Charging Strategies and Implications for Corporate Electric Vehicle Fleets

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***Abstract*—Employees are increasingly using electric vehicles (EVs) as their choice of company car. This means modern companies are becoming owners of EV fleets that need to charge on company premises. Without an effective charging strategy the cost of running an EV charging infrastructure for a large fleet of company EVs quickly becomes prohibitive. For this purpose, we investigate three different charging strategies: (i) a "naive" baseline strategy, (ii) intelligent charging (using an optimal schedule) and (iii) multi-location intelligent charging (i.e. allowing charging at home). Experimental results from simulations show how the selection of a charging strategy affects the number of adequately charged EVs as well as infrastructure utilization. Multi-location intelligent charging is the most effective strategy.**

I. Introduction

The increasing electrification of company car fleets can have a significant business impact due to infrastructure investments in company premises, energy costs and effects on sustainability Key Performance Indicators (KPIs). The majority of companies are not prepared for large-scale EV fleet management [1] nor the complex ways it intertwines with their operations and impacts their business. The question is especially pertinent for stakeholders such as the EV drivers, the EV owner (in this case the company), the EV fleet manager and the company sustainability officer. Companies with large EV company-car fleets expect to reap the benefits from an effective management of EVs. This can be realized by managing their charging in an intelligent manner and by developing new business areas. These areas go significantly beyond straightforward applications of intelligent charging and involve the complete life cycle of EVs. Additionally, it affects components of the infrastructure such as EV charging points, energy storage assets or alternative energy resources (solar panels, wind turbines, combined heat and power).

Overall, the topic of company-owned EV fleets can be perceived as a complex system in the area of technology, business and economics [2]. Its constraints and capabilities set the context within which business decisions need to be taken. This work focuses on company-owned EV fleets and aims to provide insights into how surrounding issues can be addressed. Companies may capitalize on the opportunities it offers while also shedding light on the challenges that are posed. As such, the aim is to approach mainly two research questions: (i) What is the impact of intelligent charging vs. uncoordinated charging for the company? (ii) When does it make sense to consider alternatives such as charging at home? These questions are addressed experimentally by simulating and analyzing three charging strategies defined in section II. Empirical results of the simulations are followed by a discussion providing insights into how this approach can benefit the company and affected stakeholders.

II. Motivation and Scenarios

A. Business Motivation

The proportion of EVs in company fleets is driven by different factors including political measures, climate change efforts and a sustainability Zeitgeist. In addition to external motivators, the company of the future has a vested interest in expanding its EV fleet in order to capitalize on new business opportunities. For instance, EV fleets can be considered as a battery swarm [3] and consequently may be utilized in demand-side management scenarios [2]. This way, existing company costs may be reduced by methods such as storing excess energy. Alternatively, new revenue streams may be generated by participating in energy markets as a commercial prosumer [4]. Many fleet-related company costs stem from the installation and maintenance of the EV charging infrastructure and from the electricity for charging the EVs.

In this context, an intelligent charging strategy is one that actively assigns EVs to charging stations and takes into account the state of charge (SoC) of each car at arrival as well as the infrastructure. Such strategies can play a crucial role especially when combined with demand response (DR) and company EV fleets [5].

In intelligent charging, cost minimization [6] and peak shaving [7] are two common goals. Overall, economically relevant scenarios with existing company-owned EV fleets are less commonly addressed. However, evolving infrastructure and EV capabilities are expected to play an increasingly essential role [3].

B. EV Fleet Charging Strategies

We present three charging strategies a company might use to deal with its EV fleet.

1) Strategy 1 – Baseline: The simplest strategy that a company can follow in order to adapt to increasingly large numbers of EVs in its fleet is to proceed with minimal infrastructure investments and process changes within fleet management. An initial investment in charging infrastructure aims to accommodate the existing EV fleet and provides a limited number of charging spots and a minimal grid connection. This static sizing of infrastructure is not supplemented by intelligent charging. In other words, charging processes are not actively managed. Instead, EVs charge on a first-come-first serve basis. Upon arrival on company premises, EVs find a free charging spot, plug in and charge. A simple energy load management system is used where charging processes are refused when the overall load reaches infrastructure limits. Charging processes continue irrespective of energy prices or stakeholder flexibilities as long as they do not overload infrastructure capabilities. This approach is used as the baseline.

