Grid Integration of PV Based Electric Vehicle Charging Stations: A Brief Review

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***Abstract*— Solar photovoltaics (PVs) and electric vehicles (EVs) can play a critical role in bringing down global carbon emissions and promoting green energy. Charging of EVs is dictated by their dependency on the grid. The inclusion and integration of PVs in the EV charging schemes will minimize their grid dependency and add flexibility to the system. Further, EVs can function as storage for both the grid and the PV systems to reduce the uncertainty in PVs' intermittency. Due to their complementary nature, PV-based EV charging stations have been discussed rigorously in the literature. This paper briefly reviews the contemporary literature on the modeling of grid-connected PV-based EV systems. The paper compiles the assessment of various modeling components and their parameters for optimal charging scenarios to aid readers in realizing modeling complexities and opportunities. In the end, the review concludes with a synopsis of future research directions for PV-based charging systems.**

Keywords—Electric vehicle, Solar photovoltaics, Ancillary services, PV based charging station.

I. Introduction

The transportation sector is one of the leading contributors to greenhouse gas emissions. Electric vehicles are a viable long-term solution to reduce the share of emissions in this sector. Electric vehicles are driven by the energy stored in batteries; thus, they can be cleaner, environment friendly, and energy-efficient compared to internal combustion engine (ICE) vehicles. In recent years, EVs have been going through rapid market growth in major US cities due to financial incentives, availability of new models, and expansion of public and workplace charging infrastructure [1]. Adequate charging infrastructures are required to resolve significant customer concerns regarding range anxiety. However, a large number of charging infrastructures would put the electrical grid under strain, as EV charging at home and the workplace can coincide with the system peak load. Large-scale EVs integration can create power quality issues in the distribution network, particularly voltage imbalance, harmonic distortion, and violation of voltage limits [2-4]. Also, the intermittent nature of EV loads is responsible for the thermal and unbalance loading of distribution network equipment. As a result, optimal control of EVs charging is also required to minimize the power quality and reliability issues.

In recent years, an increasing number of distributed generators have been added to the grid. Distributed generation and renewable energy sources, such as solar, wind, and biomass plants, can reduce carbon emissions, offset peak demand hours, and increase energy reliability. Adding distributed generation as an energy source for electric vehicle charging stations (EVCS) can be a feasible solution to the overloading of the grid. Using power electronics technology solar- or wind-based vehicle charging stations can reduce the burden on the electricity grid and maximize the utility of EV energy storage by preserving intermittent energy [5,6]. EV charging stations are generally connected to the low voltage distribution networks, making solar photovoltaics a more appropriate energy source. The low price and less maintenance of PV systems make them practical and cost-effective. The recent development of power conversion technologies and energy storage systems (ESS) has further strengthened their applicability.

Various aspects of PV-based EV charging have been covered in contemporary literature. The EV-PV-Grid systems comprise sub-systems that are interconnected with each other. The major sub-systems can be categorized as EV-PV-Grid interface, energy management, and charging operation. This paper briefly assesses the current infrastructure of an EV charging station and summarizes the concurrent EV charging methods. Regardless of the vast literary works, there is not enough work that assesses all aspects of EV-PV-Grid dynamics. This study aims to summarize the critical parameters of EV-PV-grid modeling, such as grid connection, charging infrastructure, and control algorithms. Finally, the paper proposes some related future research areas based on the literature review.

II. Grid Connection of EV Charging System

The earliest EV-Grid connection concept was unidirectional, portraying it as a grid-connected load. However, with the development of the vehicle to grid (V2G) technology, bi-directional energy flows between grid and vehicle are now viable. Subsequently, the EV integration methods have shifted from unidirectional to bi-directional in contemporary literature [7]. In V2G architecture, EV is considered to be a load, distributed generation, and storage system all at the same time. The initial notion is to use the stored energy of the EV battery for peak load shaving. Increased EV share and energy storage capacity can reduce peak load through a coordinated control scheme [8]. Peak shaving also depends on the parking hours, and long-term EV parking is more effective in peak reduction [9]. However, bi-directional power flows are more effective in the ancillary market: spinning reserve and voltage regulation. Several studies have focused on the reactive power compensation schemes, using the inverter dc-link capacitor of the EV charging system and voltage regulation algorithms [10, 11].

Also, voltage regulation using EV's bi-directional operation mode is more favorable in terms of revenue [12]. Similarly, EVs can assist in frequency regulation by either increasing or decreasing the charging or discharging rate. Generally, the frequency regulation approach is either executed through EV control algorithms by sensing the local frequency deviation or proposes a more centralized approach, where system operators purchase capacities from participating EV agents [13-15]. Due to its economic benefits and viability, the utilization of bidirectional operation of EV for spinning reserves is more noticeable in the literature. Additionally, voltage and frequency regulation requirements are more frequent than peak shaving. Though occasional V2G service will have an insignificant impact on EV battery, frequent V2G services such as net load shaping will gradually degrade EV battery [16]. Therefore, any financial model for V2G services requires to include and assess the EV battery degradation in their method.

