Electric Vehicles with Vehicle-to-Grid Capability

Subjects: Energy & Fuels | Transportation Science & Technology

Contributor: Fabian Rücker , Ilka Schoeneberger , Till Wilmschen , Ahmed Chahbaz , Philipp Dechent , Felix Hildenbrand , Elias Barbers , Matthias Kuipers , Jan Figgener , Dirk Uwe Sauer

Electric vehicles (EVs) with vehicle-to-grid (V2G) capability can serve various applications that are being investigated in literature and tested in the field. EVs can participate in existing markets via V2G technology such as energy trading (i.e., spot markets) and frequency control. Furthermore, V2G capability can be utilized to execute behind-the-meter energy flow optimization such as load leveling and peak shaving. Heiltmann and Friedl review factors influencing the economic success of vehicle-to-grid applications in market and behind-the-meter use cases. They find that load leveling and secondary frequency control provide the highest economic benefits for PHEV controlled charging applications. Furthermore, DSO services such as congestion management, power loss minimization, power quality improvement and voltage regulation are topics of investigation for EV participation utilizing V2G technology.

electric vehicle | battery components | calendar aging | cycle aging | battery model | liquid cooling | charging control | charger efficiency

1. Introduction

The *Transportation* sector is one of the largest contributors to greenhouse gas (GHG) emissions in the world and is the main cause of air pollution in cities. Therefore, many countries and regions around the world have sketched out pathways and adopted regulations in order to reduce GHG emissions of transportation sector. In the EU, the main elements of the *European Strategy for low-emission mobility* are “Increasing the efficiency of the transport system”, “Speeding up the deployment of low-emission alternative energy for transport” and “Moving towards zero-emission vehicles” [1]. An increased efficiency of the transport system in terms of energy and area use can be achieved with use of railway, public transport systems and the transformation to cyclist and pedestrian friendly urban areas. Examples for low-emission energy alternatives for transport are bio fuels, electricity, renewable synthetic fuels and hydrogen. In the EU, electricity is a low-emission alternative energy as the share of renewable energy in the electricity sector has increased to 34.1% in 2019 [2]. The global number of electric vehicles (EVs) has increased by 400% from 2016 to 2019 to 4.79 million and is expected to rise in the future [3]. The primary use of EVs is transportation and mobility. However, especially privately owned vehicles but also commercial fleet vehicles are only used for mobility for a small portion of the day. As an example, a privately used vehicle in Germany is parked for 97% of the time [4]. In contrast to privately owned vehicles, commercially used vehicles, such as delivery trucks, tend to have predictable operating and idle times which make them especially interesting for the provision of vehicle-to-grid services. Also, an increasing number of electric delivery vehicles and trucks are registered in the EU [5]. EVs therefore offer the potential for secondary use acting as storage systems connected to an electricity grid or a load. Via an internal or external charger, power can be exchanged with the traction battery of the EV. Several use cases for the secondary use of EVs are being investigated or are already commercially offered. For example, in behind-the-meter use cases an EV can be used as a storage system for on-site energy consumption optimization or an uninterrupted power supply (UPS). For grid services, EVs can also play an important role. They can offer TSO services such as frequency containment reserve and DSO services such as congestion management and power quality improvement. The interplay between EVs and renewable energy sources in grids is extensively studied in order to increase the share of renewable energy and avoid grid congestion. Furthermore, EV chargers can be used to form a microgrid by maintaining its voltage and frequency.

For the simulation of the operation of an EV, an EV model is essential. In the case of the simulation of an EV connected to a grid, the parameterization of the charger and the charging process control is also important. This holds especially true for the development and testing of control algorithms for energy-management systems in order to offer aforementioned services to grid or site operators via vehicle-to-grid (V2G) functionality. In addition, the provision of V2G services adds additional loading to the traction battery of the EV. As the traction battery is an EV’s most expensive component, the evaluation of the impact of V2G services on the battery lifetime is important for the economic assessments of such services.

2. Electric Vehicles with V2G Capability

The relevant parts of an EV model for V2G applications are the *battery model*, the *charger model* and the *charging control model*.

Battery models in literature have been mainly divided into three categories for the electrical component: Physics-based electrochemical models, equivalent circuit models and data-driven models [6].

Physics-based electrochemical models trace back to the work of Newman and Tiedermann [7] and were extended by Fuller [8] for lithium-ion batteries with intercalation. An extensive review of the electrochemical processes in a battery can be found in [9]. In a single-particle model, a radial diffusion equation describes the lithium-ion diffusion in the solid phase of one representative particle for each electrode [10]. In pseudo-two-dimensional (P2D) models each electrode is composed of several spherical particles and the impact of the electrolyte is taken into account. Numerous partial differential equations describe the reactions inside the cell which leads to a large number of unknown variables that need to be identified using global optimization methods.

