Journal of Energy Storage 52 (2022) 104917

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Research papers

Optimal power tracking for autonomous demand side management of electric vehicles

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ARTICLE INFO

Keywords:
Electric vehicle charging
Demand side management
Distribution grids
Peak demand reduction
Power tracking
Unidirectional communication

ABSTRACT

Increasing electric vehicle penetration leads to undesirable peaks in power if no proper coordination in charging is implemented. We tested the feasibility of electric vehicles acting as flexible demands responding to power signals to minimize the system peaks. The proposed hierarchical autonomous demand side management algorithm is formulated as an optimal power tracking problem. The distribution grid operator determines a power signal for filling the valleys in the non-electric vehicle load profile using the electric vehicle demand flexibility and sends it to all electric vehicle controllers. After receiving the control signal, each electric vehicle controller re-scales it to the expected individual electric vehicle energy demand and determines the optimal charging schedule to track the re-scaled signal. No information concerning the electric vehicles are reported back to the utility, hence the approach can be implemented using unidirectional communication with reduced infrastructural requirements. The achieved results show that the optimal power tracking approach has the potential to eliminate additional peak demands induced by electric vehicle charging and performs comparably to its central implementation. The reduced complexity and computational overhead permits also convenient deployment in practice.

1. Introduction

Transition towards e-mobility poses new challenges for the operation of electricity networks and especially for the distribution grids. The uncoordinated and random charging activities could significantly stress the distribution system causing increased peak demands, severe voltage fluctuations, increased losses, increased transformer and cable ageing, sub-optimal generation dispatch, degraded system efficiency and economy, as well as increasing the likelihood of blackouts due to network overloads [1–4]. These undesirable impacts can be mitigated by proper coordination of EV charging with demand response strategies. Electric vehicle (EV) loads offer high temporal flexibility since they are available for charging over prolonged periods of time. Therefore, the flexibility of the EV demand can be exploited to improve the operation of distribution networks through various load management strategies with the objective to provide valley filling and/or peak shaving services, reduced distribution network losses, reduced ageing of transformers and lines, and increased renewable energy penetration [5,6].

The integrated functions of smart grids in the domains of communication, networking, monitoring and advanced control enable automated energy management systems. These systems result in improved load management and energy efficiency [7]. Decentralized autonomous demand side management (ADSM) is one such management strategy in which the computations are distributed over the respective participating appliances. Scalability due to the reduced dimension of the associated optimization problems permits it to be feasible even at high EV penetration. These features, in conjunction with the reduced communication requirement, render decentralized ADSM a cost-efficient solution for EV charging management compared to the centralized ADSM approaches [8]. In literature, ADSM strategies for EV charging are proposed to reduce the detrimental impacts for the grid operation, many of which have been focused on flattening the load curve. Although the EV scheduling is determined locally, existing approaches often need bi-directional communication between a central entity and the EVs.

Ma et al. [9] propose a decentralized non-cooperative game theoretic approach for the charging management of an infinite homogeneous Plug-in electric vehicle (PEV) population, where the PEVs are coupled

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https://doi.org/10.1016/j.est.2022.104917
Received 7 October 2021; Received in revised form 8 April 2022; Accepted 15 May 2022
Available online 26 May 2022
2352-152X/

Nomenclature

ADSM	autonomous demand side management
DSO	distribution system operator
ESS	energy storage system
EV	electric vehicle
LV	low voltage
OPF	optimal power flow
OPT	optimal power tracking
PEV	plug-in electric vehicles
SOC	state of charge
TOU	time of use
C_j^B	battery capacity of the jth EV (kWh)
E	total energy requirement of the EVs for a given time frame for driving (kWh)
E_{avg}	average energy consumption of an EV during driving (kWh/km)
E_j	energy requirement of the jth EV for the optimization time window (kWh)
$E_{j,s}$	energy requirement of the jth EV at time s for driving (kWh)
N^{EV}	number of EVs in the grid
N^T	number of time steps
D	aggregated non-EV load profile for a given time frame (kW)
D_t	aggregated base load power at time t (kW)
$P_{j,t}$	charging power of the jth EV at time t (kW)
$P_{j,max}$	charging power of the jth EV at time t (kW)
$P_{j,\,t}$	maximum charging power of the jth EV (kW)
$P_{j,min}$	minimum charging power of the jth EV (kW)
R_{max}	maximum driving range of an EV (km)
S_t	broadcasted power signal at time t (kW)
S_t^+, S_t^-	positive and negative parts of the broadcasted power signal respectively at time t (kW)
$S_{j,\,t}^+$	tracking signal for the jth EV at time t (kW)
$SOC_{j,\,0}$	initial SOC of the jth EV (%)
$SOC_{j,\,t}$	SOC of the jth EV at time t (%)
$SOC_{j,\,max}$	maximum SOC of the jth EV (%)
$SOC_{j,\,min}$	minimum SOC of the jth EV (%)
Z	valley fill level (kW)
Δt	time step (s)
$\eta_{j,c}$	charging efficiency of the jth EV

through a common price signal. The method aims to minimize the generation cost through valley filling using the aggregated PEV demand. The utility collects the individual charging schedules of all the EVs and broadcasts the updated total demand (aggregated EV demand and non-EV demand). Each of the EVs determines its optimal charging schedule to minimize the cost and reports back to the utility. A penalty is imposed if the charging schedule of an EV deviates from the average changing schedule of the population. The process is iterated until the charging strategies are in Nash equilibrium.

In contrast, an iterative optimal decentralized protocol to achieve valley filling for both homogeneous and heterogeneous EV fleets is suggested by Gan et al. [10]. The utility determines and broadcasts a control signal (e.g. electricity price) to incentivize the EVs to shift their electricity consumption to the time slots with lower demands. In response, the EVs update their schedules to minimize the total electricity cost and the penalty for deviating from the previous iteration, and report them back to the utility. The utility progressively guides the EVs by altering the control signal in response to the received EV schedules.

Although both the methods in [9,10] achieve the objective of the load valley filling, they suffer from the longer execution times due to the iterative nature.

In contrary, Binetti et al. [11] propose a decentralized non-iterative real-time EV charging strategy to shift the charging to night valleys. The algorithm sequentially determines the charging schedules of each EV taking into account an estimate of the non-EV load for the planning horizon. Each time when an EV connects, it receives the aggregated load profile from the Distribution system operator (DSO). With this information, EV solves an optimization problem locally to achieve valley filling and reports obtained schedule to the DSO. The DSO updates the aggregated load profile with the newly received charging schedule and whenever a new EV connects, the updated aggregated load profile is communicated. Although the method is decentralized and requires limited information exchange, it necessitates a bi-directional communication channel between the grid operator and the EVs. And there exists the risk of forming adverse second peaks if a large number of EVs grid-connect at the same time [12].

A decentralized offline valley filling algorithm for EV charging, solving a joint optimum power flow (OPF)-EV problem is presented by Chen et al. [13]. In addition, the authors also present a decentralized online algorithm that dynamically tracks the valley filling characteristic. In the online algorithm, the utility broadcasts the valley level to all EVs in a given time step, and each EV computes its charging rate locally to track the received valley level and reports its schedule back to the utility. Afterwards, the utility updates the next valley level based on the collected charging schedules. The results indicate that the proposed decentralized online method achieves near optimality. However, the authors consider only a small set of EVs (9 EVs) in the results presented. But at high EV penetrations, the results may not achieve the valley filling due to simultaneity in charging.

Nimalsiri et el. [14] propose a decentralized method for EV charge scheduling by exploiting the notion of water-filling to track a forecasted energy generation profile. The charge profile of each EV is determined one at a time at the plug-in time of the EV. Upon receiving the expected aggregated demand profile and the energy generation profile from the operator, a given EV determines its' charging profile locally to track the generation profile and sends it to the operator. Then the aggregated demand profile is updated with the received charging profile. The simple arithmetic operations applied to the classical water filling algorithm, facilitates easily integration into local controllers.