The bi-directional operation of EVs can be efficient with the addition of renewable energy (RE) sources. Integration of RE sources will provide more flexibility in EV charging. Solar and wind energy can be feasible renewable sources integrated with the charging stations. Several studies have been performed to check the feasibility of a standalone wind energy source with an energy storage system for EV charging [17, 18]. However, wind energy based EVCS in the urban area will be impractical as wind turbines require space and large establishments obstruct wind flow. Solar PVs are ubiquitous in urban residential and commercial areas. Unlike wind turbines, PV modules can be installed on rooftops that allows access to solar irradiance and have no drawbacks related to environmental pollution. Integrated PV and energy storage systems provide flexibility in electricity generation. Thereby, solar PV is a more sensible option for EVCS as a renewable source. Moreover, peak PV generation concurs with working hours when the majority of the EVs will be parked. Consequently, the concept of "charging-by-stopping" is gradually substituted by the notion of "charging while parking" [19]. Daytime charging using a PV-based EVCS has several advantages- reducing EV charging load and impact and substantial savings of EV charging costs [20]. In [21], EV charging by either PV-Grid or standalone PV systems with energy storage is proposed and infer PV-Grid system is more profitable than standalone PV charging due to limited PV and battery capacity. Overall, PV-based EVCS strengthens the operation of V2G mode and subsequent grid services.

III. Development of EV-PV-Grid Model

The universal framework for the EV-PV-Grid model has several aspects, including projection, architecture, and system control. Fig. 1 displays a common framework of the EV-PV-Grid model. Both EV charging demand and PV generation are stochastic. Therefore, a robust forecasting model is required to estimate the charging demand and PV generation. EV charging demand also relies on the diversity of consumer behavior. In [22], a stochastic EV charging model based on real-life charging data and conditional probability distribution of vehicle usage, state of charge, and charging time is presented. Several studies in the literature consider both deterministic and stochastic methods to determine the variation of EV charging demand [23,24]. Deterministic models investigate the variation of charging for varied vehicle use with fix charging strategy based on charging conditionality, charger distance, and availability. On the other hand, stochastic models take specified vehicle use and generate stochastic charging patterns. In essence, EV charging demand projection requires the reflection of multiple variables for an efficient model.

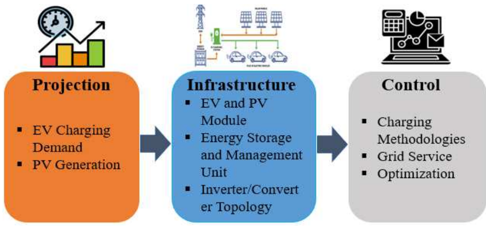

Fig. 1 A common framework of the EV-PV-Grid model

The EV-PV-Grid connection has two viable approaches: EV charging by the PV and grid or a standalone PV system. Both methods require an energy storage system to store energy for night-time operation. The PV-Grid charging system has more flexibility, as the grid can carry out charging during inadequate solar energy or low capacity of the battery. Both approaches comprise inverters/converters, a battery management system, and a central control system. The PV-based charging system will require fewer converters and operates more efficiently for the dc mode of charging operation. In [25], a PV-based dc fast-charging system is proposed with a bidirectional non-isolated dc-dc converter as a dc charger. The charging operation could be optimized using various scheduling algorithms. The most common scheduling methods are centralized and decentralized scheduling. In centralized scheduling, EV aggregators or EV fleet operators collect the required charging information for EVs and determine optimal charging strategy, while in decentralized scheduling, EV owners can decide their charging schedule. The role of EV aggregators in the decentralized method is to develop a bidding plan based on EV charging demand projection for the given time. In both methods, bids are approved by the grid system operator.

IV. Projection of Stochastic Parameters

The initial modeling of the EV-PV-Grid model involves the development of an efficient projection model to estimate EV charging demand and PV generation.

A. *EV Charging Demand*

Travel behavior of users and their charging preferences are the primary source of unpredictability in EV charging demand. Variability in vehicle usage is observed among individual users over several days. Similarly, charging preference describes the situation under which users charge their vehicles, along with charging location and charging strategy. All related variabilities need to be considered in the charging load projection model. Most models apply probabilistic distribution or Monte Carlo based modeling to capture this diversity. Table 1 displays a summary of various models to estimate EV charging load [23-34].

