Optimal Operation of Electric Vehicles to Enhance the Flexibility Provision in Active Distribution Grids

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***Abstract*—The continuously increasing integration of electric vehicles (EVs) introduced significant challenges to modern power systems, while at the same time offering big opportunities for more optimal and effective operation. This study presents an operational day-ahead scheduling optimization framework to mitigate the negative impacts of EV charging while maximizing flexibility services in active distribution networks. The presented framework employs a non-linear optimal power flow model that ensures compliance with network constraints and accommodates EV user preferences. The proposed methodology is validated through realistic test case scenarios to illustrate its operational feasibility. The results reveal that in suburban areas, flexibility during working hours is limited, while flexibility during return-home hours is significantly higher. In general, the increasing adoption of electric vehicles offers substantial potential for effectively managing distribution networks.**

***Index Terms*—Electric Vehicle, Flexibility, Optimal Operation, Optimization, Optimal Power Flow, Active Distribution Grids.**

NOMENCLATURE

Indices

k, m	Index of buses.
d	Index of loads.
ev	Index of EVs.
der	Index of distributed energy resources.
t	Index of time period.
s	Index of flexibility activation scenario.
$\uparrow$ / $\downarrow$	Index of upward / downward flexibility.
$slack$	Index of fixed reference slack bus.
tra	Index of transformer.
inj	Index of injection.

Sets

Ω^B	Set of buses
Ω^d	Set of loads where Ω_k^d indicates set of loads connected to bus k.
Ω^L	Set of lines connecting buses.
Ω^{ev}	Set of EVs where Ω_k^{ev} indicates set of EVs connected to bus k.
Ω^{der}	Set of PVs where Ω_k^{der} indicates set of PVs connected to bus k.
Ω^T	Set of time intervals.
Ω^S	Set of scenarios with: $s = 0$ for full downward EV flexibility activation, $s = 1$ for full upward EV flexibility activation.

This project has received funding from the EU's Horizon Europe Framework Programme (HORIZON) under the GA n. 101120278 - DENSE.

Symbols

$\lvert \bullet \rvert$	Denotes the amplitude of a complex number.
$\overline{\bullet}$ / $\underline{\bullet}$	Upper/Lower bound of a quantity.
$\hat{\bullet}$	Denotes the estimate value of the quantity.

Parameters

P, Q, S	Active, reactive, apparent power.
$C_{s,t}$	Penalty coefficient of flexibility.
ΔT	Time interval.
$f_{der}(p)$	Function of power factor angle of der in terms of active power p.
f_d,f_{ev}	Power factor angle of d and ev.
k_{ev}	Next trip distance (km) of ev.
η_{ev}	Avarage consumption per km of ev.
Y_{km}	Network admittance matrix.
G_{km}	Real part of the admittance matrix.
B_{km}	Imaginary part of the admittance matrix.
ϵ	Small value $\approx 10 \cdot e - 5$.
t_{ev}^L	Critical start time for charging of ev.
t_{ev}^{dep}	Departure time of ev.
$E_{ev,t}^{min}$	Minimum stored energy of ev which varies over time.

Variables

$v_{s,k,t}$	Voltage of bus k.
$\theta_{s,km,t}$	Voltage phase angle difference between busses k and m.
$I_{s,km,t}$	Current flow from bus k to bus m.
$P_{s,ev,t}^{flex}$	Upward/downward flexibility power of ev.
$P_{ev,t}^{ch}$	Charging power of ev.
$E_{ev,t}$	Available battery energy capacity of ev.

I. INTRODUCTION

The increasing integration of Renewable Energy Sources (RES) and the extensive use of Electric Vehicles (EVs) are introducing new levels of uncertainty and variability to modern power systems. These developments impose significant challenges to the system operators in maintaining power balance in real time and dealing with the fluctuating nature of RES production and the unpredictable charging patterns of EVs [1]. As a result, flexibility and operational scheduling in power systems require innovative approaches to address temporal and spatial power flow imbalances [2].

