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# On-Off based Charging Strategies for EVs Connected to a Low Voltage Distribution Network

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**Abstract**—The development of appropriate Electric Vehicle (EV) charging strategies has been identified as an effective way to accommodate an increasing number of EVs on Low Voltage (LV) distribution networks. Most research studies to date assume that future charging facilities will be capable of regulating charge rates continuously, while very few papers consider the more realistic situation of EV chargers that support only on-off charging functionality. In this work, a distributed charging algorithm applicable to on-off based charging systems is presented. Then, a modified version of the algorithm is proposed to incorporate real power system constraints. Both algorithms are compared with uncontrolled and centralized charging strategies from the perspective of both utilities and customers.

**Index Terms**—Distributed algorithms, Power system simulation, Electric vehicle, Mixed-integer-linear-programming

## I. INTRODUCTION

Full EV and Plug-in hybrid cars are considered to be a green alternative to the normal combustion engine vehicles. Even though this point might be disputed, see [1], many vehicle manufacturers are investing heavily in developing full electric and plug-in hybrid vehicles, for example the Nissan Leaf [2] and the Toyota RAV4 EV [3]. Also, in many countries there are financial and other incentives for drivers of EVs and a public charging infrastructure is provided [4], [5]. These measures lead to an expected increase in the penetration of such vehicles [6], [7]. With increasing numbers, the charging load will grow and, if there is uncoordinated coincident charging of many vehicles, the power grid is likely to be overloaded. This will lead to higher power losses, higher peak demand, reduced transformer life, and voltage instability [7], [8], which ultimately means poorer power quality and increased cost for the consumer. Therefore, EV charging control is regarded as a necessity to mitigate against

these effects and to increase the possible penetration level of EVs.

Numerous algorithms exist to coordinate vehicle charging in various ways (see for example [1], [6], [7], [9], [10] and [11]). Due to the expected high number of agents participating, a centralized control strategy would incur a prohibitively high communication load, so that many authors propose distributed algorithms, for example from the above only [6], [11] present centralized solutions. In this paper, we also suggest a distributed algorithm with minimal communication requirements.

In previous work the authors investigated an algorithm which requires only the broadcast of a single bit signal to govern EV charging [10]. This assumed a continuously adaptable charge rate. However, such an assumption may not be valid if vehicle chargers only support binary control, i.e. on or off operation. In [11] such limitations in charger capabilities are studied and a centralized quadratic programming approach proposed for managing the operation of on-off charging infrastructure. Also there are other appliances where binary control is most likely to be the only option, e.g. heat storage systems. For such systems there exist many control algorithms [13], [14], [15].

In previous work the authors have accordingly suggested a distributed algorithm for binary EV charging control relying on the same broadcast signal as in [12]. The focus in this paper is to validate the algorithm proposed in [12] using a realistic power grid model. The performance of the algorithm is investigated in terms of improvements to power grid stability and the impact on the customer. We compare the algorithm with a centralized version which maximizes the improvements for the power grid and an uncontrolled

scenario, which represents maximal advantage for the customers. Further, we introduce an enhancement to the original algorithm proposed in [12] that enables local grid power and voltage constraints to be taken into account.

In Section II the EV charging problem is formulated mathematically. Then Section III describes the three charging control strategies investigated in the paper. Section IV presents some simulations results and then in Section V we conclude the paper.

## II. PROBLEM FORMULATION

This section presents the EV charging problem including several realistic power grid constraints.

In our previous work [16], a mathematical framework is presented for formulating EV charging problems while considering both power system and charging infrastructure constraints for both instantaneous and temporal based optimization objectives. This framework is adapted here to incorporate two different operational constraints of the power grid, namely plug-in constraints and power system constraints. In order to reduce the technical requirements of the charging station, they support only binary control actions, i.e. on or off. Additionally, the power delivered to the EVs should be close to the maximal allowed power.