Table 1. Summary of EV Charging Demand Projection Models

Model	Remarks
Monte Carlo Simulation	- A stochastic model with high accuracy. - Computationally intensive. - Relies on historical data.

Mixed Integer Programming Optimization	- Computationally less intensive. - Scenario reduction with acceptable accuracy.
Fuzzy Logic	- Independent of historical data. - Various combinations of input parameters can be used. - Accuracy depends on the algorithm.
Spatial-Temporal Distribution	- Model temporal and spatial uncertainty. - Computationally intensive. - Detailed historical data required
Hybrid Fuzzy-Monte Carlo	- Computationally complex. - High accuracy. - Model temporal and spatial uncertainty.
Spatial Markov Chain	- Uses spatial data. - Moderate complexity.
Hybrid Markov-Monte Carlo	- Discreet state and time process. - Computationally intensive. - Depends on historical data.
Artificial Neural Network	- Uses historical data. - Consider correlation among input variables and input and output variables. - Accuracy depends on the volume and quality of the input dataset.
Probability Distribution Fitting	- Easy to implement. - Reasonable accuracy.
Information Gap Decision Theory	- Risk-based model - Handle severe uncertainty in the decision-making process. - Computationally complex.

Various input parameters of demand projection models are essentially categorized into two groups. The time-sensitive variables such as arrival, departure, travel time, and charging duration represent the temporal uncertainties, while the state of charge, nearest charger location, charging preference, and average temperature are state variables. Except for the temperature, all of these variables involve dependency on human factors. Most studies assume there would not be any significant change in user driving patterns or behavior due to EVs. Therefore, the impact of user behavior changes on charging demand has not been discussed thoroughly in the literature. Reference [35] tried to capture the influence of aggregated human behavior and proposed an agent-based model for charging demand. Besides time and state parameters, social parameters are also required to build more appropriate demand projection models.

B. *PV Generation*

A reliable EV-PV-Grid charging model anticipates an accurate projection of PV generation. Electricity generation from PV modules depends on a number of factors. Several PV power prediction models exist in the current literature. Nonetheless, these models can be categorized into three major groups: physical, statistical, and hybrid models [36]. Short or mid-term prediction intervals are generally from one hour to a week or month, while long-term prediction spans from months to a year. Table 2 summarizes the PV power prediction models in the existing literature [37-44].

TABLE 2. SUMMARY OF PV GENERATION PROJECTION MODELS

Model	Remarks
Monte Carlo Simulation	- Requires historical data. - High accuracy. - Captures future trends of PV generation.
Physical Model	- Independent of historical data. - Based on PV cell design parameters. - Accuracy depends on approaches to calculating cell temperature.
Artificial Neural Network	- High accuracy. - Relies on historical time series data. - Accuracy may vary based on the volume of training data.
Auto-Regressive Moving Average	- Uses historical time series data. - Captures both seasonal and non-seasonal variation. - Easy to implement. - Moderate accuracy.
Bootstrap	- Simple and easy to implement. - Requires historical weather data. - Missing data can reduce the accuracy - Prone to overfitting.
Probabilistic Distribution Fitting	- Depends on historical observation. - Easy to implement.
Kernel Density Estimation	- Can capture high uncertainty in the dataset - Requires large data set. - High accuracy.
Missing Data Imputation	- Fill in missing values in the historical dataset. - Increased accuracy.

Energy storage systems are very frequently used to mitigate the unpredictability of PV generation. Batteries are a practical solution for storing energy during excess generation and utilizing the stored energy during insufficient generation. Due to its convenience, battery scheduling plays a critical role in the efficient use of PV energy. Residential PV and battery systems commonly follow scheduling approaches to maximize users' financial benefits. However, a different battery scheduling approach may be required by the EV-PV-Grid system, where both EV and battery owner profit needs to be optimized. In [45], three different battery scheduling algorithms for optimal storage operation are proposed and it suggests a sigmoid function-based discharge operation after storing energy throughout excess generation during the daytime. However, a significant limitation of these studies is in disregarding the optimal size of the storage system. As energy storage systems are expensive, optimal battery sizing would be critical. Besides increasing PV generation efficiency, external batteries reduce the effect of EV load uncertainty on the grid.

V. PV-GRID CHARGING INFRASTRUCTURE

The PV-Grid-based EV charging architecture extends from connecting system components to converters and control circuits. A standard PV-Grid charging system comprises a few major components, as discussed next.