Flexibility in the context of EV refers to their ability to adapt to varying operational points to optimize energy use and support the power grid. EV flexibility provides various services

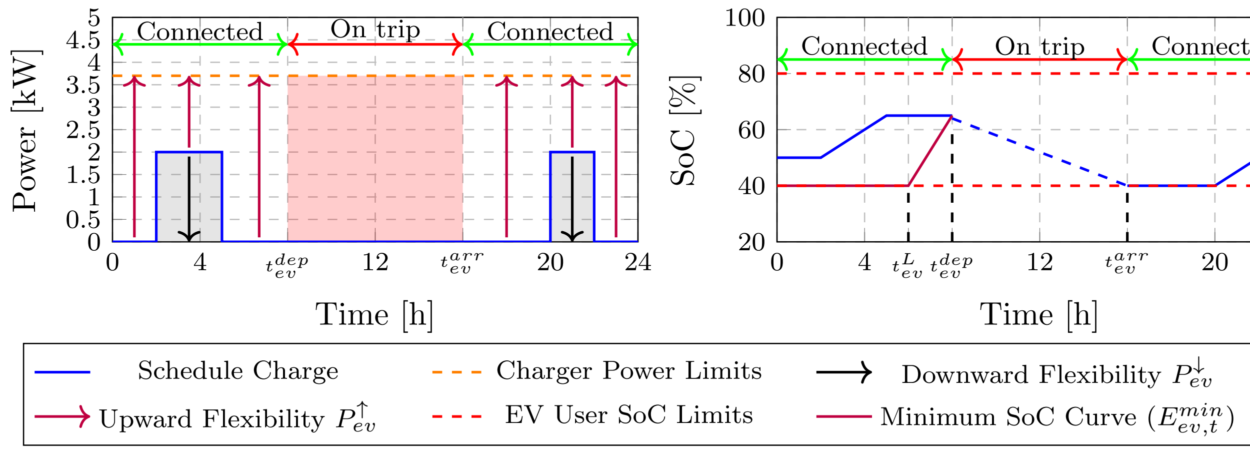


Fig. 1. Flexibility capacities, power capabilities and SoC limits considering an example of charging process

such as frequency regulation, congestion management, and voltage support. Studies reveal that EVs are parked and available to provide grid services for 90% of the time, making them a highly reliable resource for grid support [3], [4]. In fact, [1] validates that the residential sector is able to provide more flexibility than the public and workplace sectors. Furthermore, flexibility mechanisms at the Transmission System Operator (TSO) and the Distribution System Operator (DSO) interface are pivotal to leveraging distributed energy resources while addressing grid constraints [5].

EV's operation scheduling has been widely exploited in recent literature to mitigate various issues that existing power grids encounter. In particular, a hierarchical multi-period optimization model to minimize the charge cost was proposed in [6]. Similarly, the authors in [7] developed a unit commitment approach based on a centralized stochastic security optimization model to schedule the daily charge of EVs, aiming to minimize operational costs and reduce renewable energy curtailments. In [8], a multi-objective operation planning framework was presented, with the aim of achieving operational efficiency (reducing load peaks and fluctuations) and technical stability (minimizing voltage deviations). In the same way, an objective to minimize the variation of the load relative to a predefined load target (to achieve load levelling) is used in [9]. Furthermore, [10] proposed a multi-objective optimization methodology to minimize voltage variation at the fundamental frequency and total harmonic distortion using a harmonic load flow. Although these approaches optimize a specific objective and improve the operation of the EV, they do not consider the flexibility that EVs can provide to the network. Consequently, suboptimal or near-optimal solutions that could enhance flexibility services are overlooked.

At the same time, in [11] the authors proposed an AC Optimal Power Flow (OPF)-based methodology to generate DER PQ capability charts. Moreover, a fast mapping method is suggested in [12], to graphically determine the operation region of DER feasibility. However, these methodologies do not incorporate a model for EV storage systems, limiting their applicability in EV operational structures. Lastly, in [13] an attempt was made to combine operational strategies with flexibility. Although, this approach focused on real-time operations, relying solely on current conditions and ignoring network constraints.

The contribution of this paper is twofold. First, it provides valuable insights into the flexibility operation of EVs, highlighting their potential to support active distribution networks. Second, it introduces a novel operational day-ahead scheduling optimization framework that combines optimal operation scheduling with the maximization of EV flexibility services. This framework is designed to mitigate the negative impacts of EV charging while ensuring compliance with network constraints and accommodating user preferences.

The remainder of the paper is structured as follows: In Section II, the flexibility operation of electric vehicles is described. In Section III, the proposed OPF model is developed. Section IV presents the case study modeling framework for EVs, PVs, and basic load. In Section V the simulation results are discussed. Finally, conclusions are drawn in Section VI.