All these decentralized approaches [9–11,13,14] achieve a flattened load profile through managing EV charging. Although EV scheduling is decentralized, all of these methods require bi-directional communication.

In contrast to the decentralized methods proposed in the literature, we are interested in developing ADSM methods of energy storage systems (ESS) in distribution grids which only require a unidirectional communication channel owing to the advantages of reduced communication infrastructure and computational burden [15,16].

Decentralized approaches based on unidirectionally communicated pricing signals for EV charging management are discussed in the literature, but are analysed insufficiently. Cao et al. [17] propose an intelligent method to control EV charging loads in response to a TOU price in a regulated market to minimize the charging cost. However, they only analyse the mass of energy shifted to the valley periods and do not examine the effects of simultaneous charging for grid operation during valley periods. We investigated the potential of ADSM with pricing signals for EVs charging with electricity market price as the signal communicated in our previous work [18]. The results show that it leads to unfavorable distribution grid operations and tends to form a new peak during the off-peak triggered by the low electricity prices.

Vay and Anderson [19] describe a price-based decentralized approach for the ADSM of EVs. The method aims to determine the time-of-use (TOU) tariff that minimizes the charging cost without overloading the assets. The individual vehicles optimize their charging based on this TOU tariff. Two variants of the proposed approach have been examined: one with a system-wide tariff and the other with different tariffs at different nodes. The decentralized approach with system-wide prices leads to high simultaneity in charging, therefore does not lead to a smooth load profile. Although the decentralized approach with nodal prices results in a load profile close to perfect valley filling, it is problematic to set different prices for different groups of EV customers.

In previous research, we propose that with unidirectional communication, power signals are more efficient than pricing signals for exploiting the demand side flexibility [20]. The objective of this study is to control the demand side flexibility of EV loads using a unidirectionally communicated power signal to achieve a flattened demand curve at the distribution grid level. The main contributions of the paper are listed below.

- We propose an autonomous decentralized, hierarchical algorithm for exploiting EV flexibility. The proposed method achieves valley filling by optimally tracking a power signal. The solution to the tracking problem is formulated as a convex optimization which demands reduced computational overhead and communication contrary to the methods reported. Therefore, it can be easily integrated into an embedded local controller attached to charging infrastructure and is also suitable for high EV penetrations due to its scalability.
- A load flow simulation of a distribution grid is conducted to evaluate the impact of the proposed optimal power tracking (OPT) based ADSM method on the grid operation. Most of the relevant literature analyse the power balance and often lack the investigation of performance indicators in relation to the grid operation. In contrast, we further analysed the performance indices including the grid voltage, line overloading and power losses to provide a better insight into the grid operation.
- The evaluation is performed over a wide range of EV penetrations to demonstrate the impact of the method on grid operation and computational costs for varying EV densities.
- A benchmark centralized solution is provided to evaluate the computational advantages (computational costs and scalability) of the proposed decentralized solution.
- A comparison on the charging rates and the average charging times between the centralized and decentralized solutions is discussed. This illustrates the impact of the ADSM on the EV charging time, so far not reported in literature.

The rest of the paper is organized as follows: In Section 2, we present the formulation of the optimization problem and in Section 3 we show the simulation framework we used including the models of different elements in the grid model. Section 3 includes the results representing the performance indicators used for the comparison followed by the conclusion in Section 5.

2. Approach

In this paper, we proposed an ADSM for EV charging management by tracking a power signal hence referred to as OPT. The solution to the tracking problem is formulated in a decentralized form to enable easy integration to embedded controller at the EV charging infrastructure. The objective of the proposed decentralized ADSM approach is to charge the EVs such that the aggregated non-EV load and the EV charging load profile is flattened as much as possible. We assume that the non-EV loads have no flexibility for demand response and are only interested in the potential of ADSM in EV load. Charging schedules of the EVs are determined to fill the valleys of the non-EV load profile, thereby achieving a load profile as flat as possible. We do not consider V2G within the scope of this study.

We formulate the proposed OPT problem in a two-layer structure and the overall concept is presented in Fig. 1. In the first layer as depicted in Fig. 1(a), the power signal to be tracked is determined by a central entity using two estimates: 1) the forecasted non-EV load profile D 2) the predicted aggregated EV demand E. Forecasting aggregated EV demand can be justified by the multiple methods proposed in the literature, some of which are k-nearest neighbor, pattern sequence algorithms, lazy learning algorithms, auto-regressive integrated moving average methods, modified pattern-based sequence forecasting methods etc. [21]. Short-term aggregated load prediction is realized in the literature using statistical based methods such as linear regression, auto-regressive integrated moving average and seasonal decomposition or artificial intelligence methods such as bio-inspired/evolutionary computational methods, neural networks techniques, support vector regression, machine learning, deep learning, agent-based systems [22].

The solution to the classical water filling problem [23] is used to determine the constant power level (fill level) Z, to optimally allocate the EV charging demand over the time steps of the planning horizon. The fill level Z is obtained by solving,

$$\sum_{t=1}^{N^{\mathrm{T}}} max\{(Z-D_t),0\}\Delta t = E, \tag{1}$$

for Z. The power signal S_t which is broadcasted to all the EVs is the difference between the non-EV load profile and the valley fill level Z at each time interval, i.e.,

$$S_t = Z - D_t. \tag{2}$$

The second layer of the OPT approach includes the local control mechanism where each local controller attached to EVs firstly determine the positive part S_t^+ and the negative part S_t^- of the received power signal S_t. Then the signal S_j^+ is scaled as given in Fig. 2(b) with the purpose of obtaining the signal to be tracked by the jth EV using a prediction on the required energy demand of the jth EV, i.e.,

$$S_{j,t}^+ = \frac{E_j}{\sum_{t=1}^{N^T} S_t^+ \Delta t} S_t^+. \tag{3}$$

Each EV tracks $S_{j,\ t}^+$ with minimal deviation. Hence, we refer to the approach proposed as Optimal Power Tracking. When individual EVs track the locally scaled global signal, the aggregated effect leads to a flattened global load profile at the transformer. The OPT approach only requires the predicted non-EV load profile D at the transformer and the total aggregated EV demand E at the central entity. The information related to the EV (SOC, availability, arrival and departure times, usage, specifications etc.) is required locally, therefore sensitive EV information is not communicated to a central entity unlike in the other bidirectional based optimization approaches. The predictions of the EV specific information can be realized either using traditional statistical models such as time series method, auto regressive integrated moving average, regression analysis, Kalman filtering etc. or artificial intelligence methods such as artificial neural networks, support vector machines, and deep learning methods [24].

Within the scope of our study, we present the deterministic solution to the scheduling problem assuming the perfect predictions to establish the feasibility of the optimum power tracking based decentralized ADSM method.

2.1. Decentralized OPT based EV charging

Formulating the OPT problem as a quadratic problem is straightforward, but leads to a computationally expensive implementation. Therefore, we propose a formulation as a linear problem which can be easily integrated into a simple embedded hardware attached to EV charging infrastructure.