In electrical equivalent circuit models an electrical circuit is proposed and its components are parameterized through measurements such as impedance spectroscopy, pulse tests and open-circuit voltage (OCV) measurements. Equivalent circuits can vary in their number and type of components which has an impact on the accuracy and computational complexity of the model. The simplest model is the Rint model that consists of an ideal voltage source in series with a resistor [11]. In order to account for transient processes with different time constants such as the charge-transfer and diffusion phenomena, RC networks can be utilized. In [12][13] the Rint model is extended with one RC element.

Other studies use data-driven methods, i.e., machine learning, to parameterize battery models [14][15][16]. Further studies also model the hysteresis behavior of the OCV of lithium-ion batteries as was done in [17] for $LiCoO_2$ cells and in [18] for $LiFePO_4$ cells. In the study conducted by Tran et al. the hysteresis effect was stronger in lithium-ion batteries with LFP and NCA chemistry compared to NMC and LMO chemistry [19]. In addition to integer-order models also fractional-order models are used for equivalent circuit models, which can offer 15–30% higher accuracy than their integer-order analogues but add complexity [20]. Electrical battery models are coupled with thermal models as the electrical parameters, such as the inner resistance, are temperature dependent. An example for the coupling of a thermal 3D model with a P2D model can be found in [21]. Yang et al. employ machine based learning to the thermal parameterization of EV Li-Ion batteries from external short circuit experiments [22]. The researchers here choose to parameterize a electrical dual polarization electrical model (2RC) in order to achieve a good trade-off between computational complexity and accuracy for charging processes and dynamic vehicle-to-grid profiles.

In addition to an electro-thermal battery model, an aging model of the traction battery is relevant for EV simulation models. The researchers conduct accelerated cycle and calendar aging tests and evaluate the aging trend with periodic check ups which include a capacity test (full discharge), impedance spectroscopy and pulse tests. This approach was also carried out by Ecker et al. [23][24]. In [25] the authors used differential voltage analysis in order to evaluate calendar and cycle aging of a $LiFePO_4$ cell. Further extensions of a battery model treat mechanical stress during charging and discharging [26][27] or lithium-plating [28].

Within the AVTE project, conducted in the US, numerous EVs were operated and extensively tested. Among others, also the Smart e.d. was tested. The researchers conducted battery tests, such as static capacity tests and pulse power characterization tests along the lifetime of the EV. After two years of operation and 19,000 km the traction battery of the Smart e.d. lost 6.6% of its capacity and 15.9% of its 30 s discharge power capability at 80% depth-of-discharge (DOD) [29]. For an EV model for V2G applications a *charger model* and a *charging control model* are essential components.

In [30], the authors developed an on-board charger prototype that achieves a peak efficiency value of 97.3% in boost operation mode and 97% in buck operation mode. The on-board charger developed by Radimov et al. is a bi-directional, three-stage, on-board charger with a peak efficiency of 96.65% [31]. Schram et al. determined the V2G round-trip efficiency of a Renault Zoe with a bi-directional on-board charger to be 85.1% and of a Nissan Leaf connected to an external charging station to be 87.0% [32]. Due to the increasing demand for power electronic devices that are also used in EV powertrain systems researchers work on their improvements. One important improvement is the development of wide-bandgap SiC and GaN based power semiconductor devices allowing enhanced performance and improved power density [33]. Dini and Saponara propose a model-based approach for the design of such bidirectional onboard charger electric vehicles [34]. For V2G services that require fast power provision, the delay of the power provision after the power set-point request is an important specification of the charging system. Furthermore, the difference between power request (set-point) and power output is of importance. These factors are often overlooked in literature but have been measured in previous research projects. In the Parker project, grid services were offered with a V2G setup using commercial DC-chargers and commercial EVs using CHAdeMO DC-charging. The researchers set power set-points and evaluated that the provided power by the charger lagged 7 s behind the requested power and the set-point error was 8.7%. The maximum charger efficiency of the 10 kW chargers was 86% and the efficiency exhibited a large drop at charging power below 20% of the rated power [35]. Another project that investigated V2G services with EVs was the INEES project in Germany. In this project, experimental 10 kW DC charging stations were used with VW eUps that use a CCS plug system. The power set-point was reached almost instantaneously with this setup [36]. In the provision of power by a fleet of EVs it was observed that the power set-point for the fleet was reached within 1 s [37].

