ELECTRIC VEHICLE CAR PARK CHARGING SIMULTANEITY AND GRID CONNECTION POWER REQUIREMENT ANALYSIS

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Keywords: electric vehicle, power analysis, charging simultaneity, grid capacity, smart charging

Abstract

The increasing market penetration of electric vehicles (EV) induces changes in many industries. Developers of real estate, large residential buildings and car parks must include future e-mobility shares into their current project planning to ensure that the rising numbers of EVs can be handled by the building's infrastructure. This paper discusses a tool for simulating various charging scenarios of large centralized electric vehicle parking solutions and compares the outcome with respect to the simultaneity factor to current planning rules and real-world experiences. Additionally, the involvement of charging algorithms is simulated and the impact on needed power capacity for local transformers is analysed. Besides verifying that the observable simultaneity of charging is mostly in line with other studies, this work provides a more detailed investigation of different use cases such as home, work and shop charging. Furthermore, it is proven that simple peak shaving can drastically reduce the maximum power of EV parks without interfering with the usage patterns of the vast majority of EV owners.

1 Introduction

With 20% of the total EU greenhouse gas (GHG) emissions in 2018 [1], road transport represents one of the main contributors to climate change and global warming. In the nationally determined contributions of the historic Paris agreement on climate action, countries worldwide have formalized measures to reduce their transport-related GHG emissions by, inter alia, increasing the share of electric mobility [2].

Annually, the International Energy Agency comprehensively assesses recent e-mobility developments and policy changes around the world. In their *Global EV Outlook 2020* report, the authors describe two prospective scenarios for 2030 [3]: In the conservative *stated policies scenario*, they estimate the 2030 global light-duty electric vehicle (EV) stock to 135 million which accounts for 8% of the total car stock. An analysis of the more optimistic *sustainable development scenario* results in a projected share of 13%. These estimations include plug-in EVs as well as hybrid EVs.

Since EVs usually charge their batteries via the electric grid, their projected increase on the market poses a challenge for many actors. Grid operators in conjunction with policy makers and charge point operators have to take measures to keep the future electricity supply reliable [3]. Companies such as real estate developers must include far future EV shares in their projects today, e.g. by ordering appropriate transformer and feeder capacities from local grid operators.

In order to facilitate electric capacity planning for these actors, the Austrian consortium *Österreichs Energie* provides a planning rule for the expectable total electric power of collectively charging EVs, namely the charging simultaneity factor (CSF; see definition in section 2.4 and in [4]) which depends on the number of EVs [5]. The authors state that for uncoordinated charging without tariff incentives, the CSF is a declining curve and is to be expected at around 0.4 for 10 EVs, at 0.27 for 50 EVs and at 0.24 for 100 EVs. It should be mentioned that their CSF curve is based on the utilisation of 11 kW electric vehicle supply equipment (EVSE) for each EV.

In a pilot project described in [6], the total charging power of an EV car park with 12 EVSEs has been measured for a period of 6 weeks. The resulting CSF is 0.22 (referred to the total rated power of the EVSEs) or 0.34 (referred to the supported AC charging powers of the EVs), respectively. Statistical modelling approaches have been used in [7] to calculate a CSF curve similar like it is shown in [5]. The determined maximum CSF values are 0.6 for 10 EVs, 0.36 for 50 EVs and 0.23 for 100 EVs.

For worst case estimations it is sometimes practice to use 0.5 as the CSF. This has been done in [8], where the impact of different charging strategies on the distribution grid is assessed. However, using a constant factor without considering the number of EVs neglects the assertions from [5] and [7].

EV smart charging algorithms are a highly investigated research topic, see the relevant review papers [9] and [10]. One of the most frequent methods being used for EV car parks is peak shaving, where the maximum charging power is limited to a certain threshold often determined by external capacity constraints. Such a control approach is taken in [11] with an additional influencing factor, namely the state of charge (SoC)