The charging schedule for the jth EV is determined by solving the L1-Norm, non-linear optimization problem

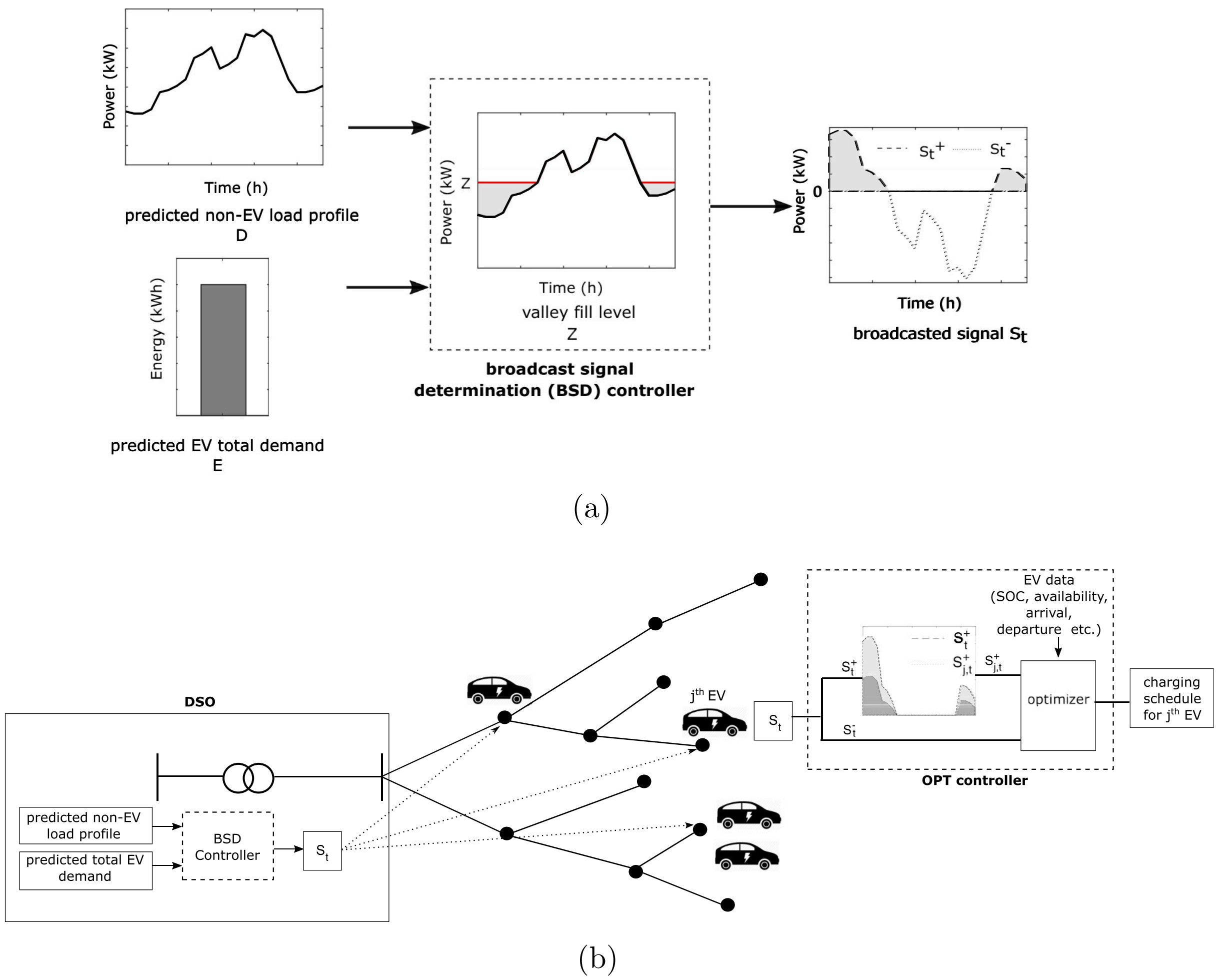

Fig. 1. OPT concept: (a) broadcast signal determination (BSD) controller for determination of the broadcasted power signal using the valley fill level Z based on the predicted non-EV load profile D and the total EV energy demand for the optimization horizon E (b) localized OPT controller for decentralized EV charging scheduling.

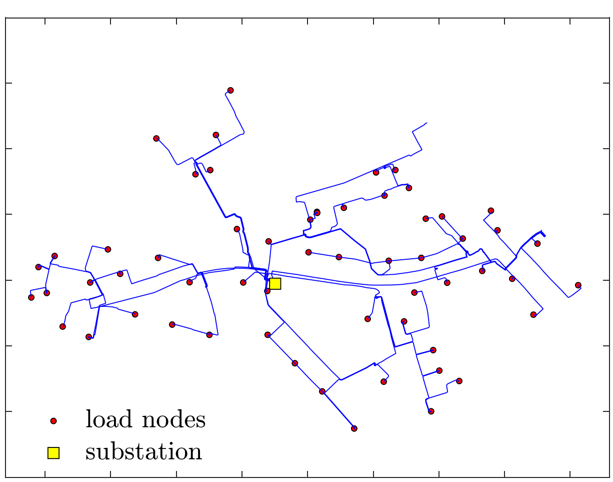

Fig. 2. Low voltage distribution grid.

$$min \sum_{t=1}^{N^{T}} \left(\left| S_{j,t}^{+} - P_{j,t} \right| \left(1 + S_{t}^{-}\right) + \left| P_{j,t+1} - P_{j,t} \right| \right) \Delta t \ \text{ s.t.} \tag{4}$$

$$P_{j,min} \leq P_{j,t} \leq P_{j,max} \quad \forall t, \tag{5}$$

$$SOC_{j,min} \leq SOC_{j,t} \leq SOC_{j,max} \quad \forall t, \tag{6}$$

$$P_{j,t} = 0 \quad \text{for } t, \text{where the EV is not at home.} \tag{7}$$

The charging rate of the EV can be varied continuously within the upper and lower limits given by the constraints (5). Constraints defined in (6) guarantee that the SOC of the EV battery always remains within the upper and lower operational bounds. The constraint defined in (7) is used to ensure that the charging of the EV occurs only when it is available at the point of charging, thus optimization of the charging at public charging infrastructure is not considered. The SOC of the jth EV at time step t is calculated by

$$SOC_{j,t} = SOC_{j,0} + \frac{1}{C_j^{\mathrm{B}}} \left\{ \sum_{s=1}^{t} \eta_{j,c} P_{j,s} \Delta t - \sum_{s=1}^{t} E_{j,s} \right\}. \tag{8}$$

Note that charging and discharging of a given EV do not occur simultaneously.

The negative part S_t^- of the broadcasted signal S_t is merely used as a weighting factor and serves as a penalty for charging activities during high demand periods of the non-EV load profile. The term $|P_{j,\,t+1} - P_{j,\,t}|$ in (4) is included to avoid high charging rates during deep valley periods. As the aggregated effect might lead to power spikes during deep valley periods, the term penalizes high gradients in charging.

The optimization problem (4) is non-linear in its original form but can be reformulated to an equivalent linear form by adding the auxiliary variables $a_{j,t}$, $b_{j,t}$ rewriting the objective function as in (9), and adding the constraints (10)–(13).

$$min \sum_{t=1}^{N^{T}} \left[a_{j,t} \left(1 + S_t^{-} \right) + b_{j,t} \right] \Delta t \quad \text{s.t.} \tag{9}$$

$$-a_{j,t} \leq S_{j,t}^{+} - P_{j,t} \leq a_{j,t} \quad \forall j, \forall t, \tag{10}$$

$$-b_{j,t} \leq P_{j,t+1} - P_{j,t} \leq b_{j,t} \quad \forall j, \forall t, \tag{11}$$

$$a_{j,t} \geq 0 \quad \forall j, \forall t, \tag{12}$$

$$b_{j,t} \geq 0 \quad \forall j, \forall t. \tag{13}$$

2.2. Centralized OPT based EV charging

The centralized implementation of the problem for scheduling EVs to achieve valley filling by tracking a power signal defined in Section 2.1, is performed to provide a comparative assessment to the decentralized implementation. In the centralized solution, the aggregated charging power of all the EVs available for charging should track the power signal S_t^{+}. The objective function of the centralized solution is given by,

$$min \sum_{t=1}^{N^{T}} \left(\left| S_t + - \sum_{j=1}^{N^{EV}} P_{j,t} \right| \left(1 + S_t^{-} \right) + \sum_{j=1}^{N^{EV}} P_{j,t+1} - \sum_{j=1}^{N^{EV}} P_{j,t} \left| \right. \right) \Delta t \tag{14}$$

subjected to the constraints (5)–(7).

2.3. Uncontrolled EV charging

As a benchmark, we simulate the uncontrolled EV charging scenario where the EVs start charging at maximum charging rate as soon as they arrive at the point of charging until fully charged. This case gives a general understanding of the effects of increasing EV penetration levels in the distribution grids. It also serves as a benchmark to understand the potential improvements in the distribution grid operation with the proposed OPT algorithm.