A. *Maximum Power Point Tracking Converter*

The MPPT is a unidirectional dc-dc converter that enables PV to function at peak power points based on solar irradiance and cell temperatures. Standard dc-dc converters, such as buck, boost, buck-boost, and Cuk converters, are commonly used for MPPT implementation. According to reference [46], buck-boost and Cuk converters are ideal for MPPT applications due to their ability to track peak power points at all spectrums of solar irradiance. Several MPPT algorithms have been proposed in the literature, such as perturbation and observation, incremental conductance, fuzzy logic control, and partial shading-based algorithms [47]. Perturbation and observation (P&O) based MPPT is simple and easy to implement and works efficiently by employing peak current control and using instantaneous values instead of average [48]. The incremental conductance method uses instantaneous and incremental conductance to track the operating point of the PV module. This method performs better than the P&O method in terms of power extraction and time of response [49].

B. Bi-directional AC-DC Converter

Based on the direction of power flow, a bi-directional inverter/converter can function in two ways: it can run as an inverter if the excess PV power has to be fed back into the grid and operates as a rectifier if powers from the grid are required to charge the EV. Therefore, it can function in all four quadrants of the voltage/current regime. Most common bi-directional converters can be classified as isolated or non-isolated inverters with half or full-bridge topologies. Single or multiple-stage isolated converters provide galvanic isolation between the ac-dc system and block dc injection to the ac side. These high-power density converters with open-loop control for unity power factor features make them ideal for PV-EV-Grid charging scheme [50]. Single-stage ac-dc converters have low switching losses and reduced size and weight compared to multistage power inverters [51]. Due to the safety and reliability of the system, an anti-islanding protection scheme needs to be incorporated with bi-directional ac-dc converters [52].

C. Bi-directional DC Charger and Battery Management System

A bi-directional dc charger works as an interface between dc common bus and the charging unit. The charging unit can be an EV or an external energy storage system. The charging module is a combination of parallel dc-dc converters that regulate the dc voltage during charging and discharging operations [26]. According to references [53, 54], three-level bi-directional dc-dc converters with half-bridge topology are ideal for EV charging systems due to their efficiency, rapid charging capability, and flexible charging operation with constant current and voltage mode. Reference [55] proposes phase shift control of a three-level dual active bridge dc-dc converter for seamless bi-directional power transfer. The bi-directional dc converter is generally followed by the battery management system (BMS) of both EV and external storage systems. It continuously monitors the battery health and state of charge for efficient and safe operation by avoiding overcharging and complete depletion. BMS includes several sensors to detect current, voltage, and temperature states and controllers to implement charging optimization algorithms [56]. The most common optimized charging methods are constant current, constant voltage, multistage constant current, and pulse charging. Multistage constant current charging has a low charging time and high battery cycle life [57].

VI. Control and Optimization of EV Charging

Controlled EV charging is an effective mechanism for implementing the EV-based grid service system. Several methods of EV charging with or without PV have been discussed in the literature, with their advantages and disadvantages. However, all these methods can be outlined as centralized, decentralized, and price varying charging mechanisms. In Centralized charging, the EV aggregator is the heart of the EV charging operation. The selection of optimal charging strategy relies on optimizing the objective function for cost minimization, profit maximization, and voltage and frequency regulation of the system [58, 59]. This charging method is appropriate for ancillary services, as the aggregation of EVs provides an adequate estimation of EV demand and available stored energy. However, information sharing and giving up the charging and discharging control to a central authority raises concerns over user privacy and security. Decentralized charging mitigates some privacy and security issues by giving individual EVs direct control over their charging strategy. The role of the EV aggregator for this case is to prepare a bidding strategy based on estimated EV demand and grid requirement. After the approval of bidding by the grid operator, the EV aggregator relays the charging/discharging price and time to the participating EVs. Users will choose to charge or discharge in a certain period based on the price and convenience. The advantage of this method is user privacy and ease of implementation, while uncertainty over a number of participating EVs makes this approach less capable for ancillary and backup grid services.

Price varying charging approach is similar to decentralized charging. However, the price of charging and discharging varies based on grid conditions, and the EV aggregator only transmits the price to the individual EVs. Time of usage (TOU) based on EV charging price has been proposed in reference [60] and shows that an optimized charging pattern could significantly reduce the user's cost. Reference [61] compares several dynamic pricing techniques, such as real-time pricing (RTP), time of usage, and critical peak pricing (CPP), and concluded that RTP provides the most flexibility in low-cost charging. However, a fully developed communication channel will be required between EV and aggregator to control and monitor charging due to real-time pricing variation. Low prices during off-peak hours in TOU-based charging can make users inclined to charge at off-peak hours and create another peak. Reference [62] proposes an RTP-based automatic demand response approach for PV-based charging station that employs a K-means clustering algorithm to reduce charging cost and regulates grid voltage with improved PV consumption. Price varying methods are less complex but require significant initial investment due to the utility side's high cost of computation and communication channels. Because of this associated high cost for varying price scheduling, centralized and decentralized concepts are more prevalent in literature [63].