2) Strategy 2 – Intelligent Charging: To improve on the first strategy, we propose a more sophisticated intelligent charging strategy to optimize charging processes for each EV with one or more objectives as goals. Objectives of interest include energy cost, a fair share of state of charge (SoC) among EVs and the utilization of available energy resources on premise. In this work, the heuristic described in subsection III-C is used to implement intelligent charging. Its goal is to optimize overall objectives while avoiding violations of load constraints.

3) Strategy 3 – Multi-location Intelligent Charging: Approaches increasing the installed charging infrastructure on company premises can only be applied to a certain extent and are limited by the prohibitive costs and time frames of improving the required infrastructure installations. This includes the number of charging stations and the grid connection. Hence for large-scale EV fleets, charging cannot be performed on company premises exclusively due to power and space limitations. Multi-location charging extends charging options beyond company-owned charging stations and includes additional locations such as the home or the public charging infrastructure. Intelligent charging, in this case, needs to take into account the total cost of charging the fleet. This depends on, for example, variable electricity prices in each charging location or potential service charges. For the sake of simplicity, this work considers the employee's home as an alternative location. This is defined as a special case of multi-location intelligent charging. Similar to *strategy 2*, the heuristic described in subsection III-C is used for charging optimization on company premises.

C. Stakeholders and Requirements

The three charging strategies described above indicate that companies are flexible as to how EV fleets are charged. Consequently, tool support is desirable for a comparative assessment of each strategy. Several stakeholders are involved with different needs and requirements.

- The driver of the EV needs to secure an adequate state of charge to carry out the activities planned for the rest of the day and until the EV recharges (on company premises or at home).
- The facility manager supervises energy needs of the fleet and needs to ensure that the installation and operation of charging infrastructure including load management are sufficient and utilized in a cost-effective way.
- The fleet manager controls the fleet size, its composition, and costs to the company. This stakeholder needs to ensure and guide the expansion of the fleet as well as its characteristics.
- The energy manager estimates and procures the necessary additional energy required by EVs from energy markets.

All of the above directly or indirectly affect corporate strategies involving EV fleets and their characteristics. To ease decision-making processes, suitable tools are required to simulate charging behaviors under a given context. Such tools support infrastructure planning, deciding company energy management strategies or creating EV fleet policies. Stakeholders may define and simulate "what-if" scenarios, observe results and fine-tune their decisions. Moreover, the tools can be used for analyzing implications of the choice of fleet strategy. This includes quantifying assumptions such as trends in the fleet size, driver behavior and the energy market.

From a functional point of view, a tool should simulate the EVs, their trips, the charging infrastructure and individual charging processes. EVs vary in technical parameters such as energy consumption and battery charging time. Drivers' traffic and driving patterns additionally affect the energy consumption of the EV. Lastly, the technical parameters of the charging stations in the infrastructure can vary.

III. Approach

A. Data

To simulate the charging strategies discussed in subsection II-B data about drivers, EVs, electricity prices and the charging infrastructure is needed as illustrated in Figure 1. Some of this data is directly available from historical public and corporate datasets while other aspects need to be collected via methods such as realistic data generation.

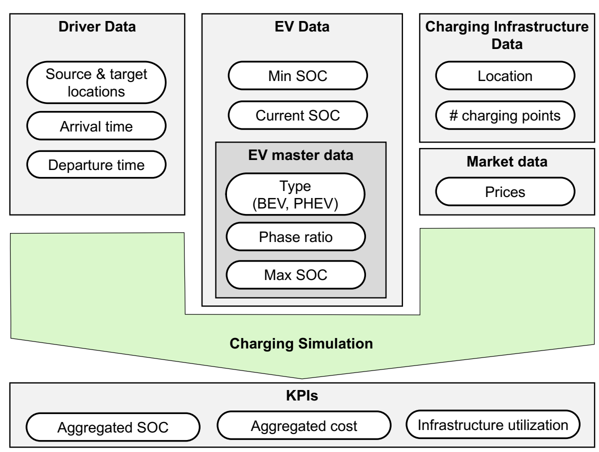

Figure 1. Simulation data

The state of charge (SoC) plays a central role in the EV dataset and is reflected by three parameters: (i) *current SoC*, reflecting the current battery charge (ii) *min SoC*, reflecting the minimum SoC to be achieved before the EV departs in order to safely reach the next charging point and (iii) *max SoC*, the maximum wished SoC.