II. Flexibility In EV Charging

Flexibility assessments in power systems are often based on the power capacity within the PQ plane. However, electric vehicles offer a more dynamic form of flexibility based on their State of Charge (SoC) [1]. Consequently, system operators must handle an additional parameter: energy availability, both upward and downward. This is critical as the preferences of the EV owners should be respected while utilizing all available flexibility. This time-dependent parameter, initially provided during day-ahead planning, is dynamically altered by the operator's actions in real-time. The analytic description of flexibility as described in this section is qualitatively presented in Fig. 1.

Beyond operation methodologies and algorithms, the implementation of flexibility services is also based on technical and

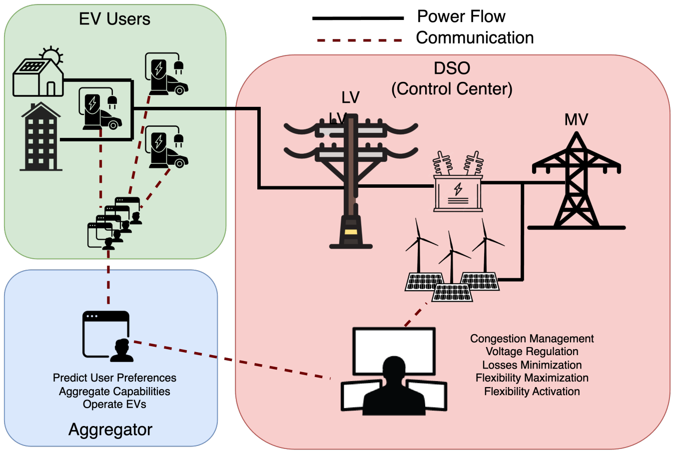


Fig. 2. Active distribution grid interactions: EV users, aggregators, DSO.

economic aspects. Communication protocols and infrastructure must be deployed for the provision of flexibility services through the effective management and observation of EVs. At the same time, connection agreements must be established between EV users and DSOs through an aggregator. Such contracts grant DSOs control over the EV charging procedure, which can hinder EV mobility needs, potentially meeting lower and higher user acceptance limits [2]. Fig. 2 presents the DSO-aggregator-EV user communication and power flow structure.

A. Minimum EV State of Charge Curve

The minimum SoC curve shown in Fig. 1 represents the scenario in which charging is postponed until time t^L_{ev} – the last time possible to achieve the minimum energy density before departure when the EV charges at maximum power. In terms of flexibility, this curve is important to ensure that user preferences are not violated. This is expressed mathematically in (1), where the difference between the departure time and the calculated charging time (T^{ch}_{ev}) corresponds to the start of the charging process as shown in the right curve of Fig. 1.

$$t^L_{ev} = t^{dep}_{ev} - \overbrace{\frac{E^{min}_{ev,dep} - \underline{E_{ev}}}{\overline{P_{ev}}}}^{T^{ch}_{ev}} \tag{1}$$

B. Upward Flexibility

Upward flexibility is defined as the ability of an EV to increase its charging power during a specific time period, which is highly dependent on its energy availability. As presented in Fig. 1, during the periods when the EV is connected and the charging power is less than the maximum, there was some upward flexibility available (purple arrows). However, since there was an upper bound of the SoC (red dashed line), the flexibility power was also limited by the maximum allowed SoC. The minimum power between those two corresponds to the available upward flexibility:

$$P^{\uparrow}_{ev,t} = min(\overline{P_{ev}} - P^{ch}_{ev,t}, \frac{\overline{E_{ev}} - E_{ev,t-1}}{\Delta T}) \tag{2}$$

C. Downward Flexibility

In this work, a unidirectional (charging) scheme is considered due to the limitations of EV converters to operate in bidirectional power flow and the degradation effect of discharging in the battery system. Therefore, downward flexibility is defined as the ability of an EV to reduce the predetermined charging power (black arrows). Similarly to upward flexibility, downward flexibility is also limited by the minimum allowable EV SoC curve (solid purple line and dashed red line):

$$P^{\downarrow}_{ev,t} = min(P^{ch}_{ev,t}, \frac{E_{ev,t} - E^{min}_{ev,t}}{\Delta T}) \tag{3}$$

III. OPF Modeling Framework

The proposed framework aims to maximize the flexibility services available from EVs. The constraints ensure power balance, compliance with network limits, operation of the DERs, user preferences, and flexibility capabilities of the EV for both full activation of upward or downward flexibility.