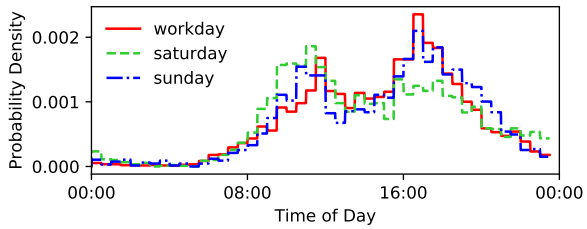

Fig. 1. Home arrival time distribution for rural areas

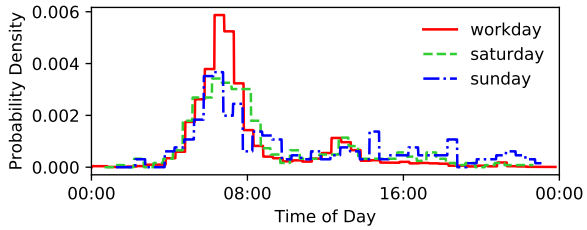

Fig. 2. Work arrival time distribution for rural areas

of the individual EV batteries. Their results show that one of the implemented peak shaving algorithms reduces the maximum power of a 10 EV car park from 168.7 kW in the uncoordinated case to 100 kW without significantly prolonging the total charging duration of the fleet.

Available literature which describes charging parameters of EV car parks is either kept very general or highly project-specific. Hence, this work aims to function as a broadly applicable data source for electric capacity planning of future EV car parks. By implementing an EV fleet simulation model and combining it with the results from a comprehensive Austrian mobility study, analyses of multiple charging scenarios are performed: The impacts of parameters such as the day, area or chosen EVSE on the resulting charging power, the CSF and the states of charge of EV batteries are investigated for residential, work and shopping use cases. Furthermore, a simple but market-ready peak shaving algorithm is implemented and its influences are evaluated and compared with the other scenarios.

2 Methodology

In order to precisely analyse the collective charging behaviour of electric vehicles, a simulation model is developed. It consists of three main pillars which are presented in this section: The modelling of the mobility behaviour, the EV fleet and the charging strategy. Furthermore, the approach for a statistical analysis is described.

2.1 Mobility Behaviour

The trip data record of a large Austrian mobility study is used to model the mobility behaviour in this work [12]. The 93175 recorded passenger car trips which are assumed to be representative for EVs are filtered by home region (rural, urban, suburban), day type (workday, Saturday, Sunday) and target destination (home, work, shop). For each of these permutations and for each EV of the fleet, an arrival time probability density function (PDF) and a daily driven kilometres PDF is calculated. The calculated arrival time PDFs for rural areas are depicted in

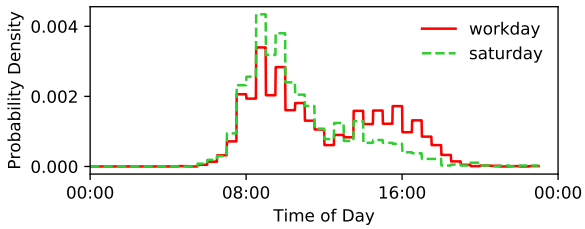

Fig. 3. Shop arrival time distribution for rural areas

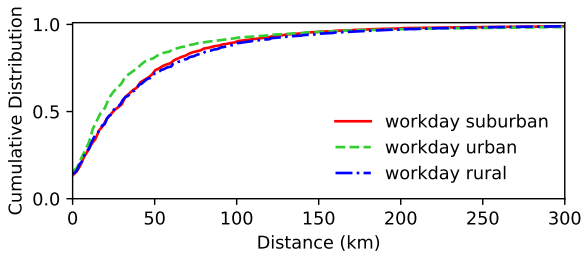

Fig. 4 CDF for the workday driving distance in different areas

Fig. 1, 2 and 3. The cumulative distribution function (CDF) for the driving distance of an EV on workdays is shown in Fig. 4. As can be seen, the share of short trips is higher for urban areas. On Sundays, however, people from urban areas have a higher share of long trips (not depicted). Fig. 4 also shows that on some workdays, people don't drive at all. On weekends, this behaviour is even more significant.

As further described in section 2.2, the fleet simulation uses these distributions as a random number generator to determine the connection time at the EVSE and the required amount of charging energy. In this work, the parking duration is set to 14 hours for home charging, to 9 hours for work charging, and to 0.5, 1 or 2 hours for shop charging.

2.2 Electric Vehicle Fleet

For the EV car park charging behaviour modeling, a fleet simulation is set up which uses an EV charging simulation model developed at the Austrian Institute of Technology [13]. The model is based on measurements of the charging process of commercial EVs and precisely replicates their constant current (CC) and constant voltage (CV) phase of Li-ion battery charging.

In order to instantiate different sizes of EV fleets and types of EVs, a list of the ten most sold EVs on the 2020 Austrian market is used as a probability distribution in this work [14]. Table 1 shows the market share and the publicly available charging and energy consumption parameters of the base models of these cars [15]. P is the maximum charging power of the respective EV type, and phases is the number of supported AC phases of its on-board charger. 'Type 11' is a generic car which represents 'other' EVs which are not in the top ten of the registration statistic.