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The current SoC at time of arrival and an EV's min SoC determines its charging needs and priority. In practice, due to a lack of widely adopted vehicle interfaces [1] the current SoC cannot be easily retrieved from the EV via the charging station and therefore needs to be estimated. This estimation can be realized, for example, via a simulation of EV routes in realistic scenarios or by means of reverse engineering on historical data.

The main data source used for the simulation in this work is a historical dataset from a company-owned fleet of EVs driven by employees. This dataset consists of approximately 500 EVs, 100 charging stations and 12000 charging processes. Electricity prices are derived from historical values of the EEX intraday energy market and are available per 15-min interval.

When applying data analysis techniques, data privacy needs to be considered. For instance, driver data contains personal information which is subject to data protection policies and hence requires anonymization. This procedure has been applied in dealing with this work.

B. Methodology

To explore charging strategies for EV fleets, tangible implications need to be quantified. One method is to calculate Key Performance indicators (KPIs). In a simulation of charging processes KPIs of interest include: (i) *aggregated SoC over all EVs*, reflecting the total charging performance and leading to the number of adequately charged EVs (those charged to least their min SoC), (ii) *aggregated cost*, the total charging cost and (iii) *grid connection utilization*, reflecting how effectively the grid connection is used. The simulation process visualized in Figure 2 consists of a series of dataset preparation and evaluation steps.

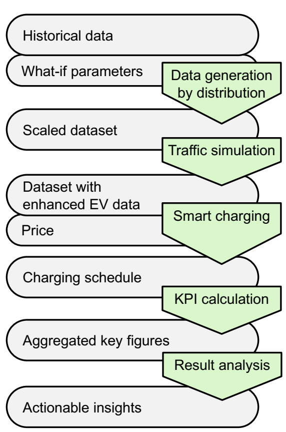

Figure 2. Simulation workflow

The starting point of the dataset preparation is the available historical data. This data represents charging activities of a fixed fleet and fixed infrastructure installation during a fixed time frame. While evaluating charging strategies the business user specifies parameters such as the fleet size, the number of charging points and fraction of fleet users charging on company premises and assess their impact.

In this work, we evaluate the statistical distribution of the historical data, extrapolate to the user-given parameter values and thus generate a scaled dataset. Strategy 3 enhances the data by using SUMO [8] and adds information such as the SoC of each EV at time of arrival thus increasing data quality.

The enhanced dataset serves as input for the data evaluation phase. Smart charging algorithms consider driver, EV and infrastructure data along with energy prices and calculate the optimal charging schedule. Based on a simulation of the schedule, KPIs are calculated and presented to the business user for inferring insights and follow-up actions.

C. Technology choices

The following technologies were chosen for data processing and simulation.

1) SUMO for traffic simulation: Simulation of urban mobility (SUMO) [8] is a well-known continuous road traffic simulation designed to simulate large road networks. Each vehicle in the simulation has its own route and is handled individually. SUMO includes specific models for EVs thus simulating the energy consumption for each vehicle. [9].

In this work, SUMO is used to approximate EV SoC information. It uses cartographic data combined with business data (such as location, arrival, and departure time statistics) to simulate trips to and from company premises. The simulated trips are applied to a battery model to compute how much energy is discharged per route. The resulting SoC estimation serves as an input to the smart charging algorithm.

2) Custom heuristic for smart charging: More formally, smart charging refers to a planning mechanism where charging processes are scheduled to optimize a given objective. Objectives include minimizing costs or maximizing the number of adequately charged EVs. Smart charging can be modeled as a mixed integer programming (MIP) model [6] with two types of decisions variables: the assignment of EVs to charging stations and the charging schedule. The schedule is expressed as a time series of charging currents per EV. Different methods have been used to perform charging optimization [6], [10], [11]. Pursuing an actual optimization approach with a MIP model offers the advantage that the best solution is guaranteed to be found as long as computation time is not a limitation. However, due to the combinatorial complexity of the charging optimization problem [6], this method scales poorly with the number of EVs and cannot be applied for real-time decision making.