We consider the specific EV charging scenario depicted in Figure 1, where the EVs are denoted by Z. The distribution network is modeled with the TN-C-S earthing system [17]. The EVs and an office building are connected to the distribution transformer, which is powered by an external the Medium Voltage (MV) level utility grid system. This scenario represents a workplace environment with EV charging. To be consistent with the framework defined in [16], the load power consumption is discretized into  $M$  discrete time slot (indexed  $1, 2, \dots, M$ ), each of length  $\Delta T$ . The power consumption of the office building is modeled by a balanced three phase load connected to the Low-Voltage (LV) bus and is given by  $S(k)$  at time slot  $k$ . In the following context,  $c_i(k)$  is defined as the charge rate for each connected EV at time  $k$ . Let  $P_{loss}(k)$  refer to the total power losses in the distribution network at time  $k$ .  $N$  denotes the total number of EV charge points installed in the network, while  $N(k)$  refers to the active charge points at time  $k$ , i.e. where an EV is connected. Therefore the total power flow measured at the transformer side at time  $k$  can be defined as:

$$P_{TR}(k) = S(k) + \sum_{i=1}^{N(k)} c_i(k) + P_{loss}(k) \quad (1)$$

The connection and disconnection time for the  $i$ -th EV are specified as  $a_i$  and  $b_i$  respectively. This means that the  $i$ -th EV is active during the interval  $[a_i, b_i]$ .  $B_i$  denotes the battery size of the  $i$ -th EV and  $SOC_i(k)$  its State-of-Charge (SOC) at time  $k$ . Furthermore, to simplify our problem description, the index set of all EVs connected to each phase (i.e. PhaseA, PhaseB and PhaseC) is defined by  $\mathfrak{I}_E^1$ ,  $\mathfrak{I}_E^2$  and  $\mathfrak{I}_E^3$  respectively, where  $E$  represents the EV area.

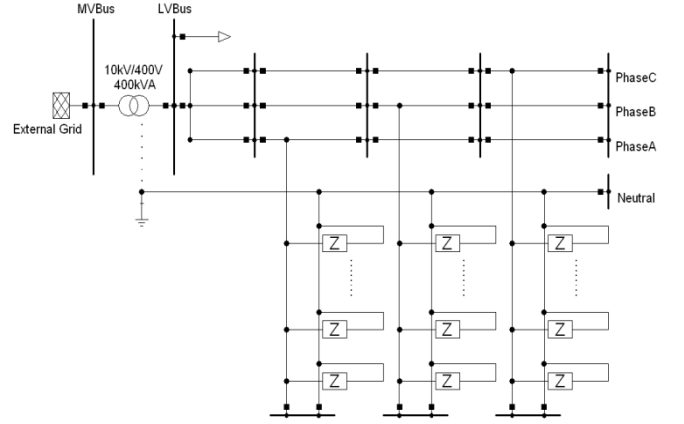


Fig. 1: Schematic diagram of the distribution network

### ➤ Objective Function

Our overall objective in this work is to maximize the total power delivered to all charging EVs at each given time  $k$ , while honoring the available power (at the transformer) and local power grid constraints. Thus, the objective function we wish to maximize can be expressed as:

$$\mathcal{F}(\mathbf{c}(k)) = \sum_{i=1}^N c_i(k) \quad (2)$$

### ➤ Plug-in constraints

With plug-in constraints we model the facts that an EV charger can only operate when an EV is plugged and can either be switched on at maximum power  $P_{max}^i$ , or switched off, and hence consuming no power. Therefore the plug-in constraint can be defined as follows:

$$\text{If: } a_i \leq k \leq b_i$$

$$c_i(k) = 0 \text{ or } c_i(k) = P_{max}^i \quad (3)$$

$$\text{If: } k \leq a_i \text{ or } k \geq b_i \text{ or } SOC_i(k) = 100\%$$

$$c_i(k) = 0 \quad (4)$$

### ➤ Power system constraints

There are many power system concerns with regard to large numbers of EVs charging simultaneously. These include significant voltage drops, exceeding phase current, transformer overloading, voltage unbalance and power factor dropping below acceptable limits [18]. In the context of our work, only the following constraints are considered, namely significant voltage drops, transformer overloading and single phase overloading. Hence, the associated power system constraints are given by:

$$\sum_{i \in \mathfrak{I}_E^r} c_i(k) \leq P_{rate}^r \quad r \in \{1, 2, 3\} \quad (5)$$

$$P_{TR}(k) \leq P_a(k) \leq TR_{max} \quad (6)$$

$$V_i(k) \geq V_{min}, \quad i \in \{1, 2, 3 \dots N\} \quad (7)$$

where  $P_a(k)$  denotes the total available power that can be provided to the LV transformer at given time  $k$ . Let  $TR_{max}$  represent the maximum power flow that can be tolerated on the transformer for normal operation, i.e., the rating of the transformer. The maximum loading level for each single phase is given by  $P_{rate}^r$ , (e.g.  $r = 1$  for PhaseA).  $V_i(k)$  denotes the voltage measured at the  $i$ -th charging point at time  $k$  in the parking lot. The minimum voltage limit on the network is defined as  $V_{min}$ .

