Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

MODELING AND SIMULATION TO IMPROVE REAL ELECTRIC VEHICLES CHARGING PROCESSES BY INTEGRATION OF RENEWABLE ENERGIES AND BUFFER STORAGE

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ABSTRACT

The present study explores a simulation model combining system dynamics and discrete-event simulation for an electric vehicle charging system. For the representation of the charging demand the model employs data from an actual facility for vehicle charging. While being connected to the electrical grid, the system is augmented by a solar photovoltaic installation and stationary battery energy storage. Multiple simulation runs were performed to analyze the considered energy system over a 1-year period and compare relevant output parameters for different system configurations and system locations. Results show that a solar photovoltaic installation can be effectively integrated. For the degree of self-sufficiency, high values of 87 % can be achieved with combined solar photovoltaic and battery energy storage systems.

1 INTRODUCTION

Mitigating climate change is one of the greatest challenges facing society and politics today. The transport and energy sectors together are responsible for about 54 % of total annual greenhouse gas emissions in the United States (United States Environmental Protection Agency) and for about 60 % in Germany (Appunn et al.). To reduce greenhouse gas emissions, governments worldwide have proclaimed ambitious targets for the expansion of renewable energies as well as the electrification of transport. For instance, Germany's 2030 targets for greenhouse gas emission reductions amounts to a total of 65 % compared to 1990 levels (Appunn et al.). The most important means to reach these targets in the energy and transport sector are the growth of renewable energies and introduction of electric vehicles (EVs). Substantially increasing the number of EVs in service necessitates the expansion of charging infrastructure in terms of charging capacity and locations. Locations include residential areas, public points of interests, as well as workplaces. Parking infrastructure at workplaces could become increasingly important since the EVs of employees can be charged during daytime rather than peak power demand times which typically occur in the morning and evening hours.

To further enhance the sustainability and environmental benefits of EV utilization, parking infrastructure with EV charging facilities can be combined with local renewable power generation. For instance, a solar photovoltaic (PV) system can partly supplement the charging demand of EVs and reduce the amount of electricity needed from the power grid. However, since solar PV systems only provide energy intermittently and thus generation does not always occur during EV charging times, system efficacy may be enhanced if a stationary battery energy storage (BES) system is installed as well. The BES can be charged from a solar PV system during periods of high electricity generation and low EV charging demand, and discharged when the charging demand exceeds the local generation from the solar PV system.

An installation comprising EV charging power demand, a solar PV system and a stationary BES constitutes a complex energy system. Determining the size of the solar PV system as well as the stationary BES and controlling the energy flows between the various subsystems in an efficient and sustainable manner is an important consideration for stakeholders and decision-makers in this field. While existing systems can be analyzed and findings can be transferred to other use cases, it is often not possible to account for differences in system configuration and/or system control. Accordingly, it is sensible to model a system before implementation. The model can then be employed to simulate the behavior under actual operating conditions and to determine the optimal dimensioning and control of the components. In addition, it is possible to vary the system configuration in the design stage to determine the parameters that majorly impact system behavior.

With the present paper, the authors contribute a simulation model combining system dynamics and discrete-event simulation for the aforementioned EV charging energy system. In contrast to earlier studies, the model employs real data from the Adaptive Charging Network (ACN), described by Lee et al. (2016), for the representation of the charging demand, which is considered in conjunction with solar PV and BES. For the interactions between the components, a rule-based strategy was utilized. Due to the flexibility of the model, various system configurations can be explored, including different size solar PV systems as well as BES capacities and charging/discharging rates. Moreover, the EV charging infrastructure can be analyzed for regions with different solar radiation. By performing multiple simulation runs over a 1-year period, the considered energy system was analyzed and relevant output parameters were compared.

The paper is structured as follows. Section 2 reviews the current state of research in the field of energy system modeling and simulation. Section 3 briefly describes the selected modeling approach and gives an overview of the modeled components. Results are presented and discussed in Section 4. The paper concludes with a summary of major findings and an outlook on future work.

2 RELATED WORK

2.1 Modeling and Simulation of Energy Systems

The consideration of sector-coupled energy systems, which include renewable power generation and EVs, has become increasingly important in recent years due to the trend towards greater sustainability (Strobel et al. 2022). Modeling and simulation is a widely used approach to study such systems and explore scenarios with respect to different performance metrics such as self-consumption rate or degree of self-sufficiency. Publications in this field differ with regard to the modeling approach, input data, or the considered scenarios. Bazan and German (2012) combine system dynamics and discrete-event simulation to study sector-coupled energy systems at the level of a residential community. The simulation is component-based, considering electricity and heat as energy sources that can also be exchanged between several households within the residential community. One studied scenario showed that sector coupling can provide increased profit for all households while less energy has to be purchased from external grids. A simulation model for a microgrid with several local electricity producers was developed by (Annuk et al. 2021), who considered wind generators and solar PV systems as independent sources of electricity. Results show that the size of generators and buffer battery system have an impact on the demand cover factor.