Because of the general need for real-time planning [12] in the scenarios we investigate a custom smart charging heuristic is proposed. The custom heuristic for smart charging used in this work is implemented in Java and consists of a prioritized lookup scheme based on a day-ahead plan. That is, one day in advance a dataset of predicted EVs and expected charging infrastructure is created by a forecasting method and an optimal charging plan is created for this dataset. During real-time smart charging, the charging schedule for each EV is determined by lookup in the day-ahead plan. In addition, an algorithm is implemented to coordinate day-ahead with

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real-time planning. The reconciliation step is necessary to accommodate for unexpected changes such as deviating EV arrivals or charging infrastructure going out of service [11].

D. Experimental setup

This section describes how the simulations discussed in section III are carried out and how results are interpreted.

Each charging strategy's behavior can be observed by varying simulation parameters. For instance, the impact on KPIs can be observed by varying a single parameter such as the number of cars. The number of charging stations available in the infrastructure is equal to the number of cars while the grid connection is kept constant at 1MW. Based on the current company fleet composition, the fleet is considered to consist of 75% Battery Electric Vehicles (BEVs) and 25% Plug-in hybrids (PHEVs) during simulations. The inclusion of PHEVs has an impact on the overall charging as they typically possess a smaller battery compared to BEVs and also plays a role in prioritization within smart charging, as these vehicles are not immobilized if the battery is drained. In order to make results comparable across the three charging strategies, the starting parameters for each EV are ensured to be the same by using the same starting random seed. This means particularly the starting SoC for each car is independent of the total number of cars and the charging strategy being simulated.

As described in subsection III-B, a KPI relevant to stakeholders is the number of adequately charged EVs which are those that are charged to at least their minimum SoC. In the first and second charging strategies, the minimum SoC is set to a conservative estimate of 50% of the total EV battery capacity. In practice, however, each EV requires an individual minimum SoC that depends on how the EV is used until its next charge. The third charging strategy refines the minimum SoC for each EV by using SUMO [8]. In SUMO, the desired minimum SoC is calculated by simulating trips over road networks to company premises. Since the battery behavior in SUMO is close to real-world behavior [13] this is considered an adequate and realistic measure for this work.

An additional KPI is the grid connection utilization, which indicates how effectively the power available to the charging infrastructure is used. Consequently, it also acts as a measure of how effective an intelligent charging algorithm is at redistributing charging processes. For example, if the grid connection allows for a maximum of 1MW capacity and the sum of charging processes at a given point in time is 0.75MW then there is a 75% utilization of the grid connection. The mean utilization is defined as the utilization across all timeslots of 15 minutes.

IV. Empirical Results

The simulations of the three charging strategies discussed in section II are carried out under conditions discussed in section III and subsection III-D. The raw results are shown in Figure 3 and Figure 4.

Figure 3 shows how the number of adequately charged EVs grows steadily but slower for *strategy 1* compared to the other two strategies. *Strategy 1* reflects the status quo (first come, first serve without optimization) and is used as the baseline for the assessment of the other strategies as well as discussions in this work. In this strategy, no charging processes are delayed. This means if an EV cannot charge when it is first connected to a charging point it will not be charged at all, for example as a result of the grid capacity being reached.

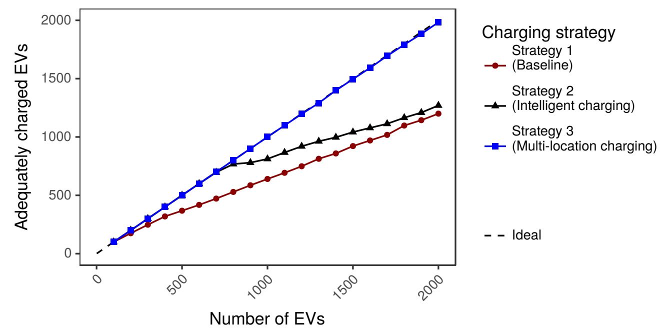

Figure 3. Simulation results showing the number of adequately charged EVs over the total number of EVs, indicating the strategy charging effectiveness

By contrast, in *strategy 2*, EVs are prioritized by the heuristic described in subsection III-C according to their current and minimum SoC at time of arrival. Consequently, the number of adequately charged EVs is always higher, indicating a more effective charging strategy. This can be observed in Figure 3. Additionally, for approx. 1.800 EVs, *strategy 1* and *strategy 2* do not differ much, indicating that the maximum number of EVs that can be accommodated by the infrastructure may be reached. Lastly, both strategies differ from *strategy 3* in high EV populations. This is due to the fact that charging is also available somewhere else than company premise, allowing for a higher number of EVs to be charged as they can continue charging at home.