A. Objective

$$\max_{P^{ch}_{ev,t}, P_{s,ev,t}} \sum_{\mathrm{ev}\in\Omega^{\mathrm{ev}}} \sum_{t\in\Omega^{T}} \sum_{s\in\Omega^{S}} C_{s,t} \cdot P^{flex}_{\mathrm{s,ev,t}} \tag{4}$$

where $C_{s,t}$ is chosen based on the preferences of flexibility over time. Otherwise, it can be a constant value.

B. Constraints

1) Power Balance: Depending on the maximum upward/downward flexibility to ensure safe operation, two power flow balance constraints must be met at each period. Equations (5)-(6), based on the predicted generation of DER, denote active and reactive power by considering a $cos\phi(p)$ reactive power controller for the DERs. Then, (7)-(8) define the active and reactive power of the EV, also considering the flexibility provision of the EVs while maintaining a constant power factor for EVs. Finally, the power flow balance equations are presented in eqs. (9)-(12). The following constraints are added for each $s \in \Omega^S$, $k \in \Omega^B$ and $t \in \Omega^T$.

$$P^{der}_{k,t} = \sum_{\mathrm{der}\in\Omega^{der}_{k}} \hat{P}_{der,t} \tag{5}$$

$$Q^{der}_{k,t} = \sum_{\mathrm{der}\in\Omega^{der}_{k}} \hat{P}_{der,t} \cdot \tan\left[f_{der}(\hat{P}_{der,t})\right] \tag{6}$$

$$P^{ev}_{s,k,t} = \sum_{\mathrm{ev}\in\Omega^{ev}_{k}} \left(P^{ch}_{ev,t} + P^{flex}_{s,ev,t}\right) \tag{7}$$

$$Q^{ev}_{s,k,t} = \sum_{\mathrm{ev}\in\Omega^{ev}_{k}} P^{ch}_{ev,t} \cdot \tan(f_{ev}) \tag{8}$$

$$P^{inj}_{s,k,t} = P^{der}_{k,t} - P^{ev}_{s,k,t} - \sum_{\mathrm{d}\in\Omega^{d}_{k}} \hat{P}_{d,t} \tag{9}$$

$$Q^{inj}_{s,k,t} = Q^{der}_{k,t} - Q^{ev}_{s,k,t} - \sum_{\mathrm{d}\in\Omega^{d}_{k}} \hat{P}_{d,t} \cdot tan(f_d) \tag{10}$$

$$P^{inj}_{s,k,t} = |v_{s,k,t}| \sum_{\mathrm{m}\in\Omega^{\mathrm{B}}} |v_{s,m,t}| \left(G_{km}\cos\theta_{s,km,t} + B_{km}\sin\theta_{s,km,t}\right) \tag{11}$$

$$Q_{s,k,t}^{inj} = |v_{s,k,t}| \sum_{\mathrm{m}\in\Omega^{\mathrm{B}}} |v_{s,m,t}| \left(G_{km}\sin\theta_{s,km,t} + B_{km}\cos\theta_{s,km,t}\right) \tag{12}$$

2) Network Limits: The branch currents, transformer loading, voltage operational limits and slack bus assumptions for each $s \in \Omega^S$ and $t \in \Omega^T$ take on the form:

$$\underline{v_k} \leq |v_{s,k,t}| \leq \overline{v_k}, \qquad \forall k \in \Omega^B \tag{13}$$

$$|v_{\text{s,slack,t}}| = 1, \quad \theta_{s,slack,t} = 0 \tag{14}$$

$$|I_{s,\text{km},t}| \leq \overline{I_{km}}, \qquad \forall km \in \Omega^L \tag{15}$$

$$\sqrt{(P_{s,tra,t})^2 + (Q_{s,tra,t})^2} \leq \overline{S_{tra}} \tag{16}$$

3) Electric Vehicle Storage: The charging schedule must meet the preferences of the EV user while keeping the charging power within the limits of the hardware capabilities. The following constraints are added for each $ev \in \Omega^{ev}$ and $t \in \Omega^T$.