VII. Future Works and Conclusion

PV integrated charging station (PVCS) provides flexibility in grid services and presents the opportunity to optimize financial benefits to both EV users and EVCS owners. This paper has reviewed some of the major areas of PVCS modeling; however, a few areas still require further investigation. Future research directions to explore are listed as follows-

- Projection of EV load demand

Incorporating the variation of user behavior during extreme weather events into the prediction model will provide more accurate projection of EV load demand.

- V2G and V2V energy transfer

User incentive model encompassing battery degradation needs to be developed for V2G and V2V power transaction Also, a peer-to-peer communication protocol can be developed for safe energy transactions between EVs.

- Hosting capacity of PV based charging stations

Both PVs and EVs in V2G mode function as distributed energy resources (DER). Feeder hosting capacity of such DER can be further investigated.

- Optimal charging control

Weather and location-based incentive plan can be introduced in the charging strategy. An event-based hybrid charging scheme accommodating both centralized and decentralized charging can be the future direction of charging optimization.

- Reliability of PV integrated charging station

The reliability of PVCS infrastructure has not been explored in the literature. The possibility of PVCS failure and its impact on grid reliability can be further assessed.

VIII. References

[1] Lutsey, Nic, Peter Slowik, and Lingzhi Jin. "Sustaining electric vehicle market growth in US cities." International Council on Clean Transportation (2016).

[2] G. A. Putrus, P. Suwanapingkarl, D. Johnston, E. C. Bentley, and M. Narayana, "Impact of electric vehicles on power distribution networks," *2009 IEEE Vehicle Power and Propulsion Conference*, 2009, pp. 827-831, DOI: 10.1109/VPPC.2009.5289760"Net Generation from Renewable Sources: Total, 2011-May 2021" Electric Power Monthly, US Energy Information Administration.

[3] S. I. Ahmed, H. Salehfar and D. F. Selvaraj, "Impact of Electric Vehicle Charging on the Performance of Distribution Grid," *2021 IEEE 12th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, 2021, pp. 1-8, DOI: 10.1109/PEDG51384.2021.9494268.

[4] Lucian Ioan Dulău, Dorin Bică, "Effects of Electric Vehicles on Power Networks", Procedia Manufacturing, Volume 46, 2020, Pages 370-377, ISSN 2351-9789, https://doi.org/10.1016/j.promfg.2020.03.054

[5] Ye, Bin, Jingjing Jiang, Lixin Miao, Peng Yang, Ji Li, and Bo Shen. 2015. "Feasibility Study of a Solar-Powered Electric Vehicle Charging Station Model" Energies 8, no. 11: 13265-13283. https://doi.org/10.3390/en81112368.

[6] Hassan Fathabadi, "Novel wind-powered electric vehicle charging station with vehicle-to-grid (V2G) connection capability", Energy Conversion and Management, Volume 136, 2017, Pages 229-239, ISSN 0196-8904, https://doi.org/10.1016/j.enconman.2016.12.045.

[7] Kempton, W.; Letendre, S.E. Electric vehicles as a new power source for electric utilities. Transp. Res. Part D Transp. Environ. 1997, 2, 157–175.

[8] Daniel Kucevic, Stefan Englberger, Anurag Sharma, Anupam Trivedi, Benedikt Tepe, Birgit Schachler, Holger Hesse, Dipti Srinivasan, Andreas Jossen, "Reducing grid peak load through the coordinated control of battery energy storage systems located at electric vehicle charging parks", Applied Energy, Volume 295, 2021, 116936, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2021.116936.

[9] Arango Castellanos, J.D., Dhanasekaran Velayutha Rajan, H., Rohde, AK. , "Design and simulation of a control algorithm for peak-load shaving using vehicle to grid technology." SN Appl. Sci. 1, 951 (2019). https://doi.org/10.1007/s42452-019-0999-x

[10] M. C. Kisacikoglu, B. Ozpineci, and L. M. Tolbert, "Examination of a PHEV bidirectional charger for V2G reactive power compensation," in Proc. IEEE Applied Power Electronics Conf. and Expo., Palm Springs, CA, Feb. 2010, pp. 458-465.

[11] Y. Mitsukuri, R. Hara, H. Kita, E. Kamiya, Y. Kataoka, S. Taki and E. Kogure, "Validation of voltage regulation method in distribution system utilizing electric vehicles", in Proc. of IEEE Innovative Smart Grid Technologies Conf., Washington, DC, Jan. 2012.

[12] X. Wu, L. Li, J. Zou and G. Zhang, "EV-based voltage regulation in line distribution grid," *2016 IEEE International Instrumentation and Measurement Technology Conference Proceedings*, 2016, pp. 1-6, doi: 10.1109/I2MTC.2016.7520568.

[13] H. Liu, Z. Hu, Y. Song, and J. Lin, "Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands," IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3480–3489, Aug. 2013.