References

1. European Comission. A European Strategy for Low-Emission Mobility, SWD(2016) 244 Final; European Comission: Brussel, Belgium, 2016.
2. European Commission Eurostat, Energy Dashboard. Available online: https://ec.europa.eu/eurostat/cache/infographs/energy_dashboard/endash.html (accessed on 10 October 2021).
3. IEA. Global EV Outlook 2020; Technical Report; International Energy Agency: Paris, France, 2020.
4. Infas Institut für Angewandte Sozialwissenschaft GmbH. Mobilität in Deutschland 2017-Ergebnisbericht; Infas Institut für Angewandte Sozialwissenschaft GmbH: Bonn, Germany, 2017.
5. Osieczko, K.; Zimon, D.; Płaczek, E.; Prokopiuk, I. Factors that influence the expansion of electric delivery vehicles and trucks in EU countries. J. Environ. Manag. 2021, 296, 113177.
6. Wang, Y.; Tian, J.; Sun, Z.; Wang, L.; Xu, R.; Li, M.; Chen, Z. A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. Renew. Sustain. Energy Rev. 2020, 131, 110015.
7. Newman, J.; Tiedemann, W. Porous-electrode theory with battery applications. Aiche J. 1975, 21, 25–41.
8. Fuller, T.F.; Doyle, M.; Newman, J. Simulation and optimization of the dual lithium ion insertion cell. J. Electrochem. Soc. 1994, 141, 1.
9. Newman, J.; Thomas-Alyea, K.E. Electrochemical Systems, 3rd ed.; Wiley-Interscience: New York, NY, USA, 2004.

10. Romero-Becerril, A.; Alvarez-Icaza, L. Comparison of discretization methods applied to the single-particle model of lithium-ion batteries. J. Power Sources 2011, 196, 10267–10279.
11. Johnson, V. Battery performance models in ADVISOR. J. Power Sources 2002, 110, 321–329.
12. Li, Y.; Li, K.; Xie, Y.; Liu, B.; Liu, J.; Zheng, J.; Li, W. Optimization of charging strategy for lithium-ion battery packs based on complete battery pack model. J. Energy Storage 2021, 37, 102466.
13. Liaw, B.; Nagasubramanian, G.; Jungst, R.; Doughty, D. Modeling of lithium ion cells—A simple equivalent-circuit model approach. Solid State Ion. 2004, 175, 835–839.
14. Mingant, R.; Petit, M.; Belaïd, S.; Bernard, J. Data-driven model development to predict the aging of a Li-ion battery pack in electric vehicles representative conditions. J. Energy Storage 2021, 39, 102592.
15. Tang, X.; Zou, C.; Yao, K.; Lu, J.; Xia, Y.; Gao, F. Aging trajectory prediction for lithium-ion batteries via model migration and Bayesian Monte Carlo method. Appl. Energy 2019, 254, 113591.
16. Tang, X.; Liu, K.; Li, K.; Widanage, W.D.; Kendrick, E.; Gao, F. Recovering large-scale battery aging dataset with machine learning. Patterns 2021, 2, 100302.
17. Carlier, D.; Saadoune, I.; Ménétrier, M.; Delmas, C. Lithium Electrochemical Deintercalation from O 2 LiCoO2: Structure and Physical Properties. J. Electrochem. Soc. 2002, 149, A1310.
18. Tran, M.K.; Mevawala, A.; Panchal, S.; Raahemifar, K.; Fowler, M.; Fraser, R. Effect of integrating the hysteresis component to the equivalent circuit model of Lithium-ion battery for dynamic and non-dynamic applications. J. Energy Storage 2020, 32, 101785.
19. Tran, M.K.; DaCosta, A.; Mevawalla, A.; Panchal, S.; Fowler, M. Comparative Study of Equivalent Circuit Models Performance in Four Common Lithium-Ion Batteries: LFP, NMC, LMO, NCA. Batteries 2021, 7, 51.
20. Zou, C.; Zhang, L.; Hu, X.; Wang, Z.; Wik, T.; Pecht, M. A review of fractional-order techniques applied to lithium-ion batteries, lead-acid batteries, and supercapacitors. J. Power Sources 2018, 390, 286–296.
21. Habedank, J.B.; Kraft, L.; Rheinfeld, A.; Krezdorn, C.; Jossen, A.; Zaeh, M.F. Increasing the Discharge Rate Capability of Lithium-Ion Cells with Laser-Structured Graphite Anodes: Modeling and Simulation. J. Electrochem. Soc. 2018, 165, A1563–A1573.
22. Yang, R.; Xiong, R.; Shen, W.; Lin, X. Extreme Learning Machine-Based Thermal Model for Lithium-Ion Batteries of Electric Vehicles under External Short Circuit. Engineering 2020, 7, 395–405.
23. Ecker, M.; Gerschler, J.B.; Vogel, J.; Käbitz, S.; Hust, F.; Dechent, P.; Sauer, D.U. Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test

data. J. Power Sources 2012, 215, 248–257.