$$E_{ev,t} = E_{ev,t-1} + P_{ev,t}^{ch} \cdot \Delta T \tag{17}$$

$$\underline{E_{ev}} \leq E_{ev,t} \leq \overline{E_{ev}} \tag{18}$$

$$E_{ev,dep} \geq \underline{E_{ev}} + \kappa_{ev} * \eta_{ev} \tag{19}$$

$$\underline{P_{ev}} \leq P_{ev,t} \leq \overline{P_{ev}} \tag{20}$$

4) Electric Vehicle Flexibility: Flexibility constraints are used to ensure operation within the technical and user preferences limits during flexibility activations (see Sections II-B and II-C). The following constraints are added for each $ev \in \Omega^{ev}$ and $t \in \Omega^T$.

$$P_{s,ev,t} \leq P_{ev,t}^{ch}, \qquad \textit{for } s = 0 \tag{21}$$

$$E_{ev,t-1} + (P_{s,ev,t} + P_{ev,t}^{ch}) \cdot \Delta T \leq \overline{E_{ev}}, \qquad \textit{for } s = 0 \tag{22}$$

$$P_{s,ev,t} \leq \overline{P_{ev}} - P_{ev,t}^{ch}, \qquad \textit{for } s = 1 \tag{23}$$

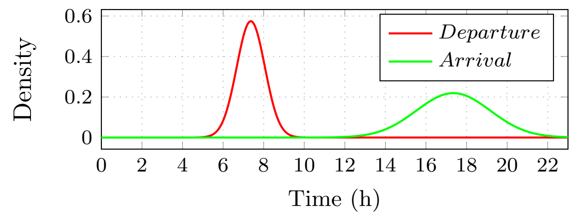
$$E_{ev,t-1} + (P_{ev,t}^{ch} - P_{s,ev,t}) \cdot \Delta T \geq E_{ev,t}^{min}, \qquad \textit{for } s = 1 \tag{24}$$

IV. Case Study Modeling Framework

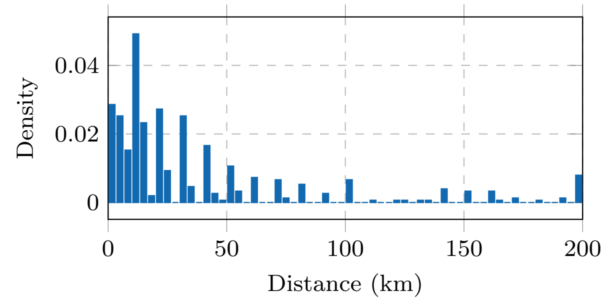
A. EV Modeling and Data

1) Driving Pattern: Understanding driving patterns is crucial to determine both the availability and charging requirements of electric vehicle owners. This information can be acquired through an input directly from the EV user or using historical data collected from the EV, based on which this information can be predicted [14]. Both strategies are implemented through an aggregator agent. In this work departure/arrival time and distance were collected through a survey aimed at car owners who rely on private vehicles for their daily commutes in Cyprus [15]. Fig. 3 shows the probability distribution function (PDF) for departure and arrival times and the distance histogram based on the survey for weekdays.

2) Electric Vehicle Type: The type of EV is essential to convert driving patterns into corresponding charging profiles, requiring knowledge of the average energy consumption and battery capacity of vehicles. Since this information is not readily available for the LV networks under study, average sales data at the European level have been used to assign EV types to each customer, using a probabilistic mass function



(a) Probability density function for departure and arrival time on weekdays



(b) Histogram of traveling distance during weekdays

Fig. 3. Results of survey on driving behaviour of car owners in Cyprus [15]

[16]. The 10 most popular EVs in Europe for 2024 [17], together with their technical characteristics were considered in this study [18].

3) EV Charging Characteristics: The IEC 62196-1 standard outlines four different charging modes from slow AC charging (3.7 kW) to fast DC charging (up to 240 kW) [19]. Based on data provided by the DSO, in Cyprus suburban areas 80% of residential buildings are detached houses equipped with a three-phase power system; therefore, 11 kW charging systems are used for those customers. The remaining (20%) are considered to have a one-phase power system and for those 3.7 kW (one-phase) charging system are considered. In this study, 20% of the customers are considered to use EVs.

B. Basic Household Load Profiles

To formulate the total household load profile, the basic household load profile is combined with the individual EV load profile. The average basic load consumption of 68 residential houses, as provided by the Cyprus DSO, is used to represent the basic load profile. For this case study, May was selected as the month that exhibits the highest difference between the peak generation of DER and the peak load consumption. Consequently, the average load profile for May was used. Moreover, in spring, the Cyprus system has the lowest inertia, thus requiring large amounts of flexibility.