3. Case study

Most of the related research in literature having the objective of valley filling focuses only on the power balance and the impact on the peak demand. Other performance indicators related to grid operations such as line load, power losses and voltage drops are equally important, yet often left non-assessed. We performed load flow simulations of a distribution grid in our study to assess these indicators. This section describes the framework including different grid elements which we used for the load flow. The load flow simulation uses the backward forward sweep flow method as proposed by Ghatak and Mukherjee [25]. The simulation tool is implemented in MATLAB® [26] and it serves as an interface to test different optimization algorithms for different demand response devices, in our case EVs [27]. The OPT linear optimization problem is solved using the MATLAB® optimization toolbox. We conducted simulations over a week with a time resolution of 15 min. The selected week was chosen from the winter season as it exhibits a higher demand with respect to other seasons. The optimization problem is solved every 24 h at noon, taking into account the forecasts for the next 36 h. We consider overlapping time windows for the optimization, to ensure that the SOC of the vehicle is always within the limits guaranteeing the energy required for the driving is delivered without failure.

3.1. Distribution grid

Fig. 2 shows the geographical representation of the low voltage (LV) grid located in Austria which is used in this study. The data used to model the grid including information of the distribution transformer, loads (location, load type, annual energy consumption), topology (connectivity, cable type, length), were provided by the local DSO, Vorarlberger Energienetze GmbH [28]. The simulated LV distribution grid comprises a 800 kVA, 10/0.42 kV step down 3-phase transformer with 52 load nodes and 103 distribution lines. The grid supplies 490 residential consumers, 9 business units and 77 other consumer units which include heat pumps, public facilities, etc. Data related to the annual energy consumption for each consumer was also made available by the local DSO. The grid simulation was conducted considering the LV side of the transformer as the slack node with a reference voltage of 1 p.u.

3.2. Non-EV load profiles

The load profiles for the residential consumers were represented by real smart meter data from a field test of the local energy provider illwerke vkw AG (VKW) [29] with a temporal resolution of 15 min. The smart meter data of 351 households over one year was used. A database for the residential power profiles was set after pre-processing the data. Then, the smart meter data were assigned to residential consumers by mapping the annual energy demand. For the non-residential loads, the standard load profiles of the Austrian clearing and settlement agency [30] were used. These standard profiles were scaled according to the annual energy consumption of the particular consumer unit. A power factor of 0.96 was selected.

3.3. EV model

In this study, the dynamic behaviour of the EV battery is considered to be linear as expressed in (8). In modelling the electric vehicle, we used the specifications for the Nissan Leaf as summarized in Table 1.

We assume that the charging infrastructure is equipped with a 3-phase 400V/16 A semi fast charger with a maximum charging power of 11 kW having a charging efficiency ηc of 0.9.

3.4. Mobility profiles

We used the Austrian mobility survey “Österreich unterwegs 2013/2014” [31] to simulate the usage behaviour of the EVs. It contains the travel details of different modes of transport including the arrival and departure time, distance driven, the purpose of the journey and the day of the week. Only the motor vehicles having private related journeys were considered. Statistical filtering techniques were used to remove inconsistencies. The journeys with distances exceeding the maximum range $R_{\max}$ of the selected type of the EV were excluded. The specific energy consumption for a unit time step was calculated using the driving distance and duration, assuming an average energy consumption E_{avg} of 0.15 kWh/km. The generated driving profiles contain the energy consumption of the given vehicle at each time step and the availability at the point of charging. Only the charging of the vehicles at the private charging infrastructure was considered. The difference between weekday and weekend trips was also taken into account in generating the EV

Table 1
EV model specifications.

η_c	0.9
C^B	24 kWh
E_{avg}	0.15 kWh/km
SOC_{max}	90%
SOC_{min}	30%
R_{max}	160 km

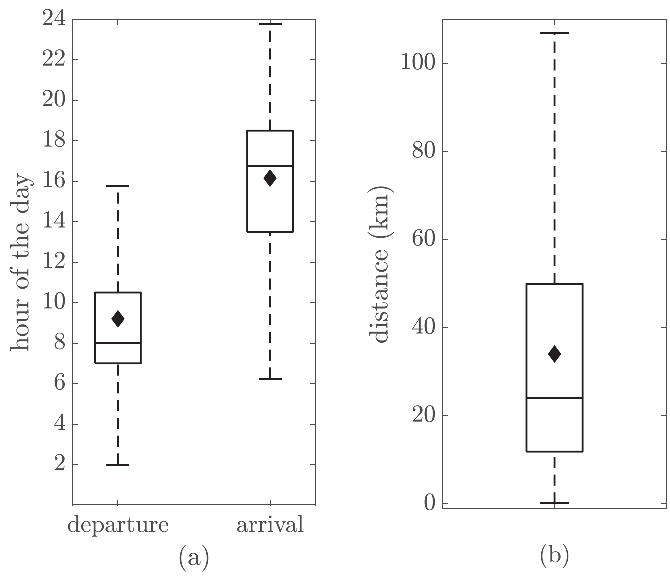

Fig. 3. A summary of the mobility profile statistics representing arrival times, departure times and daily travel distance. (a) The box plots representing the arrival and departure times for the EV profiles used in the simulation. (b) The box plot representing the daily travel distances of the EV profiles used in the simulation.

usage profiles. A total of 15,320 profiles for weekday travels and 6460 profiles weekend travels were generated for the EV user behaviour database. A summary of the mobility profiles including the arrival times, departure times and the daily travelled distances are shown in Fig. 3. The selected mobility profiles have a mean departure time of 09:20 and a mean arrival time of 16:15. The mean distance travelled by a vehicle is 34 km.

We defined the penetration rate as the number of EVs per total number of consumer units. With a penetration rate of 100%, 490 private EVs are considered to be grid-connected. We considered ten different progressively increasing penetrations. The assignment of the EVs to nodes at a given penetration rate was random and EVs were added progressively to maintain consistency. The geographical representation of the locational details for the range of EV penetrations is shown in Fig. A1, in the Appendix A.

4. Results

All the Matlab simulations were run on a server with an Intel(R) Xeon (R) CPU E5-2630 v3 @2.40 GHz processor and 31 Virtual CPUs. Load flow simulations for the considered distribution grid over a week were conducted for ten different EV penetrations (10%–100%, in steps of 10%) for the three scenarios; uncontrolled, centralized OPT and decentralized OPT. In addition, a benchmark case with no EVs is considered which is represented as 0% penetration case. This section includes a comparison of the outcomes for the above three scenarios and the benchmark scenario with no EVS. We used the minimum voltage of the nodes, maximum loading of the lines, total power losses in the lines, peak power at the grid transformer and peak to average power ratio as the indicators to evaluate the impacts on grid operation. As EV penetration increases, the dimension of the state variables in the central OPT becomes very high, making the memory requirements of the optimization problem prohibitive. Given the limited computational capacity, the centralized OPT solution to the scheduling problem is implemented only up to an EV penetration of 40%. A comparison of the execution times for the centralized and decentralized implementations is also presented.