### III. CHARGING STRATEGIES

#### A. Uncontrolled charging

With uncontrolled charging, we assume the case where each EV starts charging as soon as it is connected to a charger and continues to consume  $P_{max}^i$  power from the time it connects until it is fully charged or it is disconnected. This is in accordance with the literature; see for example [7], [19], [20]. The impact of such a scenario has been investigated from the perspective of the grid in various studies [20], [21], [22]. In this context, uncontrolled charging can be described as follows:

$$\text{If: } a_i \leq k \leq b_i \text{ and } SOC_i(k) < 100\% \quad c_i(k) = P_{max}^i \quad (8)$$

$$\text{Else:} \quad c_i(k) = 0 \quad (9)$$

#### B. Distributed charging algorithm

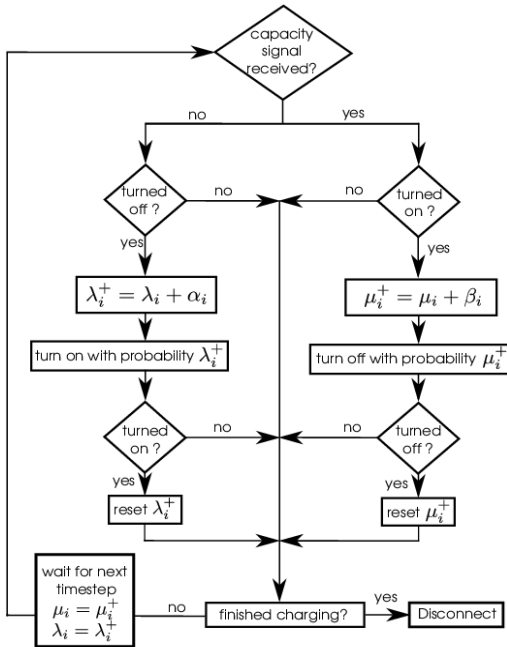


Fig. 2: Flow chart of the distributed charging algorithm

A learning automaton method is proposed in [12] to control the operation of a fleet of on-off type EV charger that seeks to maximize the utilization of the available power. An

ergodic Markov Chain based distributed control system is formulated to analyze the charging dynamics of each EV. Depending on whether a congestion signal is received or not, each EV can automatically turn on or turn off its charging according to the determined probability at each time step. This algorithm has been demonstrated to be capable of converging to the desired steady state due to the ergodic property of the overall system. The flow chart of this distributed charging algorithm is depicted in Fig.2. In this algorithm,  $u_i$ ,  $u_i^+$  and  $\beta_i$  are the parameters for the turn-off phase and  $\lambda_i, \lambda_i^+$  and  $\alpha_i$  are for the turn-on phase. For a more detailed description of the algorithm, please refer to [12].

#### C. Enhanced distributed charging algorithm

The distributed algorithm developed in [12], and outlined above, does not take into account power line constraints or minimal voltage requirements. However, maintaining these constraints is critical to meeting consumer power quality guarantees and ensuring the safe and reliable operation of the power grid. Therefore, we adapt the distributed algorithm to react to violations of these constraints. The enhancements are consistent with our previous framework in [21].

Considering the radial topology of the tested network, the minimum voltages in the network usually occur at the farthest point on each phase line [29]. To keep the voltage at all nodes within the limit, three voltage measurement devices are installed at the farthest point of each phase line. If one of the measurement devices detects that the voltage bound is violated it broadcasts a capacity event signal to the EVs connected on the same phase.

In a similar fashion, the transformer needs to have sensing functionality to measure the current (and hence power flow) in each phase line in order to monitor their loading. Then, if the actual power flow in a phase line exceeds the rated loading level, the transformer broadcasts a capacity event signal to each EV charger connected to the overloaded phase.

The distributed EV charging algorithm is otherwise unchanged, with chargers reacting in the same way to all types of capacity event. If multiple capacity events are received in the same time step, the charger reacts only to the first of these and ignores the others.