[14] E. Yao, V. W. S. Wong and R. Schober, "Robust Frequency Regulation Capacity Scheduling Algorithm for Electric Vehicles," in *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 984-997, March 2017, doi: 10.1109/TSG.2016.2530660.

[15] S. Han, S. Han, and K. Sezaki, "Development of an optimal vehicle to-grid aggregator for frequency regulation," IEEE Trans. Smart Grid, vol. 1, no. 1, pp. 65–72, Jun. 2010.

[16] Dai Wang, Jonathan Coignard, Teng Zeng, Cong Zhang, Samveg Saxena, "Quantifying electric vehicle battery degradation from driving vs. vehicle-to-grid services", Journal of Power Sources, Volume 332, 2016, Pages 193-203, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2016.09.116

[17] Noman, Fuad, Ammar A. Alkahtani, Vassilios Agelidis, Kiong S. Tiong, Gamal Alkawsi, and Janaka Ekanayake. 2020. "Wind-Energy-Powered Electric Vehicle Charging Stations: Resource Availability Data Analysis" *Applied Sciences* 10, no. 16: 5654. https://doi.org/10.3390/app10165654.

[18] Hasan Mehrjerdi, Reza Hemmati, "Stochastic model for electric vehicle charging station integrated with wind energy", Sustainable Energy Technologies and Assessments, Volume 37, 2020, 100577, ISSN 2213-1388, https://doi.org/10.1016/j.seta.2019.100577.

[19] Bhatti AR, Salam Z, MJBA Aziz, Yee KP. A comprehensive overview of electric vehicle charging using renewable energy. Int J Power Electron Drive System, 2016;7:114–23.

[20] Pinak J. Tulpule, Vincenzo Marano, Stephen Yurkovich, Giorgio Rizzoni, "Economic and environmental impacts of a PV powered workplace parking garage charging station", Applied Energy, Volume 108, 2013, Pages 323-332, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2013.02.068.

[21] Bhatti AR, Salam Z, MJBA Aziz, Yee KP, " A critical review of electric vehicle charging using solar photovoltaic", Int J Energy Res 2016;40:439–61.

[22] Constance Crozier, Thomas Mostyn, Malcolm McCulloch, "Capturing diversity in electric vehicle charging behaviour for network capacity estimation", Transportation Research Part D: Transport and Environment, Volume 93, 2021, 102762, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2021.102762.

[23] Pashajavid, E., Golkar, MA, "Charging of plug-in electric vehicles: Stochastic modelling of load demand within domestic grids", in: ICEE 2012 - 20th Iranian Conference on Electrical Engineering. doi:10.1109/Iranian CEE. 2012.6292415.

[24] Omran, N.G., Filizadeh, S., "Location-based forecasting of vehicular charging load on the distribution system.", IEEE Transactions on Smart Grid 5, 632–641, 2014

[25] Ratil H. Ashique, Zainal Salam, Mohd Junaidi Bin Abdul Aziz, Abdul Rauf Bhatti, "Integrated photovoltaic-grid dc fast-charging system for electric vehicle: A review of the architecture and control", Renewable and Sustainable Energy Reviews, Volume 69, 2017, Pages 1243-1257, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2016.11.245.

[26] Su, J.; Lie, T.; Zamora, R. "Modelling of large-scale electric vehicles charging demand: A New Zealand case study.", Electric Power Systems Research. 2019, 167, 171–182.

[27] Khodayar, M.E.;Wu, L.; Shahidehpour, M., "Hourly Coordination of electric vehicle operation and volatile wind power generation in SCUC.", IEEE Trans. Smart Grid 2012, 3, 1271–1279.

[28] Xinwei Li, Alan Jenn, "An integrated optimization platform for spatial-temporal modeling of electric vehicle charging infrastructure", Transportation Research Part D: Transport and Environment, Volume 104, 2022, 103177, ISSN 1361-9209, https://doi.org/10.1016/j.trd.2022.103177.

[29] Soroudi, A.; Ehsan, M., "A possibilistic–probabilistic tool for evaluating the impact of stochastic renewable and controllable power generation on energy losses in distribution networks—A case study.", Renew. Sustain. Energy Rev. 2011, 15, 794–800.

[30] Mahmoud Shapero, Joakim Munkhammar, "Spatial Markov chain model for electric vehicle charging in cities using geographical information system (GIS) data", Applied Energy, Volume 231, 2018, Pages 1089-1099, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2018.09.175.

[31] F. J. Soares, J. A. P. Lopes, P. M. R. Almeida, C. L. Moreira, and L. Seca, “A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid,” presented at the 17th Power Syst. Comput. Conf., Stockholm, Sweden, 2011.