We compared the valley filling capability of the proposed decentralized OPT algorithm against its central implementation. Fig. 4 shows the power profile at the distribution transformer at 40% EV penetration on an example winter day, where the two OPT scenarios and the uncontrolled scenario are compared. In the event of uncontrolled charging, the charging time of the EVs coincides with the peak demand period of the non-EV load profile. Caused by the high simultaneity of the charging events in the uncontrolled scenario, the peak demand in this example case increases from 380 kW to 515 kW. Both the OPT algorithms shift the charging of the EVs to valley hours as they try to follow the reference signal as much as possible. With the decentralized OPT solution, individual EVs track the scaled reference power signal locally, and the aggregated result eventually leads to a flattened load curve. During the daytime and the early morning hours, OPT fails to follow the tracking signal, mostly due to the absence of the EVs at the point of charging. Nevertheless, the constraints defined in the optimization problem always guarantee that the SOC of the EVs remain within the specified limits and fulfil the driving requirements. To benchmark the effectiveness of tracking the reference signal, we computed the mean absolute deviation (MAD) between the valley fill level Z and the total demand

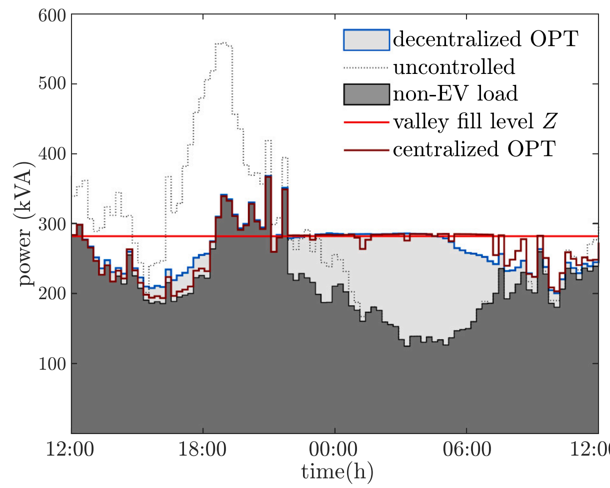

Fig. 4. Power variation at the distribution grid transformer at 40% EV penetration on an example winter day for centralized OPT, decentralized OPT and uncontrolled charging scenarios.

$$MAD = \frac{1}{N^{\mathrm{T}}} \sum_{t=1}^{N^{\mathrm{T}}} |Z_t - \left(D_t + \sum_{j=1}^{N^{\mathrm{EV}}} P_{j,t} \right)|, \tag{15}$$

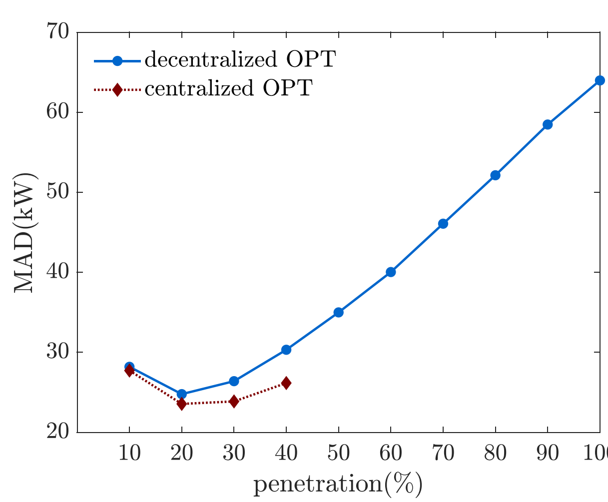

Fig. 5. Mean absolute deviation between the valley fill level Z and the total demand for the centralized and decentralized OPT scenarios.

for the centralized and decentralized OPT scenarios which are shown in Fig. 5. As depicted in Fig. 5, the centralized OPT performs better in realizing the objective of tracking the reference power signal. However, the insignificant discrepancy between the two confirms that the decentralized OPT even with less information exchange is capable of yielding a comparable result to the centralized OPT, offering a compelling alternative to centralized OPT.

To provide a more concise summary of the results, we compare the impact of the two OPT algorithms on the aggregated demand profile for the different penetrations considered in Fig. 6(a). The peak load in the uncontrolled scenario increases with increasing penetration and exceeds the rated capacity of the transformer at an EV penetration of 90%. The peak load in both the OPT scenarios always stays well below the transformer capacity and remains almost the same for all the penetrations considered. OPT achieves this by avoiding EV charging during peak hours and by regulating the charging rates during the valley hours to stay below the valley fill level *Z*. In this manner, both OPT scenarios are capable of reducing the stress on the distribution grid transformers that could be caused by random charging. Most interestingly, decentralized OPT solution with lower computation complexity is also capable of realizing comparable results as the centralized solution at all the EV penetration ranges. These results are also reflected in the peak to average power ratio(PAPR) as depicted in Fig. 6(b).

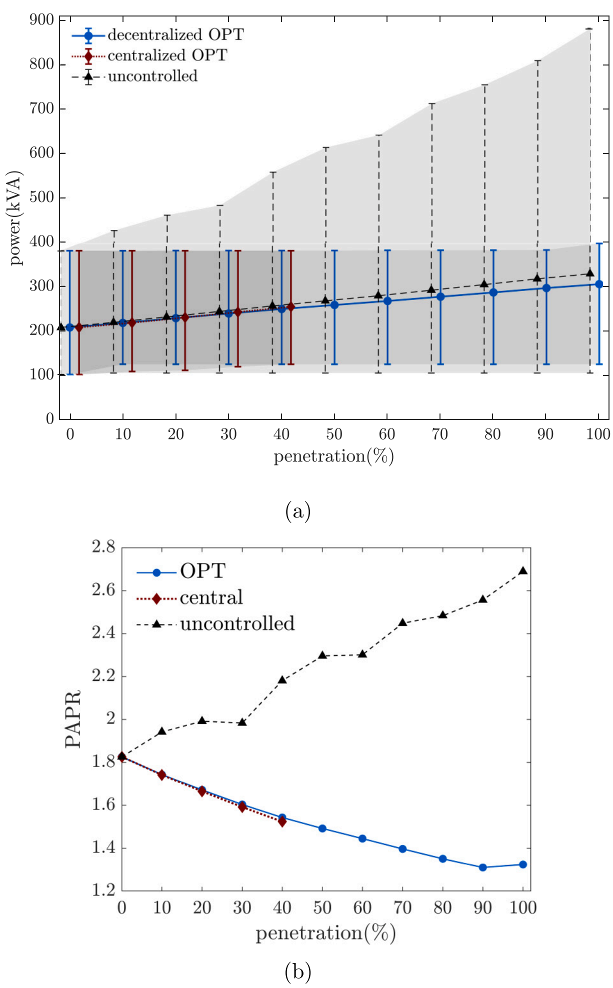

Fig. 6. (a) Bar chart indicating peak, mean and the minimum power at the distribution grid transformer for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season. (b) The peak to average power ratio (PAPR) for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

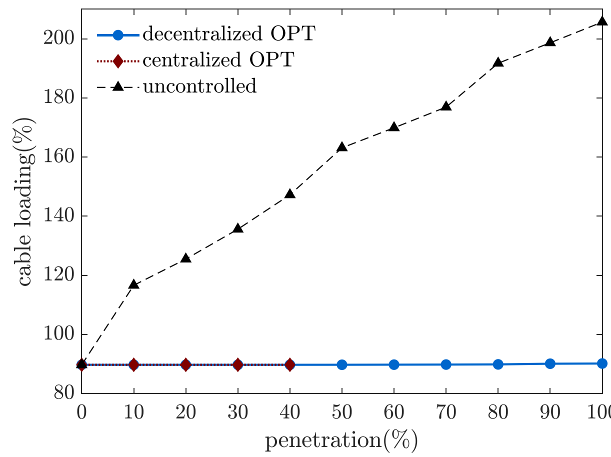

Fig. 7. Maximum resulting cable loading of the distribution cables for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

Uncontrolled charging can lead to high current flows in the distribution cables and may even exceed their rated current limits. To assess the impact of different scenarios considered towards the current flow of the cables, we analysed the degree of the loading on the cables; defined as the percentage ratio between the current flow and the rated current of a cable. Fig. 7 shows the comparison on the maximum loading of the grid cables over a week for the three scenarios at different penetrations. The cable loading exceeds the permissible limits even at 10% penetration in case of uncontrolled charging. However, with both OPT scenarios, the observed maximum cable loading remains the same and does not exceed the permissible limits even at high penetrations. Therefore, OPT supports the integration of EVs into distribution grids and reduces the requirement of cable enhancements. Table 2 provides an overview related to the number of cables exceeding the rated capacity in the simulated week for the uncontrolled charging scenario. For both OPT scenarios, no violations in the cable overloading are observed over all the penetrations.