It is assumed that each EV driver participates in charging and connects the car upon arrival at the car park. The required amount of energy is determined by the EV consumption, the driven kilometres, the charging efficiency and the season. For charging in winter and summer, the energy consumption of the

Table 1 List of chosen EV types and characteristics [14][15]

Type	Share (%)	P (kW)	Phases	Battery (kWh)	Consumption (kWh/100km)
type 1	18.1	11	3	52	14.8
type 2	13.0	22	3	41	16.1
type 3	10.4	7.2	2	45	16.1
type 4	7.0	7.2	1	39.2	16.7
type 5	5.4	7.2	1	39.2	15.4
type 6	4.9	11	3	71	23.1
type 7	4.3	11	3	38	16.1
type 8	3.4	7.2	2	36.8	16.6
type 9	2.5	7.2	2	35.8	16.8
type 10	2.4	7.2	2	32.3	15.8
type 11	28.6	11	3	50	16

EVs is set 20% and 15% higher than the values from Table 1, respectively. This is due to heating and air conditioning. The charging efficiency which takes into account the losses of the power electronics and the battery is set to 95%.

2.3 Charging Algorithms

The EVSE is modeled in such a way that the AC charging restrictions from IEC 61851-1 Annex A apply [16]. Accordingly, the allowed charging power is communicated to the EV by sending an integer target current which must be larger than 6 A and lower than 80 A. For 3-phase systems, this target current indicates the current limit per phase.

The number of available EVSEs is set equal to the EV fleet size, which means that in uncontrolled charging, queues are not considered.

However, a peak shaving algorithm is also implemented which dynamically adjusts the maximum charging power of each EVSE in order to meet a predefined power limit for the EV car park. If in use, the algorithm constantly checks how many cars have already arrived and are demanding a charging process. This number is used to equally distribute the available car park power among the EVs while taking into account the minimum phase current of 6 A. If too many EVs try to charge simultaneously, this minimum limit causes a condition where some EVs have to wait in a queue until other cars finish charging or leave their parking spot.

2.4 Statistical Analysis and Scenario Description

As described in section 1, the CSF is frequently used for electric power capacity planning in EV car park projects. Equation 1 defines the CSF according to [4]:

$$\mathrm{CSF}(n) = \frac{P_{S,max}}{\sum_{i=1}^{n} P_{rated,i}}, \tag{1}$$

where $P_{S,max}$ is the maximum measured power of all EVSEs within the considered time period, $P_{rated,i}$ is the rated power of each EVSE, and n is the number of EVSEs. In this work, $P_{rated,i}$ is set to 11 or 22 kW, respectively. Due to the lower charging power of some EV types in use (see Table 1) it can be expected that the CSF is smaller than 1.0 even if all EVs charge at the same time.

In the simulations of this work, the CSF, the maximum power $P_{S,max}$ and other parameters such as battery states are investigated for different sizes of EV fleets. This is done by simulating the charging behaviour of multiple home, work and shopping EV car park scenarios for a time span of a winter season. Winter is chosen due to the higher energy consumption of the EVs. Workdays, Saturdays and Sundays are simulated as well as rural, urban and suburban areas. No scenario mixes between home, work and shop charging are considered, and each EV initiates only one charging session per day, based on its calculated mobility pattern.

Five different charging strategies are simulated:

- *11 kW Uncontrolled Charging*: EVSE power limit of 11 kW
- *22 kW Uncontrolled Charging*: EVSE power limit of 22 kW
- *Strict Peak Shaving*: Car park power limit of 50 kW
- *Moderate Peak Shaving*: Car park power limit of 80 kW
- *Weak Peak Shaving*: Car park power limit of 110 kW

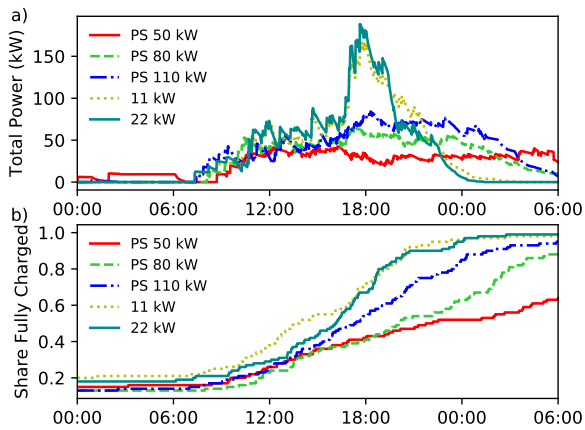

Fig. 5 Home charging: Worst case time series for the 100 EV scenario on workdays in rural areas. PS = peak shaving. a) Total car park power, b) Share of fully charged vehicles