Literature pertaining to energy systems relevant to the subject matter of this paper is often focused on the analysis of different scenarios from a cost perspective. In their study, Aldhanhani et al. (2017) sought to meet the electricity demand of EVs through local generation. Three scenarios were compared, i.e., first a diesel generator, then renewable energy sources such as solar PV and wind turbines, and finally a combination of both. In addition, stationary BES systems were considered. Using the HOMER simulation software (HOMER Software, Boulder, CO, USA) the optimal sizing of the components was determined so that demand is always met at the lowest possible total cost. Charging profiles and weather data were modeled using real data from the University of Waterloo and the NASA Surface Meteorology and Solar Energy website. From 25-year simulation runs, the lowest cost was found for the stand-alone systems when combining diesel generator and renewable generation. The potential of EV charging at the workplace was discussed by Mouli et al. (2016). For this purpose, a solar PV system was combined with each charging station while also allowing for connection to the electrical grid. A model for the solar PV system located in the Netherlands was then set up and analyzed in the computing platform MATLAB (MathWorks, Portola Valley, CA, USA) using real data at 1-minute resolution. EV charging profiles were modeled synthetically to generate charging processes during daytime hours (8:30 am - 5:30 pm). The results revealed a significantly lower yield in the winter months, which cannot even be increased to a considerable extent by adjustable PV panel orientations. Yang and Ribberink (2019) presented a model for direct current (DC) fast charging at a highway service center in Canada. In their model, a grid-connected system was augmented by a solar PV unit and/or a lithium-ion BES, each with different capacities. The authors compared different system configurations and used real-world data for traffic volumes for modeling the charging demand and charging profiles. Weather profiles for PV generation were also based on real data from Canadian sources. They used the TRNSYS simulation software (University of Wisconsin, Madison, WI, USA) to simulate different scenarios and collect data. The results show that the amount of energy imported from the grid can be decreased by incorporating a solar PV system.

While the technical literature considered above is based on simulation and modeling of theoretical systems, there is also research that examines the behavior of real systems. For instance, Esfandyari et al. (2019) considered a charging station for two small EVs at a campus in Ireland. The station features a solar PV system, BES, and a grid connection. In the simulation, the generated energy of the solar PV system was first calculated using real data with a 1-minute resolution and compared with measured values. Due to the northern location of Ireland, a strong difference in generation was ascertained between summer and winter months. Therefore, the degree of self-sufficiency was found to range between 53 % and 89 %, with the self-consumption percentage varying between 3 % and 83 %. Most of the energy is drawn from the BES system and only a small proportion is sourced directly from the solar PV system. It was shown that the system can realize monthly carbon dioxide savings of up to 591 kg.

2.2 Adaptive Charging Network

In contrast to various other studies, such as by Mouli et al. (2016), the present work considers an energy system based on real charging demand data in order to assess the contribution of electricity from solar PV systems. For this purpose, real-world data from the ACN was employed. The ACN was developed at California Institute of Technology ('Caltech', Pasadena, CA, USA) and consists of over 80 charging ports in a car parking facility on the Caltech Campus. The data of charging processes from 2016 onwards is publicly available. Lee et al. (2019) provide a detailed description of the data as well as use cases that can be derived from it. In Meenakumar et al. (2020), ACN data was used to determine the potential benefits of vehicle-to-grid technologies, i.e., systems in which energy can be temporarily withdrawn from vehicles when connected to charging points. Utilizing machine learning and deep learning techniques, Khan et al. (2020) employed ACN data to make predictions about the charging behavior of electric vehicle users.

In the present study, ACN data was used to derive profiles for the charging demand of a parking facility. For this purpose, the input data derived from the `connectionTime`, `doneChargingTime` and `kWhDelivered` fields as described by Lee et al. (2016) and Lee et al. (2021). In contrast to related works that typically study different components and dimensions for a fixed site with a certain basic configuration of charging profiles, the modeling work presented herein accommodates different locations in addition to the variation of the solar PV system and energy storage capacity. The present approach thus allows simulating the same system for different external conditions.

3 METHODOLOGY

3.1 System Dynamics and Discrete-Event Simulation

Similar to Bazan and German (2012) and Pruckner and German (2013) a framework was created combining system dynamics and discrete-event simulation. This technique is also known as hybrid simulation (Zulkepli et al. 2012). The flow of energy, such as from solar PV electricity generation or charging and discharging of BES, are variables that change continuously with respect to time. So, the technique of system dynamics simulation is used to represent power flows. In contrast, electricity demand derives from real EV charging events based on the ACN, meaning the power flow representing the charging demand is influenced by discrete events. For instance, a single EV charging event can be described by its start and end time which are discrete points in time, and hence, an EV charging session can be modeled as an discrete event. The simulation was realized using the commercial software AnyLogic 8 (AnyLogic, Oakbrook Terrace, IL, USA). The software supports hybrid simulation by combining different simulation techniques, including system dynamics and discrete-event simulation, and the development of component-based simulation frameworks.