Compliance of the permissible voltage ranges specified in the standards such as ANSI C84.1 is a mandatory requirement for the operation of the distribution grids. The uncontrolled charging can lead to unacceptable voltage drops and cause violation of the specified standards. As shown in Fig. 8, at penetrations above 80%, the minimum voltage of the grid nodes over the simulated week falls below 0.9 p.u. and cause violation in the voltage standards. In OPT scenarios, the minimum nodal voltages do not fall below the standard limits even at high EV penetrations. Therefore it is evident that OPT not only mitigates the peak power problems but also any probable voltage quality problems. A summary of the voltage violations in the uncontrolled scenario is given in Table 2.

Fig. 9 presents the total power losses in the distribution cables over the selected week. The OPT scenarios result in lower total power losses

Table 2
Voltage violations and line overloading for uncontrolled charging, eliminated in OPT scenarios.

Penetration	$N^{\text{Nodes}}_{V<0.9}$	$N^{\text{Lines}}_{\text{loading}>100\,\%}$
10	–	2
20	–	2
30	–	2
40	–	5
50	–	8
60	–	8
70	–	8
80	–	10
90	2	10
100	3	13

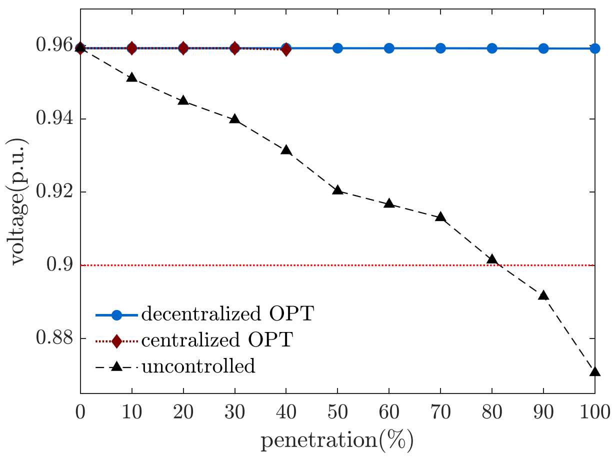

Fig. 8. Minimum nodal voltage in the distribution grid transformer for the decentralized OPT, centralized OPT and uncontrolled charging scenarios for a period of a week in winter season. The dotted straight line represents the lower tolerance boundary of voltage.

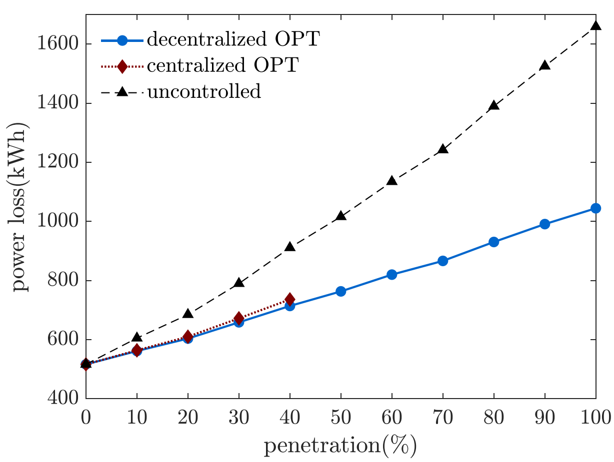

Fig. 9. Total power losses in the distribution cables for the decentralized OPT, centralized OPT and uncontrolled charging scenarios over a period of a week in winter season.

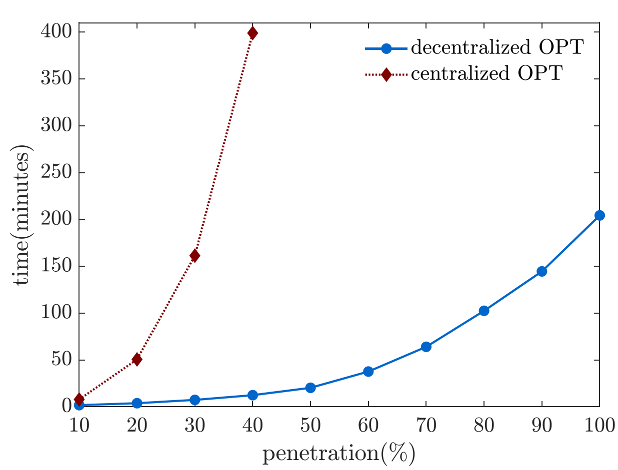

Fig. 10. Computational costs to solve the load management problem for the decentralized OPT and centralized OPT scenarios for a period of a week.

compared to the uncontrolled scenario due to the distribution of the charging events over time which in turn leads to distribution of currents over time. At 100% penetration, the decentralize OPT limits power losses nearly to half from that of the uncontrolled scenario. As such OPT also contribute to improve the efficiency of the grid operation.

The key indicators presented above concerning the grid operation, clearly indicate that the decentralized method performs as good as the centralized equivalent, despite the reduced information exchange. Furthermore, the execution time between the two methods exhibits a clear difference as depicted in Fig. 10. As can be seen in the plot, even at 40% penetration the simulation time for the centralized implementation is around 400 min. The memory requirement for the optimization of the central OPT is very high due to the increasing number of state variables at high penetrations making it debatable for practical implementations. In our simulation, the optimization of the individual EVs are performed sequentially, but in practice this process will be performed in parallel. Hence, the simulation time will be even lower than the values indicated in Fig. 10.

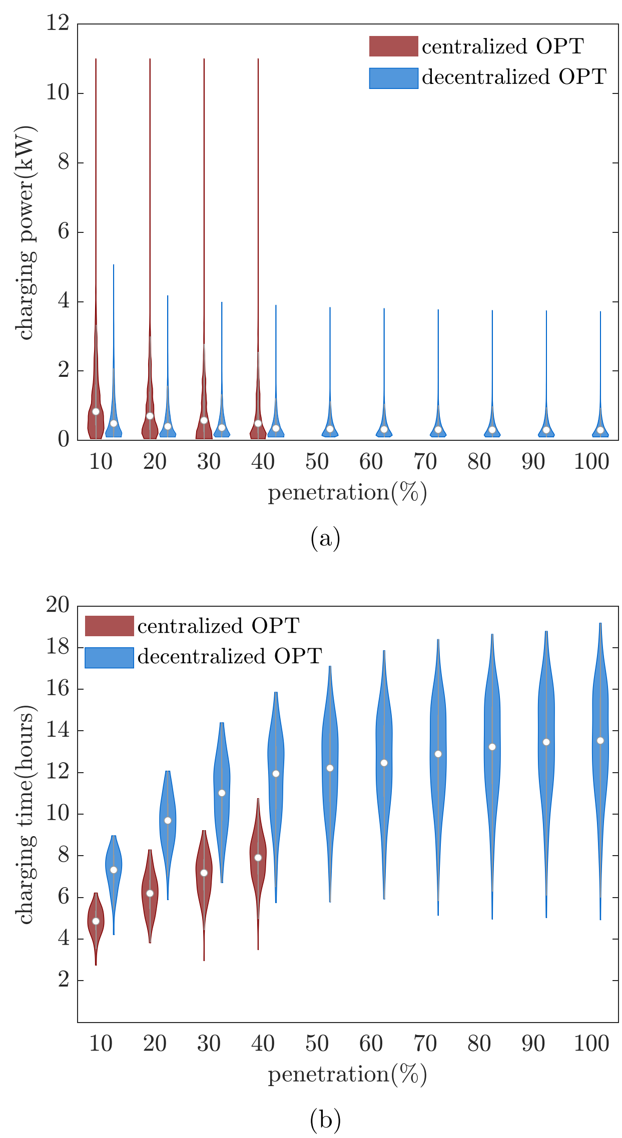

Fig. 11. Comparison of the charging rate and the average charging time between the centralized and decentralized OPT implementations over the range of penetrations (a) charging rate for the decentralized OPT and centralized OPT scenarios for a period of a week. (b) Average charging time per day for the decentralized OPT and centralized OPT scenarios for a period of a week.