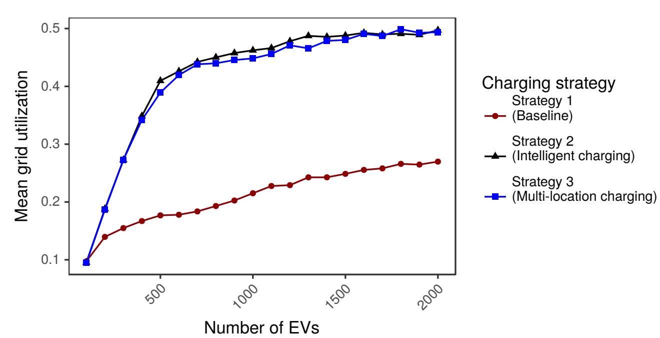

Figure 4. Grid connection utilization subject to the number of EVs

Figure 4 depicts the mean grid connection utilization per simulation. Strategies 2 and 3 lead to a saturation of the grid capacity at around 50%. At the saturation level, a high utilization indicates a higher number of adequately charged EVs. This relationship can be observed by comparing Figure 3 and Figure 4. For example, in *strategy 2* the saturation is reached with 700 EVs, indicating a point at which both the number of adequately charged EVs and the utilization slows.

A more detailed inspection of simulations with a single

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parameter setting enables stakeholders to observe charging behavior throughout the day. This includes a time series view of the grid connection utilization and the distribution of SoC. For example, Figure 3 may raise the question as to why strategies 1 and 2 appear to converge to each other.

Figure 5 shows the power consumption throughout the day for each strategy in three separate simulations involving 2000 EVs. The area under the curve corresponds to the total amount charged, which is almost twice as high for *strategy 2* compared to *strategy 1*. Consequently, the mean grid connection utilization is higher for *strategy 2*.

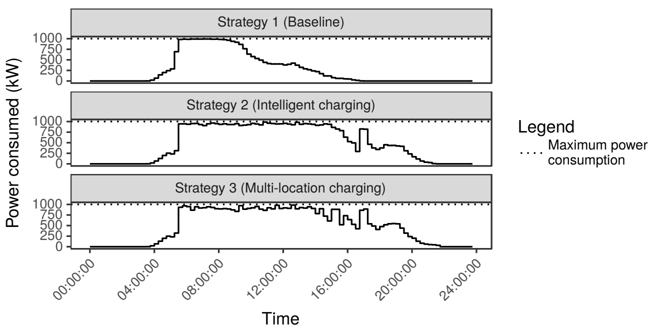

Figure 5. Comparison of power consumption for each strategy over time

Strategies 2 and 3 maximize the number of EVs with an adequate SoC. This is achieved by prioritizing EVs by the difference between the current and minimum SoC. Assuming a variable energy price, a secondary goal is to minimize energy costs. In the simulation, some charging processes were delayed resulting in a higher utilization and a small peak in the afternoon. Overall, applying either *strategy 2* or *3* allowed more EVs to charge than *strategy 1*.

Figure 6. Distribution of SoC in each strategy simulated with 2000 EVs

However, the significant benefits of *strategy 2* seem to contradict the observations in Figure 3, which depicts only a marginal difference to *strategy 1*. One approach to analyzing this discrepancy is to examine the distribution of the final SoC as illustrated in Figure 6. Comparing the histograms for strategies 1 and 2, the differences for extreme SoC values become evident. In particular, SoCs below 0.3 are less common in *strategy 2* than in *strategy 1*. From this one can infer that while *strategy 2* produces EVs below the adequate SoC there are fewer EVs close to the lower levels of EV battery capacity.