3.2 Modeling of Basic Components

Figure 1 depicts a schematic of the different components of the model. The system dynamics flow variables represent the energy flows between different system components. In order to maintain a balance between supply and demand, meaning the state variable *site* should be always zero, control of the flow variables is necessary. This control is accomplished by the auxiliary variables *balanceStorage* and *balance*. The corresponding algorithms for calculating the charging rate, discharging rate and the grid import and export are shown in Algorithm 1, Algorithm 2 and Algorithm 3.

Algorithm 1 Calculate charging rate for battey

$balanceStorage = charging - solar\_power$
if $balanceStorage < 0$ && $storage < capacity$ **then**
  if $|balanceStorage| \leq maxPower$ **then**
    $storeEnergy = |balanceStorage|$
  else
    $storeEnergy = maxPower$
  end if
else
  $storeEnergy = 0$
end if

The overarching notion for the model is that the charging demand of the parking facility should always be covered first by solar PV electricity generation. If the latter is not sufficient, the BES system is discharged. If the BES is empty or the discharge rate is insufficient, the charging demand is supplemented from the external grid (see *purchaseFromGrid* in Figure 1). In the case that electricity generation exceeds the charging demand, the BES is charged. If the BES is already fully charged or the charging rate is insufficient, excess generated electricity is necessarily fed into the external grid (see also *sellToGrid* in Figure 1). In the following, the modeling of charging demand, solar PV system, stationary BES are described.

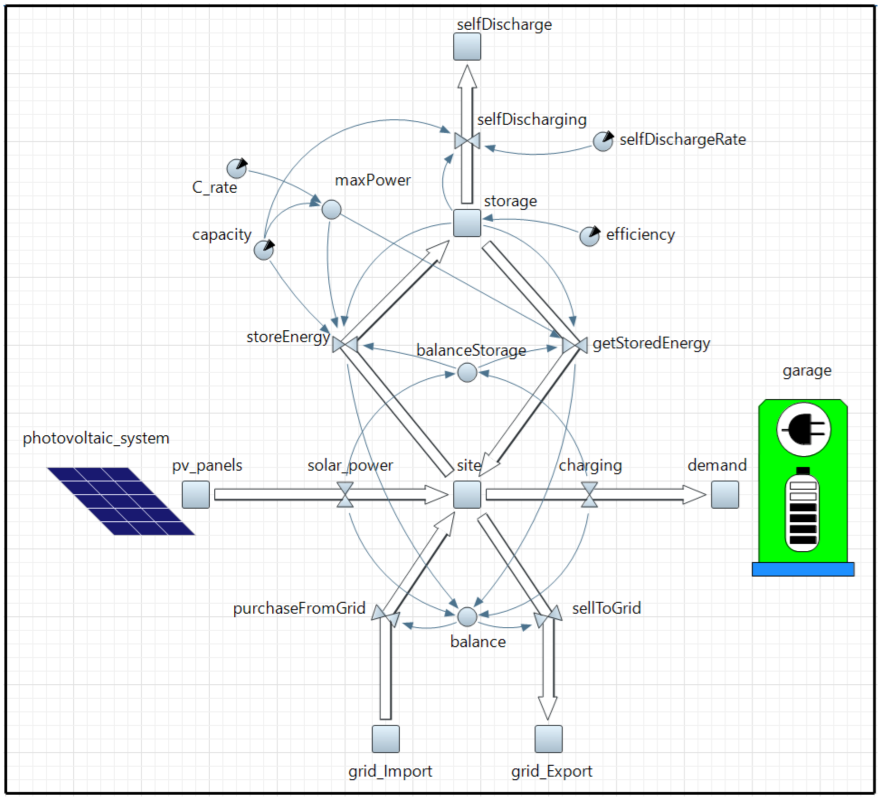

Figure 1: Overview of the main model.

Algorithm 2 Calculate discharging rate for battery

$balanceStorage = charging - solar\_power$
if $balanceStorage > 0$ && $storage > 0$ **then**
  if $balanceStorage \leq maxPower$ **then**
    $getStoredEnergy = balanceStorage$
  else
    $getStoredEnergy = maxPower$
  end if
else
  $getStoredEnergy = 0$
end if

Algorithm 3 Calculate grid import and export

$balance = charging + storeEnergy - solar\_power - getStoredEnergy$
if $balance > 0$ **then**
  $purchaseFromGrid = balance$
  $sellToGrid = 0$
else
  $sellToGrid = |balance|$
  $purchaseFromGrid = 0$
end if

Table 1: Attributes of charging demand input file data.

Attribute	Data type	Description
`connectionTime`	Date	Date when the user plugs in
`disconnectionTime`	Date	Date when the user unplugs
`doneChargingTime`	Date	Date of the last non-zero charging rate
`kWhDelivered`	double	Measured Energy Delivered
`stationID`	String	Unique identifier of the electric vehicle supply equipment
`arrivingTime`	double	Amount of miliseconds between starting date and connection date

3.2.1 Charging Demand

As mentioned above, the modeling of the charging profiles is based on the ACN. Corresponding data for an arbitrary observation period (e.g., the year 2020) is directly introduced into the simulation model via an application programming interface (API) using files in JavaScript Object Notation (JSON) format. The JSON files contain the attributes shown in Table 1 for each charging event and are concatenated via a for-loop to form a list containing all charging events for the specified time period.