[32] Hamidreza Jahangir, Hanif Tayarani, Ali Ahmadian, Masoud Aliakbar Golkar, Jaume Miret, Mohammad Tayarani, H. Oliver Gao, “Charging demand of Plug-in Electric Vehicles: Forecasting travel behavior based on a novel Rough Artificial Neural Network approach”, Journal of Cleaner Production, Volume 229, 2019, Pages 1029-1044, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2019.04.345.

[33] Gupta, Neeraj. “Gauss-Quadrature-Based Probabilistic Load Flow Method With Voltage-Dependent Loads Including WTGS, PV, and EV Charging Uncertainties.” *IEEE Transactions on Industry Applications* 54 (2018): 6485-6497.

[34] Soroudi, A.; Keane, A., "Risk-averse energy hub management considering plug-in electric vehicles using information gap decision theory.", In Power Systems; Springer: Singapore, 2015; Volume 89, pp. 107–127.

[35] K. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil and H. B. Gooi, "Agent-Based Aggregated Behavior Modeling for Electric Vehicle Charging Load," in *IEEE Transactions on Industrial Informatics*, vol. 15, no. 2, pp. 856-868, Feb. 2019, DOI: 10.1109/TII.2018.2823321.

[36] Ulbricht, R., Fisher, F., Lehner, W., Donker, H., “First Steps Towards a Systematical Optimized Strategy for Solar Energy Supply Forecasting.”, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases. Prague, 2013.

[37] Y. Murakami, Y. Takabayashi and Y. Noro, "Photovoltaic power prediction and its application to smart grid," *2014 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, 2014, pp. 47-50, DOI: 10.1109/ISGT-Asia.2014.6873762.

[38] Alberto Dolara, Sonia Leva, Giampaolo Manzolini, “Comparison of different physical models for PV power output prediction.”, Solar Energy, Volume 119, 2015, Pages 83-99, ISSN 0038-092X, https://doi.org/10.1016/j.solener.2015.06.017.

[39] T. Hiyama and K. Kitabayashi, "Neural network-based estimation of maximum power generation from PV module using environmental information," in IEEE Transactions on Energy Conversion, vol. 12, no. 3, pp. 241-247, Sept. 1997, DOI: 10.1109/60.629709.

[40] Rui Huang, T. Huang, R. Gadh and Na Li, "Solar generation prediction using the ARMA model in a laboratory-level micro-grid," *2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*, 2012, pp. 528-533, DOI: 10.1109/SmartGridComm.2012.6486039.

[41] S. I. Ahmed, P. Ranganathan and H. Salehfar, "Forecasting of Mid- and Long-Term Wind Power Using Machine Learning and Regression Models," *2021 IEEE Kansas Power and Energy Conference (KPEC)*, 2021, pp. 1-6, DOI: 10.1109/KPEC51835.2021.9446250.

[42] Afzaal, Muhammad U., Intisar A. Sajjad, Ahmed B. Awan, Kashif N. Paracha, Muhammad F.N. Khan, Abdul R. Bhatti, Muhammad Zubair, Waqas u. Rehman, Salman Amin, Shaikh S. Haroon, Rehan Liaqat, Walid Heidi, and Iskander Tlili, "Probabilistic Generation Model of Solar Irradiance for Grid-Connected Photovoltaic Systems Using Weibull Distribution", *Sustainability* 12, no. 6: 2241. https://doi.org/10.3390/su12062241.

[43] Lotfi, Mohamed, Mohammad Javadi, Gerardo J. Osório, Cláudio Monteiro, and João P.S. Catalão. 2020. "A Novel Ensemble Algorithm for Solar Power Forecasting Based on Kernel Density Estimation" Energies 13, no. 1: 216. https://doi.org/10.3390/en13010216

[44] Kim, Taeyoung, Woong Ko, and Jinho Kim. 2019. "Analysis and Impact Evaluation of Missing Data Imputation in Day-ahead PV Generation Forecasting" Applied Sciences 9, no. 1: 204. https://doi.org/10.3390/app9010204.

[45] Castello, Charles C., Tim J. LaClair and L. Curt Maxey. “Control strategies for electric vehicle (EV) charging using renewables and local storage.” *2014 IEEE Transportation Electrification Conference and Expo (ITEC)* (2014): 1-7.

[46] R. F. Coelho, F. Cancer and D. C. Martins, "A study of the basic DC-DC converters applied in maximum power point tracking," *2009 Brazilian Power Electronics Conference*, 2009, pp. 673-678, DOI: 10.1109/COBEP.2009.5347723.

[47] S. Saravanan, N. Ramesh Babu, “Maximum power point tracking algorithms for photovoltaic system – A review”, Renewable and Sustainable Energy Reviews, Volume 57, 2016, Pages 192-204, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2015.12.105.