Overall we conclude that the intelligent charging approach in *strategy 2* leads to more EVs being adequately charged compared to the *strategy 1*. Further improving on *strategy 2*, *strategy 3* offers a significantly more precise estimation of the minimum SoC, leading to a more effective distribution of available charging power to EVs. This, in turn, increases the number of adequately charged EVs.

The limiting factor in all cases is the connection to the grid, which is why the grid utilization is an important KPI.

V. Discussion

Intelligent charging [1] is an essential area of research especially in the context of company-owned EV fleets. Such fleets have specific characteristics which need to be taken into consideration. This includes a predictable presence of EVs and the potential to calibrate its composition and usage via company policies. This work shows an initial approach focusing on the issues around charging via three sample strategies. Insights were generated about an EV fleet and its impact.

The results of the three strategies, discussed in section IV, show that as hypothesized, the way cars are charged affects the overall fleet SoC as well as the utilization of the grid connection. This suggests there is a clear need for algorithms that intelligently charge the company EV fleet and support actions that benefit company business processes.

The simulation parameters we considered may be supplemented by additional parameters to more accurately predict the EV battery utilization between charging sessions. Alternatively, charging processes of the EV can be adjusted to be compliant with other company goals such as CO_2 reduction, asset retention or participation in demand response via energy marketplaces. Additional parameters include data from the employee's schedule, the average distance traveled per weekday, reaction to price signals or energy storage strategies. In the simulation itself, the limiting factor of the grid connection may be addressed by promising areas of research such as Vehicle-to-grid (V2G) charging in conjunction with photovoltaic or other energy resources [3], [14]

Strategies 2 and 3 improve the utilization of the grid connection. When planning the charging infrastructure, the grid connection is often a costly component and one of the limiting factors [15] of charging an EV fleet. In these strategies, a smaller grid connection that is more effectively utilized can save costs. Finding a suitable size is of high interest to businesses, something that can be partially supported via the simulations presented in this work. In addition, the company can achieve improved EV user satisfaction [16] by offering its employees a higher probability of receiving an adequate state of charge.

Existing tools such as SUMO were used. In SUMO, each vehicle is modeled explicitly, has its own route and is simulated traveling through the real-world road network. This has enabled us to obtain a more accurate SoC for EVs that is close to real-world usage [13]. Outcomes of simulations in SUMO depend on input such as the road network, EV starting locations, driver behavior models and traffic situations.

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Equally significant experiences were acquired about the tools used to prepare, assess and generate data as well as about simulations. In our experiments, simulating thousands of cars has led to bottlenecks in SUMO as well as other processes in our pipeline such as the heuristic for charging optimization. More scalable algorithms or approaches based on adaptive learning [17] may make it feasible to obtain better charging optimizations by improving runtime (able to deal with dynamic changes) or delivering better results (quality of charging schedules).

As discussed in section IV, the grid connection utilization KPI shows a point of saturation that is well below 100%. The grid connection is a static component independent of time that is costly and time consuming to upgrade. In comparison, EVs typically charge on company premises only during business hours. This suggests allowing users to introduce additional components to the simulation to further increase utilization. In particular flexible prosumers [4] such as energy storage systems can be modeled and added to the simulated infrastructure. Furthermore, for more futuristic scenarios EVs can be used in addition to or in support of static storage through V2G approaches [3], [7], [12], [14].

This work concentrates exclusively on company-owned EV fleets used by employees which distances it from other smart charging approaches. Data used in this work is not constrained to EV data used by typical smart charging approaches. Instead, employee and business data supplement the EV data. This additional data is available to the company that owns the EVs.

Capitalizing on the additional data may enhance approaches that go beyond charging and include on-premise infrastructure planning, EV fleet composition (BEVs/PHEVs), co-located energy storage or interactions with energy markets.

VI. Conclusion

This work focuses on a niche in the context of modern corporate EV fleets. More specifically, issues around company-owned EV fleets used by employees are addressed. Such fleets have particular characteristics and bring significant challenges but also new opportunities for companies. We carry out simulations and assess their results via selected KPIs through the selection of three EV charging strategies. Experimental results show that the strategy followed plays a pivotal role in the number of EVs that can be adequately charged as well as infrastructure utilization. In addition, it becomes evident that the limiting factor for any charging strategy is the infrastructure grid connection to the electricity provider.