The `connectionTime` and `doneChargingTime` are of particular relevance from among the attributes shown in Table 1, given that they define the charging interval for a charging event. The charging power at each time step could be determined by dividing `kWhDelivered` by the time of the charging interval. However, such an approach ignores the fact that in reality charging power is not constant. For this reason, a realistic charging profile was approximated. For reference, the charging profile of a Nissan Altra with a lithium-ion battery was herein used (Madrid et al. 1999). As an approximation, the approach proposed by Zhang et al. (2012) was employed, dividing the charging interval into two sections, i.e., up to 15 minutes before `doneChargingTime`, charging power is considered constant, followed by a charging power linearly diminishing to 0 kW (see Figure 2). Clearly, the amount of energy supplied during the charging event must equal `kWhDelivered`. Note that other charging profiles can be considered in the simulation as well, which however is beyond the scope of the present study. For each charging session, a corresponding event is triggered using the charging event list. Consequently, the summation over the charging powers in each time step results in the total power of all vehicles charging in this time step, which corresponds to the flow variable *charging* in Figure 1.

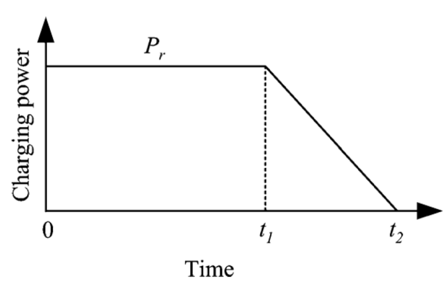

Figure 2: Function approaching the real charging profile.

3.2.2 Solar Photovoltaic System

The determination of solar PV generation is based on real data from the National Solar Radiation Data Base (National Renewable Energy Laboratory a), which provides historical values for solar radiation as well as other meteorological data for North America. The dataset used herein is the ”Physical Solar Model” with a temporal resolution of 5 minutes. In order to simulate different locations, weather data from 2019 were utilized for Pasadena, CA, USA, Vancouver, BC, Canada, and Mexico City, Mexico.

First, following the approach by Quaschning (2019), the total irradiance $E_{G,gen}$ for inclined planes was determined from the given weather data. Both direct and diffuse irradiance, elevation angle, azimuth angle, and longitude and latitude of the corresponding location were considered. From the resulting total irradiance on an inclined plane, $E_{G,gen}$ (in units of $\mathrm{W\,m^{-2}}$), the output power of the solar PV system was calculated, considering the area of the PV system, A_{PV}, the module efficiency, η_{PV}, and the installed power under standard testing conditions, P_{PV}. The efficiency η_{PV} was set to 17 % (Domínguez-Navarro et al. 2019). The P_{PV} parameter can be set in the beginning of each simulation run. A_{PV} was calculated from the efficiency and installed power using Equation (1) (Quaschning 2019).

$$A_{PV} = \frac{P_{PV}}{\eta_{PV} \cdot 1000\,\mathrm{W\,m^{-2}}} \tag{1}$$

Finally, the electricity generation, P, in each time step is obtained from the area, the efficiency and the instantaneous total irradiance, i.e.,

$$P = E_{G,gen} \cdot A_{PV} \cdot \eta_{PV}$$

The electricity generation P, corresponding to *solar_power* in Figure 1, is represented by a dynamic variable which calculation is performed cyclically at 5-minute intervals by a system dynamics model.

3.2.3 Stationary Battery Energy Storage System

Section 3.2 already detailed the algorithms for calculating the energy flows for BES charging/discharging. Hence, only the BES parameters regarding capacity, self-discharge rate and efficiency are described in the following. The capacity parameter is set before the start of the simulation and specifies the maximum capacity of the BES system in kWh. The maximum charge/discharge rate is obtained from the parameter C-rate that indicates the ratio of power and capacity (Nadeem et al. 2018). The *selfDischargeRate* parameter specifies the percentage by which the BES system is discharged per day when its state-of-charge > 0 and it is not supplying power to the system. The default value was set to 0.25 % per day (Nadeem et al. 2018). The *efficiency* parameter indicates the overall efficiency of the BES system; a value of 0.95 was used according to Nadeem et al. (2018).

3.3 Validation

To validate the developed simulation model, several plausibility checks were performed. Both the implemented model logic and the individual components were verified. For example, the functionality of the implemented solar PV model was compared with other available sources. For this purpose, the average monthly irradiance was contrasted with values from the online tool PV-Watts (National Renewable Energy Laboratory b). Overall, deviations were less than 3 %. For the validation of the charging demand, in particular the methodology to approximate the charging profile, the annual electricity demand was compared with the raw ACN data for 2019. Again, no significant differences were ascertained.