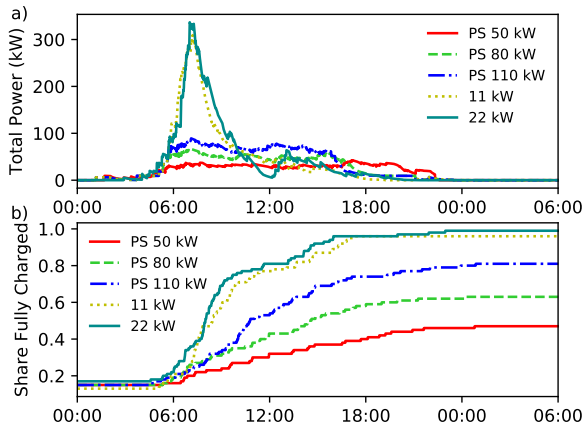

Fig. 6 Work charging: Worst case time series for the 100 EV scenario on workdays in rural areas. PS = peak shaving. a) Total car park power, b) Share of fully charged vehicles

3 Results

Due to the many possible parameter permutations of the scenarios, only the rural area type is described in full detail. However, the observed simulation results are very similar to suburban and urban areas.

Fig. 5 and 6 show the worst case time series results of the workday home and work charging scenarios with a fleet size of 100 EVs. The uncontrolled scenarios clearly show high peaks around the most frequent arrival times at home or work, respectively. There is no significant difference between the 11 and 22 kW scenario because only 13% of the chosen EVs are able to charge with 22 kW (see Table 1). The three peak shaving scenarios successfully limit the car park power but also prolong the battery refilling processes, which is depicted in Fig. 5b and 6b. Due to the narrower arrival time window in work scenarios (compare Fig. 1 and 2), the car park peak power is higher in Fig. 6. When comparing the peak shaving scenarios, the shorter parking duration in the work scenarios (9h for work vs. 14h for home) leads to a higher share of EVs which do not succeed to refill their batteries.

A broader comparison between home, work and shop charging and between different fleet sizes is depicted in Fig. 7, 8 and 9. These figures represent the worst case results throughout a winter season in rural areas, which means: The highest observed CSF (a), the highest peak power (b) and the lowest share of fully refilled batteries (c). The share of full batteries is calculated at 6 am next morning for home charging. For work and shop charging this is done after all charging processes have been stopped due to departure or full battery. The drastic reduction of the maximum charging power when using the peak shaving algorithm is clearly visible in Fig 7b and 8b. However, the strict peak shaving scenario with a limit of 50 kW is too low to recharge large EV fleets, see Fig 7c and 8c.

The resulting CSFs for uncontrolled home charging are largely in line with other studies (see section 1), especially when comparing larger EV fleets which represent a higher sample size. However, the work charging scenarios (Fig. 8) indicate a higher expectable simultaneity of charging than in literature, which should be taken into consideration when planning EV car parks at work places. Referring to this circumstance, it is again mentioned that no mixed charging scenarios are considered in this paper, which means that all drivers recharge the full daily required energy at work. This might not always be the case in reality and strongly depends on potential incentives such as free charging at work.

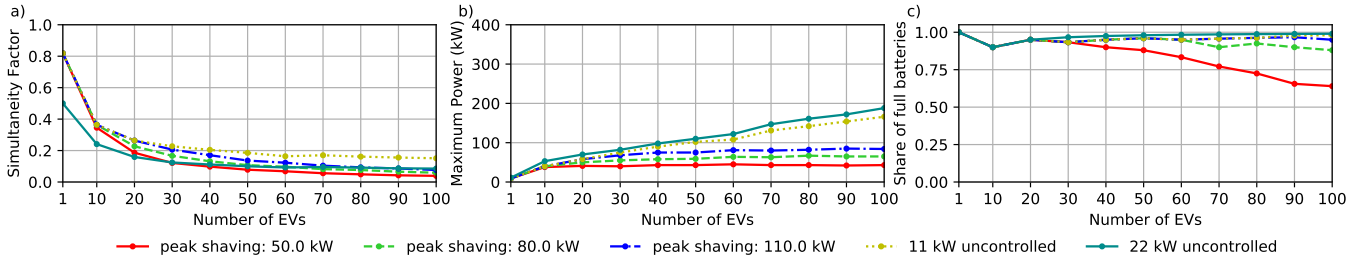

Fig. 7 Home charging scenarios in a rural area over a winter season with different EV fleet sizes. a) CSF, b) Maximum car park charging power, c) Share of full batteries next morning at 6 am