The simulation-based approach helps stakeholders by offering practical insights into how many EVs can be supported by a given charging infrastructure, subject to a charging strategy. In addition, it brings forward aspects such as the available fleet SoC or their presence on company premises. Both of these aspects can be utilized in the future for more sophisticated scenarios. This includes participating in energy markets, enhanced infrastructure planning, integrating on-premises alternative energy resources or changes in company policies.

Investigating the challenges and opportunities of company-owned EV fleets in a cross-disciplinary manner that pertains to computer science, energy and business is an area that holds significant potential and this work has only scratched the surface.

References

[1] S. Habib, M. M. Khan, F. Abbas, L. Sang, M. U. Shahid, and H. Tang, "A comprehensive study of implemented international standards, technical challenges, impacts and prospects for electric vehicles," *IEEE Access*, vol. 6, pp. 13 866–13 890, 2018.

[2] D. van der Meer, G. R. C. Mouli, G. M.-E. Mouli, L. R. Elizondo, and P. Bauer, "Energy management system with PV power forecast to optimally charge EVs at the workplace," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 311–320, Jan. 2018.

[3] S. Detzler, D. Ilić, S. Karnouskos, and C. Kindermann, "Investigating electric vehicles as a promising alternative to static storage solutions," in *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, 17–19 Dec. 2014.

[4] S. Karnouskos, "Demand side management via prosumer interactions in a smart city energy marketplace," in *IEEE International Conference on Innovative Smart Grid Technologies (ISGT 2011), Manchester, UK*, Dec. 2011, pp. 1–7.

[5] S. Detzler, C. Eichhorn, and S. Karnouskos, "Charging optimization of enterprise electric vehicles for participation in demand response," in *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*. IEEE, 8–11 Sep. 2015.

[6] M. Clemente, M. Fanti, and W. Ukovich, "Smart management of electric vehicles charging operations: the vehicle-to-charging station assignment problem," *IFAC Proceedings Volumes*, vol. 47, no. 3, pp. 918–923, Jan. 2014.

[7] K. M. Tan, V. K. Ramachandaramurthy, and J. Y. Yong, "Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 720–732, Jan. 2016.

[8] Simulation of Urban MObility. [Online]. Available: http://sumo.dlr.de/

[9] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, "Recent development and applications of SUMO - Simulation of Urban MObility," *International Journal On Advances in Systems and Measurements*, vol. 5, no. 3&4, pp. 128–138, Dec. 2012.

[10] B. Liu, M. Zhou, and G. Li, "An optimal approach for coordinating scheduling day-ahead and real-time energy market with risks," in *2006 International Conference on Power System Technology*. IEEE, Oct. 2006, pp. 1–6.

[11] S. Choi, "Practical Coordination between Day-Ahead and Real-Time Optimization for Economic and Stable Operation of Distribution Systems," *IEEE Transactions on Power Systems*, vol. PP, no. 99, 2017.

[12] G. Wenzel, M. Negrete-Pincetic, D. E. Olivares, J. MacDonald, and D. S. Callaway, "Real-time charging strategies for an electric vehicle aggregator to provide ancillary services," *IEEE Transactions on Smart Grid*, 2017.

[13] T. Kurczveil, P. Á. López, and E. Schnieder, "Implementation of an energy model and a charging infrastructure in SUMO," in *Simulation of Urban Mobility*, ser. Lecture Notes in Computer Science. Springer Berlin Heidelberg, May 2013, pp. 33–43.

[14] G. R. C. Mouli, M. Kefayati, R. Baldick, and P. Bauer, "Integrated PV charging of EV fleet based on energy prices, V2G and offer of reserves," *IEEE Transactions on Smart Grid*, 2017.

[15] Z.-Y. She, Q. Sun, J.-J. Ma, and B.-C. Xie, "What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China," *Transport Policy*, vol. 56, pp. 29–40, May 2017.

[16] H.-M. Chung, W.-T. Li, C. Yuen, C.-K. Wen, and N. Crespi, "Electric vehicle charge scheduling mechanism to maximize cost efficiency and user convenience," *IEEE Transactions on Smart Grid*, 2018.

[17] C. D. Korkas, S. Baldi, S. Yuan, and E. B. Kosmatopoulos, "An adaptive learning-based approach for nearly optimal dynamic charging of electric vehicle fleets," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2017.

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