Finally, the implemented model logic, especially the operation of the BES, was scrutinized by comparing the system dynamics flow variables for different points in time and checking for plausibility.

4 RESULTS

The main goals of the present simulation and modeling study are to investigate a) to which degree the electricity generated by the solar PV system can directly be consumed by the charging demand of the parking facility, and b) how the stationary BES system can contribute to an improved integration of the solar PV system. Thereby, the study involved dimensioning these components with regard to installed power, capacity, etc. For the evaluation the self-consumption rate and the degree of self-sufficiency were utilized. The self-consumption rate, e, describes how much of the energy generated by the solar PV system,

E_{PV}, is used in the parking facility. The self-consumption rate was calculated considering the amount of electricity exported to the grid, E_e, using Equation (2) (Quaschning 2019).

$$e = \frac{E_{PV} - E_e}{E_{PV}} \tag{2}$$

The degree of self-sufficiency, a, indicates how much of the energy demand, E_B, is covered by the energy generated by the solar PV system. The degree of self-sufficiency is determined in conjunction with the energy imported from the grid, E_i, according to Equation (3) (Quaschning 2019).

$$a = \frac{E_B - E_i}{E_B} \tag{3}$$

Results were computed analyzing the behavior of the considered energy system under varying installed power of the solar PV system and capacity of the BES system. Following the analysis of a baseline configuration, system behavior was compared for the three aforementioned locations, i.e., Pasadena, Vancouver and Mexico City. Note that input data for the year 2019 was used because for 2020 onwards, the EV charging behavior at the Caltech campus is atypical due to increased home office work brought about by the COVID-19 pandemic.

4.1 Baseline Scenario

The baseline scenario considers the parking located facility at Caltech. The total amount of energy used for EV charging in the simulated year is 94 689 kWh. The power of the solar PV system was varied from 0 to 70 kW in steps of 10 kW. A 70 kW solar PV installation generates 145 007 kWh annually based on the weather data of Pasadena. The BES capacity was varied in increments of 20 kWh from 0 to 100 kWh.

The graphs in Figures 3 and 4 depict the self-consumption rate and degree of self-sufficiency for the above parameters. In general, with increasing photovoltaic power, the degree of self-sufficiency increases and the self-consumption rate decreases. When more electricity is generated by the solar PV system, less electricity needs to be imported from the grid. On the other hand, periods in which generation exceeds demand increase, and accordingly, surplus of electricity is fed into the grid. The graphs further show that both the degree of self-sufficiency and self-consumption increase with increasing BES capacity. This is explained by the ability to charge the BES with the solar PV system when EV charging demand is low, which in turn allows drawing power from the BES during periods of high EV charging demand exceeding solar PV generation. Consequently, both power import and export from grid is reduced.

Referring to Figure 3, high values of up to 87 % can quickly be achieved for the degree of self-sufficiency with the considered installed solar PV power and BES capacity. Even without BES, the degree of self-sufficiency remains high with up to 68 %, while the self-consumption rate does not fall below 40 %. For comparison, a single-family house in Germany with a solar PV system and without BES can achieve a maximum degree of self-sufficiency of about 40 % and a self-consumption rate of less than 10 % (Quaschning 2019). The reason for the favorable integration of the solar PV system at the parking facility is the timing of charging processes. Since EV charging occurs during daytime hours, the energy demand takes a similar course as the energy generated from the solar PV system.

It is interesting to note the non-linear relationship that PV system power and BES capacity have with the degree of self-sufficiency and self-consumption percentage. Notably for BES capacities above 60 kWh, there is a diminishing return in the degree of self-sufficiency and self-consumption rate. Therefore, a BES capacity of 60 kWh was assumed for the subsequent analyzes.

At this juncture, it is worth exploring the intricacies between supply and demand in this energy system. Figure 5 shows an arbitrary 4-day history of demand for a configuration with an installed solar PV capacity of 50 kW. The time period considered is from Sunday, July 7, 2019 to Wednesday, July 10, 2019, with each hour colored to indicate whether demand is met by grid import (grey), solar PV generation (green), or from BES (red). Notably, a considerable amount of electricity is discharged from the BES on Monday

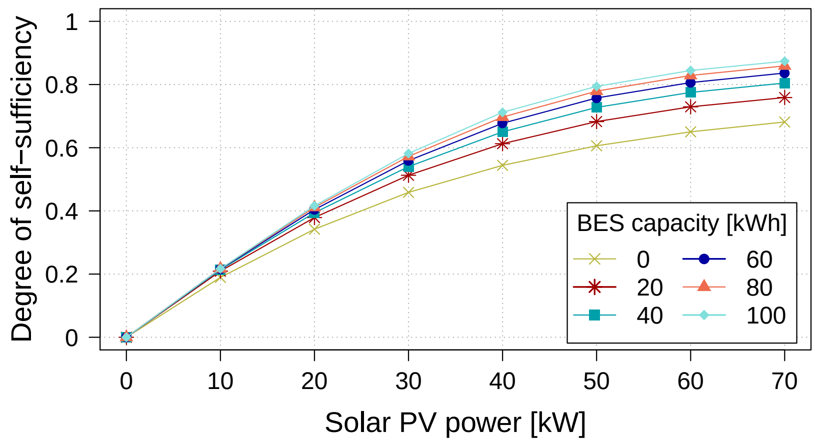

Figure 3: Degree of self-sufficiency for the baseline configuration versus installed solar PV power for different BES capacities.