#### D. Centralized charging algorithm

The centralized charging algorithm proposed here is partly inspired by the optimal EV charging algorithm in [9], where a linear programming technique is employed to solve the optimization problems. In our work, a similar framework is applied which is adapted to deal with binary control actions. A technique based on mixed-integer-linear-programming (MILP) is employed to optimize the specific charging objective defined in Section II. The voltage deviations at each node are calculated at each time step using the voltage sensitivity matrix. Hence, the voltage constraint for charging point  $i$  at time step  $k$  in Equation (7) becomes

$$u_i c_i(k) + \sum_{j=1}^N u_{ji} c_j(k) \geq (V_{min} - V_i(k)). P_{max}^i, \forall j \neq i \quad (10)$$

Here,  $u_i$  represents the voltage sensitivity at node  $i$  due to an EV charging at node  $i$  and  $u_{ji}$  is the sensitivity of node  $i$  to an EV charging at node  $j$  [9]. Let the  $N * N$  voltage constraint matrix  $A$  be a matrix containing  $u_i$  in the diagonals and  $u_{ij}$  as off-diagonal elements. Then an MILP optimization problem incorporating the voltage constraint can be defined as:

Maximize:

$$\mathbf{f}^T \cdot \mathbf{X}$$

Subject to:

$$\mathbf{A} \cdot \mathbf{X} \leq \mathbf{b}$$

where  $\mathbf{X} \in \mathbb{R}^N$  is the state of the EVs with entries either 0 or 1 representing the off and on state, respectively, of each EV.  $\mathbf{f} \in \mathbb{R}^N$  is a coefficient vector with all one entries.  $\mathbf{A} \in \mathbb{R}^{N \times N}$  is the voltage sensitivity matrix.  $\mathbf{b} \in \mathbb{R}^N$  is the vector with the maximum voltage deviation from the current node voltage to the corresponding voltage limit. These matrices are then augmented to also include the phase load constraint in Equation (5) and the transformer loading constraint in Equation (6).

Such problems can be solved by the MILP method. In our work, we apply the efficient solver *lp\_solve* [23] to calculate the optimal values at each time step in a Matlab simulation.

#### IV. SIMULATION AND RESULTS

##### A. Simulation Setup

In order to compare the performance of the different charging strategies, a low-voltage distribution network with 45 EV charge points was modeled using the OpenDSS software [24], as illustrated in Fig.1. All charge points were evenly distributed on each phase. The distance between each charge point was set to 10 meters. At the source end of the network, a 10kV/400V (400kVA) delta/wye (grounded) two windings step-down transformer was modeled. The percent resistance of each winding on the transformer was set to 0.5, and the percent reactance of the transformer from primary to secondary side was set to 2. The voltage from the external grid was set to 1.05pu and the minimum voltage level that can be tolerated on the grid was set to 0.95pu. In addition, a 50kVA safety margin was reserved for the transformer for secure operation. The distance between each section of the three phase underground cable was set to 100meters. The aggregated load profile for the office building was generated by selecting several winter load profiles from the smart meter electricity trial dataset (small medium enterprise subset) provided by the Commission for Energy Regulation (CER) in Ireland [25]. For simplicity, the power factor for the official building load was assumed to 0.95 lagging over the course of the full  $M$  time slots. The time step was set to 1 sec for a 14 hour simulation conducted from 6am to 8pm. The load profile for the office building applied in this time period is illustrated in Fig. 3. Each data point was sampled and held every half an hour.

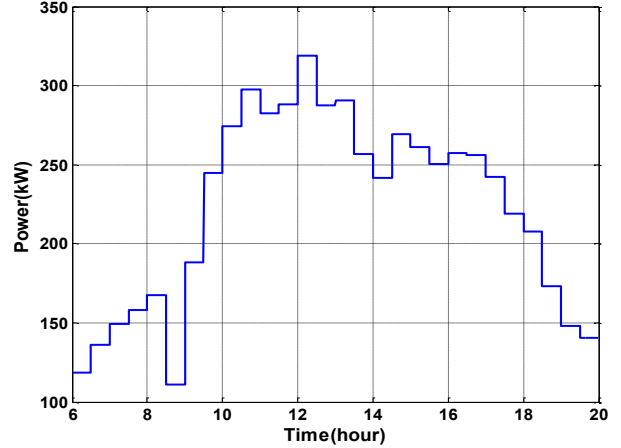


Fig.3: Office building power consumption from 6am to 8pm.