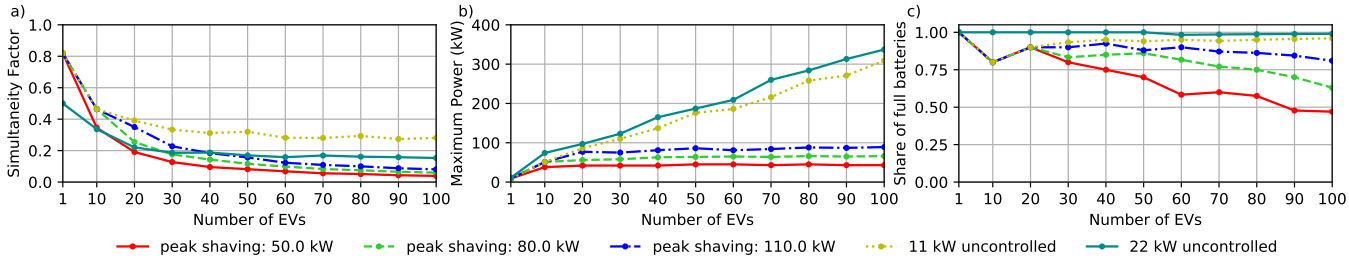

Fig. 8 Work charging scenarios in a rural area over a winter season with different EV fleet sizes. a) CSF, b) Maximum car park charging power, c) Share of full batteries after all charging processes have been stopped

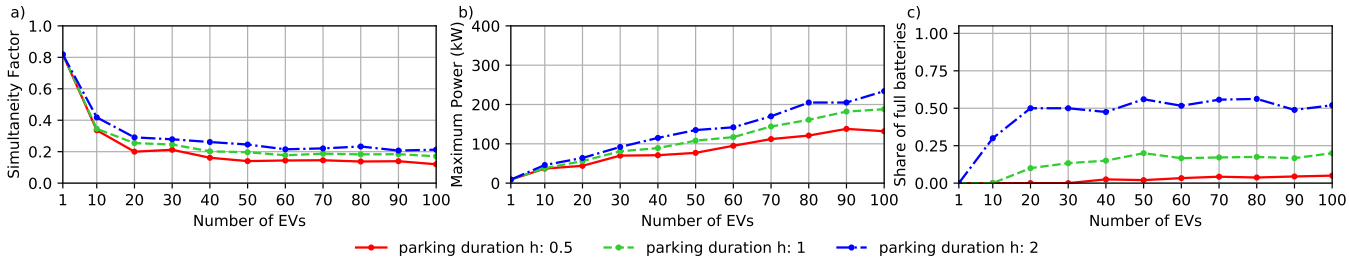

Fig. 9 Shop charging scenarios (uncontrolled charging with 11 kW) in a rural area over a winter season with different EV fleet sizes. a) CSF, b) Maximum car park charging power, c) Share of full batteries after all charging processes have been stopped

In the 11 kW shop charging scenarios (Fig. 9), no peak shaving is considered but a varying parking duration which also leads to differing results. As can be seen in Fig. 9c the shorter the parking duration, the lower is the share of batteries which can be fully recharged. A higher parking duration obviously leads to a higher CSF and larger maximum power values. It should be noted that no charging queue is assumed, so every EV can start charging when it arrives. At real EV car parks, some drivers would not be able to plug upon arrival if all EVSEs are occupied, which, in turn, would lead to a lower charging power. Hence, the shopping scenarios can be considered as an absolute worst case.

4 Conclusion

The ambition of this work is to facilitate the power capacity planning of EV car parks and to give insights to multiple impacts of different charging strategies. The simulation results show that for large EV fleets with more than 50 EVs, only 18 - 36% of the installed EVSE power is simultaneously used in the worst case situations throughout a winter season. The maximum expectable charging power for different sizes of EV fleets is presented for home, work and shopping scenarios. Such statistics are invaluable for real estate developers and other EV car park planners.