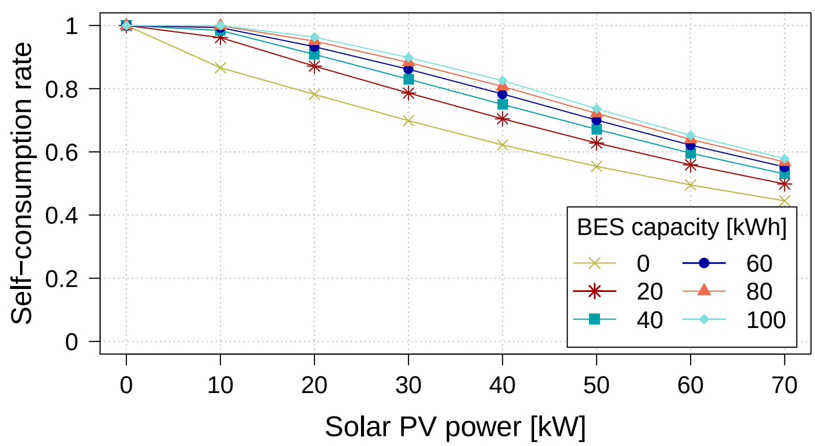

Figure 4: Proportion of self-consumption for the baseline configuration versus installed solar PV power for different BES capacities.

because only limited EV charging occurred on the weekend, allowing energy generated by the solar PV system to charge the BES. In fact, on the weekend, it is also possible to meet the charging demand without grid imports.

4.2 Comparison of Different Locations

In addition to Pasadena, the considered energy system was investigated for a more northerly and southerly location, i.e., Vancouver and Mexico City, respectively. Since the annual solar radiation is different in these locations, it is sensible to adjust the dimensioning of the PV system. For reasons of comparison, in each case, the power of the installed solar PV system was adjusted so that the annually generated energy is approximately equal for the different locations. Accordingly, the solar PV power for the Vancouver and Mexico City locations have step sizes of correspondingly 13.71 kW and 9.29 kW, as compared to 10 kW for the Pasadena location (i.e., the maximum solar PV power at the Vancouver, Pasadena and Mexico City locations are 96 kW, 70 kW and 65 kW, respectively). Results in terms of self-sufficiency and self-consumption are shown for all sites in Figure 6, showing that Mexico City is associated with

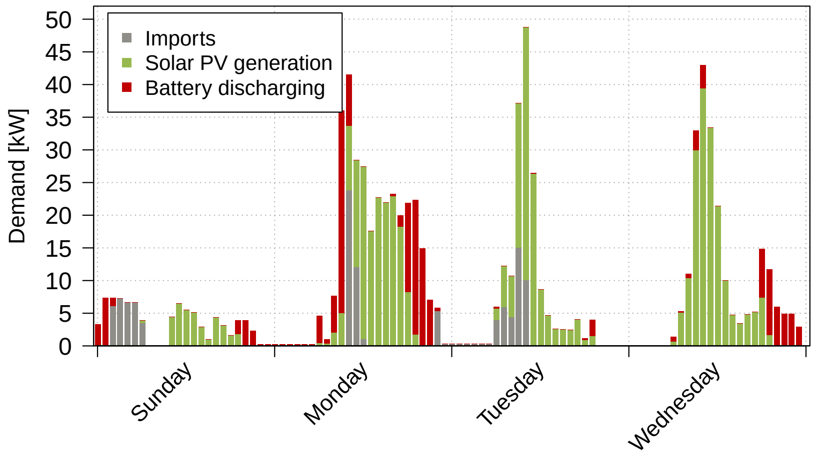

Figure 5: Proportions of EV charging demand supplied by the grid (grey bars), the solar PV system (green), and the BES (red), for an arbitrary 4-day period (the period of July 7 to 10, 2019).

the highest values, followed by Pasadena and then Vancouver. The integration of solar PV into the EV charging processes is therefore found to be less effective for more northerly locations (i.e., Vancouver is the least effective location).