C. PV Generation Profile

Statistical data used to randomly distribute the installed PV power on the rooftop in each residential building based on the probability mass function, as given by Cyprus DSO. The maximum power of the one-phase and three-phase is 4.16 kWp and 10.4 kWp respectively, based on the limits set by the DSO. Due to the geographic proximity of the households, we assume

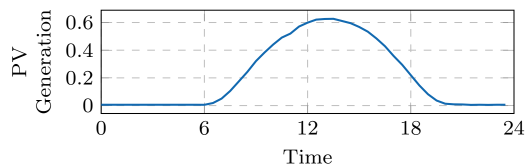


Fig. 4. Average rooftop PV generation profile for May

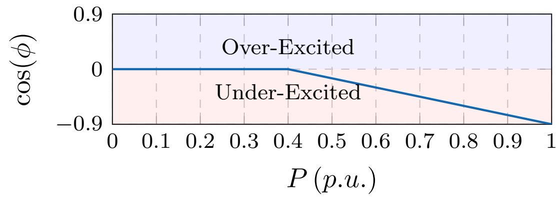


Fig. 5. Power factor variation in function of the change in PV active power production.

that the PV generation profile is the same (shown in Fig. 4) but scaled according to the installed PV capacity. The operation of PVs is according to VDE4105 [20], where DER shall actively control the power factor as a function of the active power output following a piecewise linear active power-power factor characteristic, as depicted in Fig. 5.

D. Distribution Network System Model

The proposed methodology is validated on a realistic symmetric LV distribution network based on data provided from the Cyprus DSO. The DN is considered to be located in a suburban area of Cyprus. The network comprises a substation equipped with an 11/0.4 kV, 315 kVA delta-wye (Δ-Y) transformer. Three radial feeders extend from the substation, with a total of 61 nodes as depicted in Fig. 6. Each feeder serves approximately 30-50 residential customers.

V. Results and Discussions

The optimization problem was solved using the IPOPT solver, which is well-suited for large-scale nonlinear programming. The implementation was carried out using a MacBook Pro equipped with an M4 Pro Max chip, featuring a 12-core CPU and 36 GB of unified memory. The solver successfully converged to a feasible solution in all scenarios tested, and the average computational time for solving the day-ahead scheduling problem was approximately 13 minutes.

A. Flexibility

In Fig. 7, the active power flexibility in each period for all electric vehicles available in the low-voltage network is presented. As explained above, discharging was prohibited; the minus term in the figures was used to represent the postponed charging (decrease of the charging power). It was obvious that the upward flexibility was much more than the downward flexibility since the discharging function was disabled.

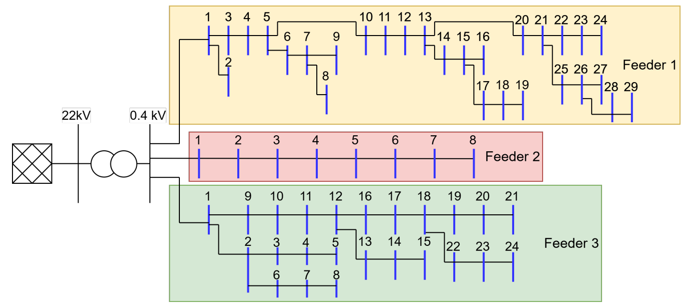


Fig. 6. Single line diagram of suburban distribution network.

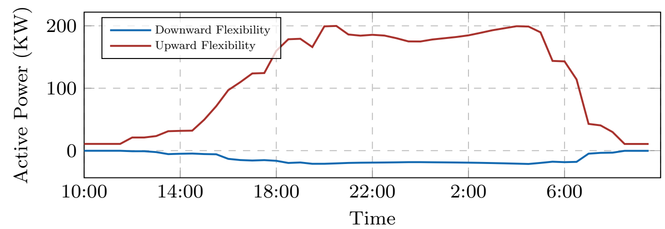


Fig. 7. Aggregate active power flexibility.

As shown in Figs. 8 and 9, the voltage and transformer operation range during maximum upward and downward flexibility activation demonstrates the potential for flexibility utilization of EVs in active distribution grids. In peak load demand hours (around 18:00) there was a maximum voltage deviation around 0.02 p.u. between maximum downward and upward flexibility activation. The upward flexibility during 18:00-05:00 can increase the transformer loading until it reaches the limits, validating the high-power capabilities of EV chargers.