Fig. 11 shows a comparison of the charging rates and the average charging time per day over the simulated week for the centralized and decentralized OPT implementations over the range of penetrations considered. The charging rate of the decentralized implementation is lower compared to that of the centralized implementation. This is attributed to the loss of global information on the EV data in the decentralized implementation. Consequently, average charging time is higher in the decentralized OPT compared to central OPT as can be seen in Fig. 11(b). Despite the lower charging rates, the decentralized OPT complies with the demanded energy delivery to all the EVs as in the decentralized OPT.

The results reveal that the uncontrolled charging of EVs leads to increased peak demands, voltage violations, cable overloading and higher power losses, hindering the healthy operation of the distribution grids. Both the centralized and decentralized OPT algorithms improve the distribution grid operation by reducing the peak demand. In addition, these two methods reduce power losses and eliminate voltage violations and cable overloading. Furthermore, the decentralized OPT with local controllers performs equally well as the central OPT. The reduced execution time together with the reduced computational load makes the decentralized OPT a more viable load management strategy especially for high EV penetrations expected in future mobility systems.

5. Conclusions

We proposed a decentralized hierarchical ADSM algorithm for the charging management of EVs where the communication requirement is only unidirectional. We formulated the charging scheduling problem as an optimal power tracking algorithm that aims to reduce the peak demand in distribution grids induced by EV charging. In the first layer, the power signal to be broadcasted is determined using only two predictions: the aggregated time-varying non-EV load profile and the total EV demand in the grid. Then in the second layer, the individual EV controllers solve a localized optimization to realize the charging schedule by optimally tracking the re-scaled broadcasted power signal. Predictions on the individual EV usage behaviour based on historic data are required locally for the scaling and tracking algorithm. We used deterministic non-EV load profiles and EV energy demands in our implementation. The effect of uncertainties related to the predictions will be considered in future implementations. We included a central implementation as a benchmark for comparison purposes.

The results demonstrate that the decentralized OPT approach eliminates the additional peak demand increments induced by EV charging and performs comparably to the centralized OPT implementation. In addition to the peak reduction, benefits also include the reduction of the power losses in the cables as well as prevention of voltage limit violations and cable overloading. A further intriguing feature of the OPT is the reduced computational overhead that makes it well suited for integrating into local embedded controllers attached to existing charging infrastructure. Despite the fact that the decentralized OPT, in contrast to the centralized OPT, leads to longer charging times due to the loss of information on the full extent of the EV data, it ensures the demanded energy delivery to all the EVs. In light of all these facts, is evident that the method is a compelling strategy for grid friendly integration of EVs with no requirement for bidirectional communication and computationally intensive infrastructure in comparison to the centralized methods.

CRediT authorship contribution statement

Muhandiram Arachchige Subodha Tharangi Ireshika: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Klaus Rheinberger:** Conceptualization, Methodology, Writing – review & editing. **Ruben Lliuyacc-Blas:** Data curation, Writing – review & editing. **Mohan Lal Kolhe:** Writing – review & editing. **Markus Preißinger:** Writing – review & editing. **Peter Kepplinger:** Investigation, Resources, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors are grateful to the project partner Vorarlberger Energienetze GmbH for providing the real data for the distribution grid model.

Appendix A. EV locations

The heatmaps illustrating the number of EVs connected to the nodes at the grid for the different penetrations considered are shown in Fig. A1. The EVs were assigned to the nodes based on the number of households at each node. As can be seen in the Fig. A1(j), the nodes with high EV numbers are distributed over the grid. Even though most EVs are connected at the end of the feeders, the performance indices lie within the safe operating bounds for all configurations.

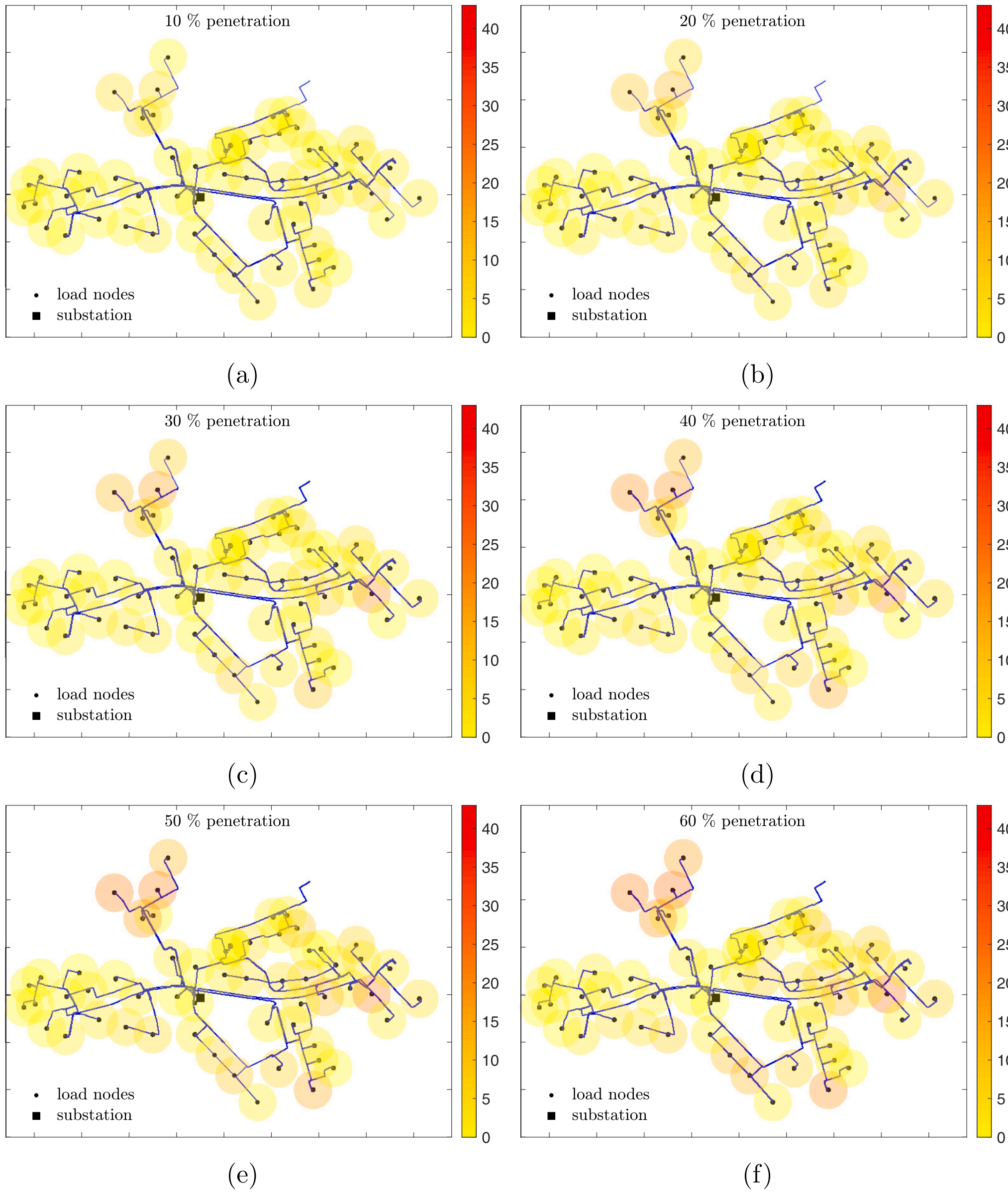

Fig. A1. Geographical representation of locational details for the different EV penetrations in the Austrian low voltage grid. The heatmap represents the number of EVs at each node at the respective EV penetration. The allocation of the EVs is based on the number of households at each node.

Appendix B. Summary of the results

A summary of the results including all the key indices we used for the evaluation and the details of the EV assignments to the different nodes for the range of penetrations is presented in Table B.1.

Table B.1
The summary of the assignation details of EV to network nodes and the results representing key performance indices for the different EV penetrations.