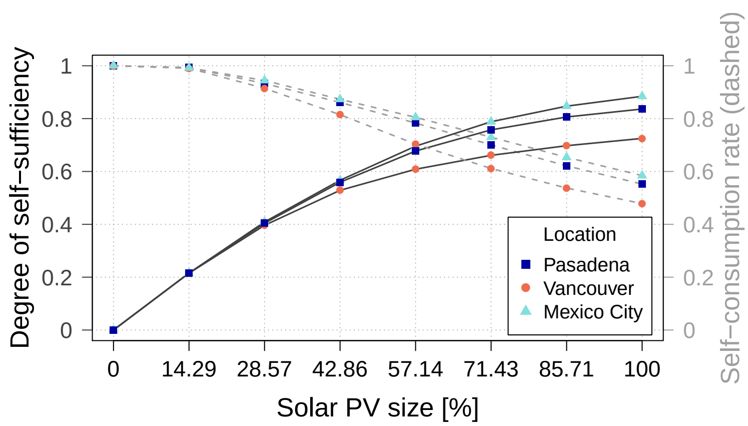

Figure 6: Degree of self-sufficiency (solid lines) and self-consumption rate (dashed lines) for different solar PV system powers for the locations Pasadena, Vancouver, and Mexico-City. Note that the percentage of the solar PV size refers to the respective maximum power value for each location.

The observations derived from Figure 6 are rationalized by the graph in Figure 7, which depicts the magnitude-ordered energy generated daily by the solar PV system for a 1-year period for the three locations. Interestingly, while the total amount of energy, i.e., the sum of daily generated energy for all days of the year, is almost identical in all three cases, the curve for the Mexico City location exhibits a moderate slope over a large period compared to the Pasadena and Vancouver locations. In contrast, the curve for the Vancouver location describes a steady significant decline throughout. Due to its northerly location, diurnal sunshine duration in Vancouver is subject to strong seasonal fluctuations, i.e., during the summer months, the solar PV system can produce significant amounts of energy, even exceeding values for Mexico City, whereas in the winter, energy generation is strongly diminished. Conversely, Pasadena and Mexico City, which are located further south, see less variation in sunshine hours throughout the year. As a result of low solar PV generation for extended times of the year, the considered EV charging facility at the Vancouver location lags behind the other locations in terms of self-sufficiency and proportion of own-consumption.

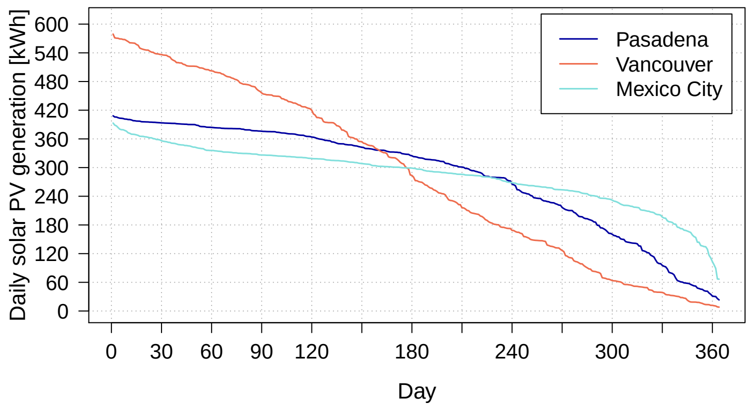

Figure 7: Magnitude-ordered energy generated daily by the solar PV system for a one-year period for the locations Pasadena, Vancouver and Mexico-City.

5 CONCLUSION

In this research study, a simulation model was developed for an energy system comprised of energy demand for an EV charging facility with solar PV and stationary BES support. The charging demand is based on real charging processes of a parking facility at California Institute of Technology campus. The model was implemented in the simulation software AnyLogic by combining the simulation paradigms system dynamics and discrete-event simulation. The model allows for different parameters to be set individually, enabling the exploration of different system and usage scenarios. The developed simulation tool can therefore be used for design decision support.

The results indicate that a solar PV system can effectively be integrated with the EV charging infrastructure. Since the electricity demand is largely during the daytime, most of the generated electricity from the solar PV system can directly be used for charging the vehicles. The stationary BES system improves the integration of the photovoltaic system by using excess generation to charge the BES, allowing energy to be used later when demand exceeds the solar PV generation. For the studied facility configurations, it is possible to reduce carbon emissions by over 80 % by reducing grid import.

For future work, the authors seek to enhance the simulation framework in several ways: 1) Besides BES systems, the scheduling of vehicle charging events could be optimized (i.e., based on the available data, the vehicle departure time is known), providing flexibility for the charging window that can be exploited to further increase the self-consumption rate; 2) in addition to photovoltaic systems, the potential of wind turbines could be considered; and 3) the EV charging profiles could be modeled with enhanced fidelity.

REFERENCES

Aldhanhani, T., A. Al-Durra, and E. F. El-Saadany. 2017. "Optimal Design of Electric Vehicle Charging Stations Integrated with Renewable DG". In *2017 IEEE Innovative Smart Grid Technologies-Asia*, 1–6. Institute of Electrical and Electronics Engineers, Inc.

Annuk, A., W. Yaïci, M. Lehtonen, R. Ilves, T. Kabanen, and P. Miidla. 2021. "Simulation of Energy Exchange between Single Prosumer Residential Building and Utility Grid". *Energies* 14(6).