The implementation of a peak shaving algorithm which takes into account the charging restrictions from IEC 61851-1 [16] proves that the simultaneity of charging and the maximum charging power of EV car parks can be dramatically reduced. At the same time – if configured appropriately – the algorithm managed to refill the vast majority of EV batteries in a timely manner.

Future work will present the impacts of additional charging strategies as well as a different sets of EV types.

5 Acknowledgements

Parts of this project have been funded by partners of the ERA-Net SES 2018 joint call RegSys (www.eranet-smartenergysystems.eu) - a network of 30 national and regional RTD funding agencies of 23 European countries. As such, this project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 775970.

6 References

[1] 'EEA greenhouse gas - data viewer', https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer, accessed 23 February, 2021

[2] ITF., 'Transport CO2 and the Paris Climate Agreement: Reviewing the Impact of Nationally Determined Contributions', International Transport Forum Policy Papers, No. 50, OECD Publishing, 2018, Paris, https://doi.org/10.1787/23513b77-en

[3] IEA., 'Global EV Outlook 2020', IEA, 2020, Paris, https://www.iea.org/reports/global-ev-outlook-2020, accessed 23 February, 2021

[4] Wieland, T., Reiter, M., Schmautzer, E. et al.: 'Probabilistische Methode zur Modellierung des Ladeverhaltens von Elektroautos anhand gemessener Daten elektrischer Ladestationen', Elektrotech. Inftech. 132, pp. 160–167, 2015, https://doi.org/10.1007/s00502-015-0299-0

[5] Österreichs Energie, 'Abschlussbericht des EP Elektromobilität', 2018, https://oesterreichsenergie.at/die-welt-des-stroms/stromnetze/e-mobilitaet.html, accessed 23 February, 2021

[6] Preßmair, G., Lampersberger, P., Hüttler, W.: 'Anschlussleistung für Wohnhausanlagen mit E-Ladeinfrastruktur - Pilotversuch und Softwaregestütztes Auslegungstool', 16. Symposium Energieinnovation, Graz, Austria, 2020

[7] Kippelt, S.: 'Dezentrale Flexibilitätsoptionen und ihr Beitrag zum Ausgleich der fluktuierenden Stromerzeugung Erneuerbarer Energien', Shaker Verlag, Aachen, 2018, ISBN:978-3-8440-5853-6

[8] F. Heymann, V. Miranda, N. Neyestani, et al.: 'Mapping the Impact of Daytime and Overnight Electric Vehicle Charging on Distribution Grids', 2017 IEEE Vehicle Power and Propulsion Conference (VPPC), Belfort, 2017, pp. 1-6, doi: 10.1109/VPPC.2017.8330961

[9] R. Fachrizal, M. Shepero, D. v.d. Meer, et al.: 'Smart charging of electric vehicles considering photovoltaic power production and electricity consumption: A review', eTransportation, Volume 4, 2020, 100056, ISSN 2590-1168, https://doi.org/10.1016/j.etran.2020.100056

[10] J. García-Villalobos, I. Zamora, J.I. San Martín, et al.: 'Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches', Renewable and Sustainable Energy Reviews, vol. 38, pp. 717-731, 2014, ISSN 1364-0321, doi: 10.1016/j.rser.2014.07.040

[11] Y. Wang and D. T. Gladwin: 'Power management of EV car parks', IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society, Lisbon, Portugal, 2019, pp. 4316-4322, doi: 10.1109/IECON.2019.8927300

[12] Bundesministerium für Verkehr, Innovation und Technologie, 'Österreich unterwegs 2013/2014', https://www.bmk.gv.at/themen/verkehrsplanung/statistik/oesterreich_unterwegs.html, accessed 23 February, 2021

[13] D. Stahleder, M. Nöhrer, F. Lehfuss, et al.: 'Implementation of a real time capable, flexible and accurate Electric Vehicle model to holistically evaluate Charging Services and Methods', Transport Research Arena (TRA) 2018, Vienna, doi: http://doi.org/10.5281/zenodo.1451354

[14] Statistik Austria, 'Kfz-Neuzulassungen Jänner bis Dezember 2020', https://bit.ly/2T63mVm, accessed 23 February, 2021.

[15] 'Electric Vehicle Database', https://ev-database.org, accessed 23 February, 2021

[16] IEC-International Electrotechnical Commission: 'IEC 61851-1:2017 - Electric vehicle conductive charging system - Part 1: General requirements', 2017