Each distribution network faces different problems based on their location, type of customers, and design structure. The network under study was a suburban network with mainly residential three-phase power supply customers. Those kinds of networks face problems during high generation time periods because of the high reverse power flow and during the early evening when residents return to home, and a sharp increase in the load profile is observed. Although flexibility was impacted by the cost parameter $C_{s,t}$, it was also affected by the connectivity of electric vehicles.

Taking into consideration the above, the results show that during the first stress period (around 12:00-14:00), where overvoltages can occur in DN, the voltage operation range after a maximum activation of the upward and downward flexibility did not present any significant variations. Therefore, flexibility activation cannot provide an important improvement in the voltage profile. In addition, during the second stress period (around 18:00-21:00), when operators observed undervoltage and overload problems, flexibility capabilities was at peak due to high connectivity. Hence, the combination of the ability to schedule the charging process and, at the same time, to utilize the flexibility was a strong tool in the hands of the operators to safely operate the distribution grid in steady-state and emergency situations.

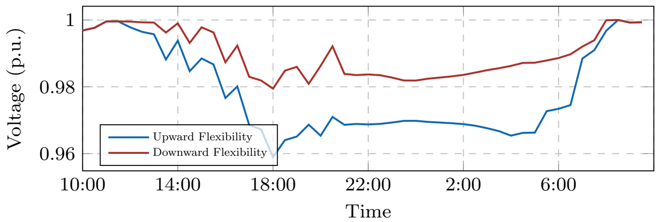


Fig. 8. Minimum voltage after maximum flexibility activations.

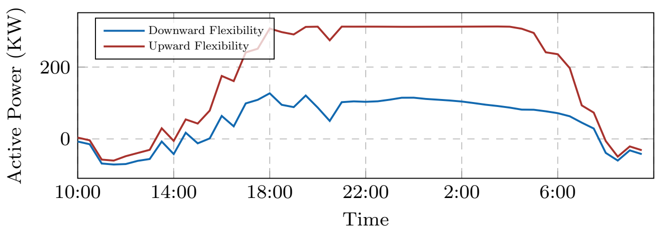


Fig. 9. Transformer loading after maximum flexibility activations.

B. Charging Power

The aggregate charging power of the electric vehicle is presented in Fig. 10. It was obvious that although most chargers have a maximum power of 11kW, the charging power of all electric vehicles does not exceed 21 kW, since the charging process was performed uniformly over time to maximize flexibility.

C. Real-time flexibility activations

As described in the Introduction, the active power flexibility that the system operator can manage in real-time strongly depends on user preferences and DSO actions. For example, if DSO decides to take some upward action in a certain period, then SoC will be affected; this change will reduce the upward flexibility and, at the same time, increase the downward flexibility for the next periods. This adjustment must be made to keep the battery level within the limits; hence, a real-time methodology is needed.

VI. Conclusions

This paper proposes an optimization framework for optimal day-ahead scheduling of EV charging. The main scope is to maximize the flexibility while maintaining the network operation within the limits. The developed optimization framework followed a non-linear OPF structure. The findings indicate that increasing EV adoption is likely to have a good potential for LV network management. However, in peak PV generation periods, there was much lower flexibility available, which may not be enough to avoid overvoltages in suburban networks.

Future work will focus on applying solving approximations to significantly reduce computational costs while maintaining the accuracy of the solution. Additionally, efforts will be directed towards developing a comprehensive algorithm capable of real-time operation. Finally, the operational scheduling algorithm will be enhanced with a more generic framework that will also control DERs and flexible loads.

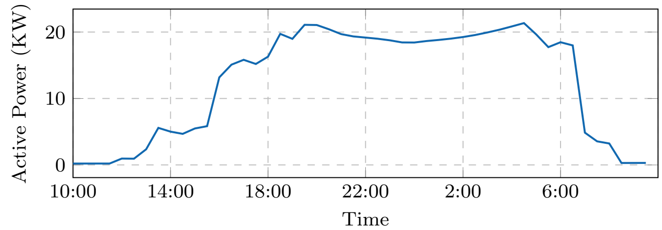


Fig. 10. EV aggregate schedule charging Power

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