The maximum charge rate of each EV was set to 3.7kW which corresponds to a nominal charging current of 16A. The battery capacity for each EV was assumed to be 20kWh and the initial energy required for each EV was normally distributed. The mean of the distribution was set to 10kWh and the standard deviation was chosen as 1.5kWh. This means 99.9% of the EVs require between 5kWh and 15kWh and 81.8% require between 8kWh and 12kWh to fully charge their batteries. We assume that an EV is able to drive 5.91km per 1kWh charge, which is consistent with the Japan 10-15mode in [26]. Hence, the energy requirement of 81.8% of the EVs corresponds to a travel range of between 47.28km and 70.92km. As shown in [27], approximately 95% of car commuters in the U.S travel less than 40miles (64.4km) during weekdays. This supports the chosen normal distribution for the energy requirements.

To be consistent with the travel pattern in [28], we assume that EVs connect between 7am and 10am (19% of all daily journeys in Irish Urban areas) with the following time distribution: 7am-8am (21%), 8am-9am (47%), 9am-10am (32%). Similarly, most of them depart again between 4pm to 7pm (21% of all daily journeys in Irish Urban area) with the following time distribution: 4pm-5pm (33%), 5pm-6pm (38%), 6pm-7pm (29%). We assume that in total 40 EVs connect, which represents 89% of available charging points. Without loss of generality, in our simulation three EVs were assumed to randomly connect to the parking lot at the beginning of the simulation time (6am).

##### B. Results

The simulation results for the charging strategies considered in this paper are compared from the perspective of both the grid operators and customers.

Power grid utilities wish to reduce power losses, voltage sag and maximize the energy that can be delivered to customers at all times. Hence, in this paper, the power utilization, the power losses in the cables and the voltage sag are investigated, see Fig. 4 to Fig. 6.

The results show that uncontrolled charging has a severe impact on the grid and could not be tolerated. The basic distributed charging strategy improves the power network performance with regard to power losses and power utilization. However, the voltage drop is still significant, as shown in Fig. 6. By using the enhanced distributed algorithm the minimum voltage is substantially improved. It is also noteworthy that the enhanced distributed strategy achieves comparable performance to the centralized solution throughout the simulation in terms of grid operation.

From the customer side performance is measured in terms of the quality of service that is delivered. This is basically the amount of energy they receive or whether their EV is fully charged before their departure. The best result in this regard is achieved by uncontrolled charging, where all the EVs can finish charging within four hours. When using the enhanced or distributed algorithms all EVs were able to finish charging before departure. In terms of customer wishes, the centralized approach behaved worst with multiple EVs not fully charged at their departure. As expected, the enhanced method is able to provide some fairness to the EVs. In other words, the centralized method provides the best solution from the grid perspective, but ignores fairness from the perspective of the customers. A detailed comparison of the charging time for the EVs can be found in Table 1, including the average charging time and the extreme values.

Therefore, the proposed enhanced distributed strategy can provide enormous benefits to both utilities and customers. At the same time the required enhancements to the existing charging infrastructure are small, as it requires only broadcast communication and measurement points at critical locations in the grid. Note that the results presented here depend on the investigated power grid. The actual improvements possible can vary when using other grid structures and need to be investigated in detail.

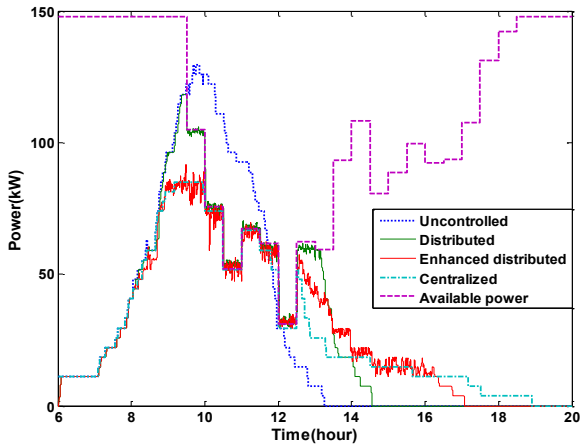


Fig. 4: Comparison of the power utilization  
Note: In this graph, the available power means the total available power that can be used for EV charging.