24. Ecker, M.; Nieto, N.; Käbitz, S.; Schmalstieg, J.; Blanke, H.; Warnecke, A.; Sauer, D.U. Calendar and cycle life study of Li(NiMnCo)O2-based 18,650 lithium-ion batteries. J. Power Sources 2014, 248, 839–851.
25. Lewerenz, M.; Marongiu, A.; Warnecke, A.; Sauer, D.U. Differential voltage analysis as a tool for analyzing inhomogeneous aging: A case study for LiFePO4|Graphite cylindrical cells. J. Power Sources 2017, 368, 57–67.
26. Renganathan, S.; Sikha, G.; Santhanagopalan, S.; White, R.E. Theoretical Analysis of Stresses in a Lithium Ion Cell. J. Electrochem. Soc. 2010, 157, A155.
27. Laresgoiti, I.; Käbitz, S.; Ecker, M.; Sauer, D.U. Modeling mechanical degradation in lithium ion batteries during cycling: Solid electrolyte interphase fracture. J. Power Sources 2015, 300, 112–122.
28. Arora, P.; Doyle, M.; White, R.E. Mathematical modeling of the lithium deposition overcharge reaction in lithium-ion batteries using carbon-based negative electrodes. J. Electrochem. Soc. 1999, 146, 3543.
29. Diaz, A.G.J. Advanced Vehicle Testing and Evaluation. Technical Report, Intertek. 2018. Available online: https://www.osti.gov/servlets/purl/1481912 (accessed on 6 March 2022).
30. Kim, D.H.; Kim, M.J.; Lee, B.K. An Integrated Battery Charger with High Power Density and Efficiency for Electric Vehicles. IEEE Trans. Power Electron. 2017, 32, 4553–4565.
31. Radimov, N.; Li, G.; Tang, M.; Wang, X. Three-stage SiC-based bi-directional on-board battery charger with titanium level efficiency. IET Power Electron. 2020, 13, 1477–1480.
32. Schram, W.; Brinkel, N.; Smink, G.; van Wijk, T.; van Sark, W. Empirical Evaluation of V2G Round-trip Efficiency. In Proceedings of the 2020 International Conference on Smart Energy Systems and Technologies (SEST), Istanbul, Turkey, 7–9 September 2020; pp. 1–6.
33. Rajendran, G.; Vaithilingam, C.A.; Misron, N.; Naidu, K.; Ahmed, M.R. A comprehensive review on system architecture and international standards for electric vehicle charging stations. J. Energy Storage 2021, 42, 103099.
34. Dini, P.; Saponara, S. Electro-Thermal Model-Based Design of Bidirectional On-Board Chargers in Hybrid and Full Electric Vehicles. Electronics 2021, 11, 112.
35. Andersen, P.B.; Toghroljerdi, S.H.; Sörensen, T.M.; Christensen, B.E.; Lodberg Höj, J.C.M.; Zecchino, A. The Parker Project 2019. Available online: https://parker-project.com/wp-content/uploads/2019/03/Parker_Final-report_v1.1_2019.pdf (accessed on 6 March 2022).
36. Arnold, G.; Brandl, R.; Degner, T.; Gerhardt, N.; Landau, M.; Nestle, D.; Portula, M.; Scheidler, A.; Schwinn, R.; Baumbusch, K.; et al. Intelligente Netzanbindung von Elektrofahrzeugen zur

Erbringung von Systemdienstleistungen—INEES. Technical report, Fraunhofer IWES, LichtBlick SE, SMA AG, Volkswagen AG, 2018. Available online: https://www.erneuerbar-mobil.de/sites/default/files/2016-09/INEES_Abschlussbericht.pdf (accessed on 6 March 2022).

37. Degner, T.; Arnold, G.; Brandl, R.; Dollichon, J.; Scheidler, A. Grid Impact of Electric Vehicles with Secondary Control Reserve Capability. In Proceedings of the 1st E-Mobility Power System Integration Symposium, Berlin, Germany, 24–27 October 2017.