Penetration	No of EVs	No. of nodes with EVs	PAPR			Minimum Voltage (p.u.)			Maximum Line loading (%)			Power Loss (kWh)			Charging Time (hours)		
			Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D
0	0	0	1.83			0.96			89.7			517			0.72		
10	49	23	1.94	1.74	1.74	0.95	0.96	0.96	116.6	89.7	89.7	605	564	562	0.74	4.65	7.28
20	98	30	1.99	1.67	1.67	0.94	0.96	0.96	125.5	89.7	89.7	685	610	604	0.75	6.17	9.64
30	148	35	1.98	1.59	1.60	0.94	0.96	0.96	135.6	89.7	89.7	790	672	659	0.74	7.06	10.95
40	196	35	2.18	1.52	1.54	0.93	0.96	0.96	147.2	89.7	89.7	911	736	714	0.75	7.86	11.72
50	245	40	2.30		1.49	0.92		0.96	163.1		89.7	1016		763	0.74		12.10
60	293	45	2.30		1.45	0.92		0.96	169.9		89.8	1135		820	0.74		12.46

(continued on next page)

Table B.1 (*continued*)

Penetration	No of EVs	No. of nodes with EVs	PAPR			Minimum Voltage (p.u.)			Maximum Line loading (%)			Power Loss (kWh)			Charging Time (hours)		
			Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D	Unc	OPT-C	OPT-D
70	342	47	2.45		1.40	0.91		0.96	176.1		89.8	1242		867	0.74		12.79
80	392	48	2.48		1.35	0.90		0.96	191.7		89.9	1390		931	0.74		13.09
90	441	49	2.56		1.31	0.89		0.96	198.6		90.1	1526		991	0.74		13.34
100	490	52	2.69		1.32	0.87		0.96	205.7		90.2	1659		1045	0.74		13.40

References

[1] S. Deilami, A.S. Masoum, P.S. Moses, M.A. Masoum, Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile, IEEE Trans. Smart Grid 2 (3) (2011) 456–467.

[2] S. Shafiee, M. Fotuhi-Firuzabad, M. Rastegar, Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems, IEEE Trans. Smart Grid 4 (3) (2013) 1351–1360.

[3] Q. Gong, S. Midlam-Mohler, V. Marano, G. Rizzoni, Study of pev charging on residential distribution transformer life, IEEE Trans. Smart Grid 3 (1) (2011) 404–412.

[4] M.T. Hussain, N.B. Sulaiman, M.S. Hussain, M. Jabir, Optimal management strategies to solve issues of grid having electric vehicles (ev): a review, J. Energy Storage 33 (2021), 102114.

[5] M. Alonso, H. Amaris, J. Germain, J. Galan, Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms, Energies 7 (4) (2014) 2449–2475.

[6] E. Veldman, R.A. Verzijlbergh, Distribution grid impacts of smart electric vehicle charging from different perspectives, IEEE Trans. Smart Grid 6 (1) (2014) 333–342.

[7] A. Mahmood, M.N. Ullah, S. Razzaq, A. Basit, U. Mustafa, M. Naeem, N. Javaid, A new scheme for demand side management in future smart grid networks, Procedia Comput. Sci. 32 (2014) 477–484.

[8] K. Zhang, L. Xu, M. Ouyang, H. Wang, L. Lu, J. Li, Z. Li, Optimal decentralized valley-filling charging strategy for electric vehicles, Energy Convers. Manag. 78 (2014) 537–550.

[9] Z. Ma, D. Callaway, I. Hiskens, Decentralized charging control for large populations of plug-in electric vehicles: application of the Nash certainty equivalence principle, in: 2010 IEEE International Conference on Control Applications, IEEE, 2010, pp. 191–195.

[10] L. Gan, U. Topcu, S.H. Low, Optimal decentralized protocol for electric vehicle charging, IEEE Trans. Power Syst. 28 (2) (2012) 940–951.

[11] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, F.L. Lewis, Scalable real-time electric vehicles charging with discrete charging rates, IEEE Trans. Smart Grid 6 (5) (2015) 2211–2220.

[12] N.I. Nimalsiri, C.P. Mediwaththe, E.L. Ratnam, M. Shaw, D.B. Smith, S. K. Halgamuge, A survey of algorithms for distributed charging control of electric vehicles in smart grid, IEEE Trans. Intell. Transp. Syst. 21 (11) (2019) 4497–4515.

[13] N. Chen, C.W. Tan, T.Q. Quek, Electric vehicle charging in smart grid: optimality and valley-filling algorithms, IEEE J. Sel. Top. Signal Process. 8 (6) (2014) 1073–1083.

[14] N. Nimalsiri, D. Smith, E. Ratnam, C. Mediwaththe, S. Halgamuge, A decentralized electric vehicle charge scheduling scheme for tracking power profiles, in: 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), IEEE, 2020, pp. 1–5.

[15] P. Kepplinger, Autonomous Demand Side Management of Domestic Hot Water Heaters, University of Innsbruck, Innsbruck, Austria, 2019. Ph.D. thesis, Dissertation.

[16] B. Faessler, M. Schuler, M. Preißinger, P. Kepplinger, Battery storage systems as grid-balancing measure in low-voltage distribution grids with distributed generation, Energies 10 (12) (2017) 2161.

[17] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, J. Li, An optimized EV charging model considering TOU price and SOC curve, IEEE Trans. Smart Grid 3 (1) (2011) 388–393.

[18] M.A.S.T. Ireshika, M. Preissinger, P. Kepplinger, Autonomous demand side management of electric vehicles, in: 2019 7th International Youth Conference on Energy (IYCE), IEEE, 2019.

[19] M.G. Vaya, G. Andersson, Centralized and decentralized approaches to smart charging of plug-in vehicles, in: 2012 IEEE Power and Energy Society General Meeting, IEEE, 2012, pp. 1–8.

[20] K. Rheinberger, P. Kepplinger, M. Preißinger, Flexibility control in autonomous demand response by optimal power tracking, Energies 14 (12) (2021) 3568.

[21] Y.-W. Chung, B. Khaki, T. Li, C. Chu, R. Gadh, Ensemble machine learning-based algorithm for electric vehicle user behavior prediction, Appl. Energy 254 (2019), 113732.

[22] A. Gligor, I. Vlasa, C.-D. Dumitru, C.E. Moldovan, C. Damian, Power demand forecast for optimization of the distribution costs, Procedia Manuf. 46 (2020) 384–390.

[23] J. Proakis, M. Salehi, Digital Communications. Great Britain, 2014.

[24] J. Zhu, Z. Yang, Y. Guo, J. Zhang, H. Yang, Short-term load forecasting for electric vehicle charging stations based on deep learning approaches, Appl. Sci. 9 (9) (2019) 1723.

[25] U. Ghatak, V. Mukherjee, An improved load flow technique based on load current injection for modern distribution system, Int. J. Electr. Power Energy Syst. 84 (2017) 168–181.

[26] MATLAB, Version: 9.9.0.1495850 (R2020b), The MathWorks Inc., Natick, Massachusetts, 2020.

[27] B. Fäßler, P. Kepplinger, M. Schuler, M. Preißinger, A method for grid simulation assessing demand side management strategies, in: Forschungsforum der österreichischen Fachhochschulen (FFH), 2018.

[28] Vorarlberger Energienetze GmbH, https://www.vorarlbergnetz.a/ online; accessed 20 December 2019.

[29] illwerke vkw AG, https://www.vkw.at/, online; accessed 15 December 2019.

[30] Synthetic load profiles apcs - power clearing & settlement, https://www.apcs.at/en/clearing/physical-clearing/synthetic-load-profiles, online; accessed 15 December 2019.

[31] R. Tomschy, M. Herry, G. Sammer, R. Klementschitz, S. Riegler, R. Follmer, D. Gruschwitz, F. Josef, S. Gensasz, R. Kirnbauer, T. Spiegel, Österreich Unterwegs 2013/2014, Ergebnisbericht zur österreichweiten Mobilitätserhebung Österreich unterwegs, 2016.