[48] X. Liu and L. A. C. Lopes, "An improved perturbation and observation maximum power point tracking algorithm for PV arrays," *2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551)*, 2004, pp. 2005-2010 Vol.3, DOI: 10.1109/PESC.2004.1355425.

[49] I. V. Banu, R. Beniugă and M. Istrate, "Comparative analysis of the perturb-and-observe and incremental conductance MPPT methods," *2013 8TH INTERNATIONAL SYMPOSIUM ON ADVANCED TOPICS IN ELECTRICAL ENGINEERING (ATEE)*, 2013, pp. 1-4, DOI: 10.1109/ATEE.2013.6563483.

[50] G. Castelino, K. Basu, N. Weise and N. Mohan, "A bi-directional, isolated, single-stage, DAB-based AC-DC converter with open-loop power factor correction and other advanced features," *2012 IEEE International Conference on Industrial Technology*, 2012, pp. 938-943, DOI: 10.1109/ICIT.2012.6210059.

[51] S. N. Vaishnav and H. Krishnaswami, "Single-stage isolated bi-directional converter topology using high frequency AC link for charging and V2G applications of PHEV," *2011 IEEE Vehicle Power and Propulsion Conference*, 2011, pp. 1-4, DOI: 10.1109/VPPC.2011.6043138.

[52] Eltawil MA, Zhao Z. Grid-connected photovoltaic power systems: technical and potential problems—A review. Renew Sustain Energy Rev 2010;14:112–29.

[53] Y. Du, X. Zhou, S. Bai, S. Lukic and A. Huang, "Review of non-isolated bi-directional DC-DC converters for plug-in hybrid electric vehicle charge station application at municipal parking decks," *2010 Twenty-Fifth Annual IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2010, pp. 1145-1151, DOI: 10.1109/APEC.2010.5433359.

[54] T. Kang, C. Kim, Y. Suh, H. Park, B. Kang and D. Kim, "A design and control of bi-directional non-isolated DC-DC converter for rapid electric vehicle charging system," *2012 Twenty-Seventh Annual IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2012, pp. 14-21, DOI: 10.1109/APEC.2012.6165792.

[55] R. Kondo, Y. Higaki and M. Yamada, "Proposition and experimental verification of a bi-directional isolated DC/DC converter for battery charger-discharger of electric vehicle," *2016 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2016, pp. 1713-1720, DOI: 10.1109/APEC.2016.7468098.

[56] Liu, K., Li, K., Peng, Q. et al. A brief review on key technologies in the battery management system of electric vehicles. Front. Mech. Eng. 14, 47–64 (2019). https://doi.org/10.1007/s11465-018-0516-8

[57] Qian Lin, Jun Wang, Rui Xiong, Weixiang Shen, Hongwen He, “Towards a smarter battery management system: A critical review on optimal charging methods of lithium-ion batteries”, Energy, Volume 183, 2019, Pages 220-234, ISSN 0360-5442.

[58] Ahmad, F.; Alam, M.S.; Shahidehpour, M., “Profit maximization of microgrid aggregator under power market environment.”, IEEE Syst. J. 2019, 13, 3388–3399.

[59] Ko, KS; Han, S.; Sung, D.K., "Performance-based settlement of frequency regulation for electric vehicle aggregators.", IEEE Trans. Smart Grid 2018, 9, 866–875.

[60] Y. Cao et al., "An Optimized EV Charging Model Considering TOU Price and SOC Curve," in IEEE Transactions on Smart Grid, vol. 3, no. 1, pp. 388-393, March 2012, DOI: 10.1109/TSG.2011.2159630.

[61] Amin, Adil, Wajahat U.K. Tareen, Muhammad Usman, Haider Ali, Inam Bari, Ben Horan, Saad Mekhilef, Muhammad Asif, Saeed Ahmed, and Anzar Mahmood. 2020. "A Review of Optimal Charging Strategy for Electric Vehicles under Dynamic Pricing Schemes in the Distribution Charging Network" *Sustainability* 12, no. 23: 10160. https://doi.org/10.3390/su122310160

[62] Q. Chen *et al.*, "Dynamic Price Vector Formation Model-Based Automatic Demand Response Strategy for PV-Assisted EV Charging Stations," in *IEEE Transactions on Smart Grid*, vol. 8, no. 6, pp. 2903-2915, Nov. 2017, DOI: 10.1109/TSG.2017.2693121.

[63] Mohammad, Asaad, Ramon Zamora, and Tek T. Lie. 2020. "Integration of Electric Vehicles in the Distribution Network: A Review of PV Based Electric Vehicle Modelling" *Energies* 13, no. 17: 4541. https://doi.org/10.3390/en13174541