Appunn, K., F. Eriksen, and J. Wettengel. "Germany's Greenhouse Gas Emissions and Energy Transition Targets". https://www.cleanenergywire.org/factsheets/germanys-greenhouse-gas-emissions-and-climate-targets, accessed by 23.03.2022.

Bazan, P., and R. German. 2012. "Hybrid Simulation of Renewable Energy Generation and Storage Grids". In *Proceedings of the Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Domínguez-Navarro, J., R. Dufo-López, J. Yusta-Loyo, J. Artal-Sevil, and J. Bernal-Agustín. 2019. "Design of an Electric Vehicle Fast-charging Station with Integration of Renewable Energy and Storage Systems". *International Journal of Electrical Power & Energy Systems* 105:46–58.

Esfandyari, A., B. Norton, M. Conlon, and S. J. McCormack. 2019. "Performance of a Campus Photovoltaic Electric Vehicle Charging Station in a Temperate Climate". *Solar Energy* 177:762–771.

Khan, S., B. Brandherm, and A. Swamy. 2020. "Electric Vehicle User Behavior Prediction using Learning-based Approaches". In *2020 IEEE Electric Power and Energy Conference*, 1–5. Edmonton, Canada.

Lee, G., T. Lee, Z. Low, S. H. Low, and C. Ortega. 2016. "Adaptive Charging Network for Electric Vehicles". In *2016 IEEE Global Conference on Signal and Information Processing*, 891–895. Washington DC, United States: Institute of Electrical and Electronics Engineers, Inc.

Lee, Z. J., G. Lee, T. Lee, C. Jin, R. Lee, Z. Low, D. Chang, C. Ortega, and S. H. Low. 2021. "Adaptive Charging Networks: A Framework for Smart Electric Vehicle Charging". *IEEE Transactions on Smart Grid* 12(5):4339–4350.

Lee, Z. J., T. Li, and S. H. Low. 2019. "ACN-Data: Analysis and Applications of an Open EV Charging Dataset". In *Proceedings of the Tenth ACM International Conference on Future Energy Systems*, 139–149. New York, NY, USA: Association for Computing Machinery.

Madrid, C., J. Argueta, and J. Smith. 1999. "Performance Characterization: 1999 Nissan Altra-EV with Lithium-Ion Battery". Technical Report No. 1, EDISON Inc., California, United States.

Meenakumar, P., M. Aunedi, and G. Strbac. 2020. "Optimal Business Case for Provision of Grid Services through EVs with V2G Capabilities". In *2020 Fifteenth International Conference on Ecological Vehicles and Renewable Energies*, 1–10. Monte-Carlo, Monaco: Institute of Electrical and Electronics Engineers, Inc.

Mouli, G. C., P. Bauer, and M. Zeman. 2016. "System Design for a Solar Powered Electric Vehicle Charging Station for Workplaces". *Applied Energy* 168:434–443.

Nadeem, F., S. S. Hussain, P. K. Tiwari, A. K. Goswami, and T. S. Ustun. 2018. "Comparative Review of Energy Storage Systems, their Roles, and Impacts on Future Power Systems". *IEEE Access* 7:4555–4585.

National Renewable Energy Laboratory. "National Solar Radiation Data Base". https://nsrdb.nrel.gov/, accesssed 21.09.2021.

National Renewable Energy Laboratory. "PVWatts". https://developer.nrel.gov/docs/solar/pvwatts/v6/, accessed 24.09.2021.

Pruckner, M., and R. German. 2013. "A Hybrid Simulation Model for Large-Scaled Electricity Generation Systems". In *Proceedings of the Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 1881–1892. Washington, D.C.: Institute of Electrical and Electronics Engineers, Inc.

Quaschning, V. 2019. *Regenerative Energiesysteme: Technologie–Berechnung–Klimaschutz*. Carl Hanser Verlag GmbH Co KG.

Strobel, L., J. Schlund, and M. Pruckner. 2022. "Joint Analysis of Regional and National Power System Impacts of Electric Vehicles—A Case Study for Germany on the County Level in 2030". *Applied Energy* 315:118945.

United States Environmental Protection Agency. "Sources of Greenhouse Gas Emissions". https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions, accessed 23.03.2022.

Yang, L., and H. Ribberink. 2019. "Investigation of the Potential to Improve DC Fast Charging Station Economics by Integrating Photovoltaic Power Generation and/or Local Battery Energy Storage System". *Energy* 167:246–259.

Zhang, P., K. Qian, C. Zhou, B. G. Stewart, and D. M. Hepburn. 2012. "A Methodology for Optimization of Power Systems Demand due to Electric Vehicle Charging Load". *IEEE Transactions on Power Systems* 27(3):1628–1636.

Zulkepli, J., T. Eldabi, and N. Mustafee. 2012. "Hybrid Simulation for Modelling Large Systems: An Example of Integrated Care Model". In *Proceedings of the Winter Simulation Conference*, edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A. M. Uhrmacher, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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