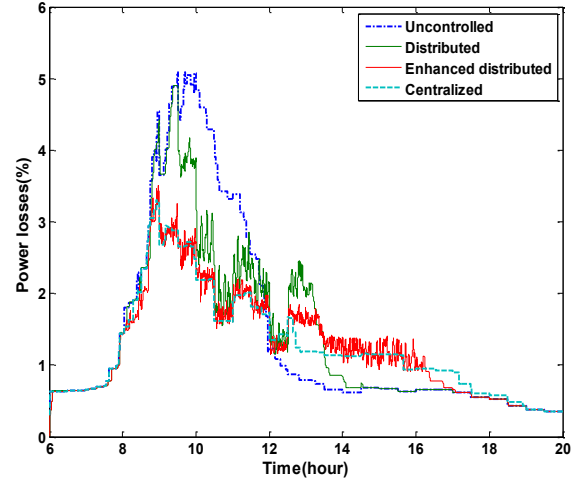


Fig.5: Comparison of the total power losses

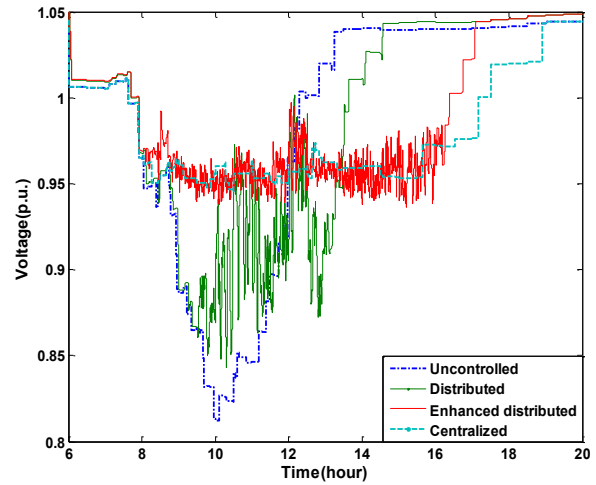


Fig.6: Comparison of the minimum voltage profile

TABLE I. COMPARISON TABLE OF THE GRID PERFORMANCE

EV Charging Strategies	Unctrl	Distributed	Enhanced	Centralized
Ave Time(h)	2.81	3.74	4.60	4.14
Std Time(h)	0.40	0.76	1.51	1.61
Min Time(h)	1.92	2.16	2.06	1.92
Max Time(h)	3.59	4.90	7.43	7.79
No. not finished	0	0	0	2
Missed(kWh)	0	0	0	5.65
Earliest EV(h:m)	08:26	08:28	08:30	08:26
Last EV(h:m)	13:15	14:33	17:42	N/A

**Unctrl:** Uncontrolled charging; **Distributed:** Distributed charging; **Enhanced:** Enhanced distributed charging **Centralized:** Centralized charging solution. **Ave Time:** Average charging time; **Std Time:** Standard derivation of charging time; **Min Time:** Minimum charging time; **Max Time:** Maximum charging time; **No. not finished:** Number of EVs not fully charged at plug-out; **Missed:** Total energy required to finish charging EVs not fully charged at plug-out; **Earliest EV:** The earliest time that an EV finishes charging; **Last EV:** The latest time that an EV finishes charging;

## V. CONCLUSIONS

In this paper, the distributed algorithm, suggested by the authors in [12], is investigated in a realistic power grid simulation. The algorithm, which is designed to control the scheduling of binary loads has very small communications needs and requires only one power measurement. The performance of the algorithm is compared with an uncontrolled charging scenario and a centralized control algorithm in respect to power utilization, power losses, minimal voltage at the nodes, and quality of service for customers.

Some modifications to the original algorithm in [12] are proposed to enable it to address local power system constraints violations, with a minimal increase in communication and measurement requirements.

Both the basic and enhanced distributed algorithms are able to lessen the impact on the grid of EV charging loads. While the basic distributed algorithm does not consider voltage constraints, the enhanced algorithm manages to keep the voltage above a minimal level.

Future work will look at adapting the algorithm to incorporate further grid constraints, in particular phase imbalance and frequency deviations. Additionally, the algorithm will be tested in a variety scenarios including domestic charging and larger networks.

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