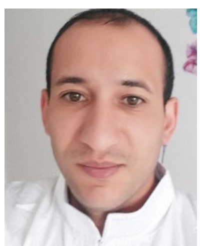

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