Optimal Electric Vehicle Charging and Discharging Strategies Under DER Compensation Programs

Preprint

Jiyu Wang,[1] Priti Paudyal,[1] Xiangqi Zhu,[2]
Harsha Padullaparti,[1] and Joe Silver[3]

1 National Renewable Energy Laboratory
2 Oregon State University
3 NineDot Energy

Presented at the 2024 IEEE Power and Energy Society General Meeting
Seattle, Washington
July 21–25, 2024

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-88139
September 2024

Optimal Electric Vehicle Charging and Discharging Strategies Under DER Compensation Programs

Preprint

Jiyu Wang,[1] Priti Paudyal,[1] Xiangqi Zhu,[2]
Harsha Padullaparti,[1] and Joe Silver[3]

1 National Renewable Energy Laboratory
2 Oregon State University
3 NineDot Energy

Suggested Citation
Wang, Jiyu, Priti Paudyal, Xiangqi Zhu, Harsha Padullaparti, and Joe Silver. 2024. *Optimal Electric Vehicle Charging and Discharging Strategies Under DER Compensation Programs: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-88139. https://www.nrel.gov/docs/fy24osti/88139.pdf.

Conference Paper
NREL/CP-5D00-88139
September 2024

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Electricity. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

Optimal Electric Vehicle Charging and Discharging Strategies Under DER Compensation Programs

Jiyu Wang[1], Priti Paudyal[1], Xiangqi Zhu[2], Harsha Padullaparti[1], Joe Silver[3]
[1]National Renewable Energy Laboratory (NREL), Golden, Colorado.
[2]Oregon State University, Corvallis, Oregon.
[3]NineDot Energy, Brooklyn, New York.
Jiyu.Wang@nrel.gov; HarshaVardhana.Padullaparti@nrel.gov

***Abstract*—The adoption of electric vehicles (EVs) is becoming increasingly popular because of environmental concerns, the greater availability of models, and increased cost-competitiveness with gas vehicles. Because EVs have both charging and discharging capabilities, they provide great potential to help electric utilities with grid operation. When the grid demand is high, EVs can discharge to the grid to reduce the peak load, and vice versa; therefore, electric utilities have designed different policies to encourage EV charging station operators to charge or discharge at certain time periods. The New York State Public Service Commission established the Value of Distributed Energy Resources (VDER), or the Value Stack, to compensate for energy created by distributed energy resources, including EVs. This paper presents an optimization-based approach to identify the "golden hours" and "golden spots," i.e., the effective time periods and geographic locations for EV charging station operators to charge or discharge under the VDER program that can provide them the highest benefit. The proposed methodology can be applied to other compensation mechanisms and distribution systems as well. By working with industry partner NineDot Energy, realistic charging station information is used in this study, and the proposed approach is tested on a distribution feeder. The results from this study can help electric utilities and EV charging station operators determine the ideal charging/discharging time and the ideal locations for the charging station(s) in their distribution systems to achieve maximized benefit.**

***Index Terms*— Electric vehicle, peak load reduction, smart grid, VDER, vehicle to grid.**

I. INTRODUCTION

The global transition to electric vehicles (EVs) has gained significant momentum in recent years because of increasing environmental concerns, greater availability of models, and increased cost-competitiveness with traditional gas vehicles [1]. Beyond their role in transportation, EVs offer the ability to both charge electricity from and discharge electricity to the electric grid [2]. This feature provides EVs great potential to support the operational efficiency of electric utilities. When the grid demand reaches its peak, EVs can discharge to the grid to reduce the peak load. Conversely, during times of low grid demand, EVs can charge from the grid to fulfill their batteries [3]–[5]. With this potential from EVs, electric utilities have designed various strategies and policies to incentivize EV owners and operators to engage in grid-balancing activities [6]–[9]. Notably, the New York State Public Service Commission has introduced the Value of Distributed Energy Resources (VDER) program, often referred to as the Value Stack. Under the VDER compensation mechanism, energy contributions from distributed energy resources (DERs), including EVs, are compensated, offering an intriguing opportunity for EV owners to reap economic benefits while supporting the grid's stability [10].

In the literature, researchers have developed a variety of studies to evaluate DER operation under the VDER program. The authors in [11] developed a model to assess the value of distributed solar and wind power systems configured as either behind-the-meter systems or front-of-the-meter systems for each parcel of land in New York to study the impacts of VDER frameworks on DER deployment; however, this method did not consider the deployment of EVs. In [12], the authors use a gradient boosting model with sample weights to estimate the probability of a household installing solar in a given census tract with the VDER framework. This study did not consider EVs, and the benefits from VDER after installation were not calculated. The approach to maximize revenue from a solar photovoltaic and energy storage system installation operation under the VDER pricing structure is presented in [13]. Although this paper considers energy storage systems, whose operation is similar to EV charging and discharging activities, it does not consider the additional constraints for EVs, such as traffic and user behavior.

In this paper, we propose an optimization-based approach to identify what the "golden hours" and "golden spots" for EV charging station operators to participate in the VDER program, where the golden hours are defined as optimal time periods to charge and golden spots are defined as optimal locations for EV charger placement, both for maximized benefit. This approach enables operators to maximize their benefits within the framework of the VDER. We used real-world data, including charging station information, charging/discharging policy, and prices from the VDER program. This proposed method is tested on a distribution feeder from the Synthetic Models for Advanced, Realistic Testing: Distribution Systems and Scenarios (SMART-DS) tool [14]. This study aims to offer valuable guidance to help EV charging station operators determine the best time periods for their charging/discharging times and locations for their charging stations within the distribution system. The contributions of this paper are as follows:

- An optimization-based approach is developed to identify the golden hours and golden spots for EV charging and discharging decisions under the VDER framework.
- This study considers the constraints from EV charging power, charging station limits, user behaviors, and EV charging station operators' expectations.
- The output of this method will contribute to the convergence of EV technology and the evolving landscape of energy utilities, shedding light on the path toward a more sustainable and efficient energy future.

The rest of this paper is organized as follows. Section II describes the VDER program. Section III introduces the details of the proposed approach. Section IV presents the selected distribution network and the results generated from the proposed method. Section V summarizes the paper and discusses potential future work.

II. VALUE OF DISTRIBUTED ENERGY RESOURCES IN NEW YORK

The New York State Public Service Commission established the VDER, a new mechanism to compensate energy created by DERs [15]. The VDER program compensates projects based on when and where they provide electricity to the grid, and compensation is in the form of bill credits. The number of credits is determined by the DER's energy value based on Locational Based Marginal Pricing (LBMP), Installed Capacity value (ICAP), environmental value, demand reduction value (DRV), and locational system relief value. After a DER is installed and connected to the grid, the electric utility will determine the value of the energy produced using the VDER program based on the electricity it injects to the grid. Then the utility will allocate the monetary value of the energy produced to the bill.

In this paper, we consider only the VDER components that are related to energy storage systems because we are focusing on EVs, which can be considered as stand-alone storage systems. The VDER for energy storage systems is calculated by the following:

- The LBMP is the day-ahead wholesale energy price as determined by New York Independent System Operator (NYISO). It changes hourly and is different according to geographic zones.
- The ICAP is the value of how well a project reduces New York State's energy usage during the most energy-intensive days of the year. Most ICAP rates change monthly.
- The DRV is determined by how much a project reduces the utility's future needs to make grid upgrades. The DRV is locked in for 10 years.

The VDER for EVs are calculated with these three values. The detailed number of each value is presented in Section IV.

III. METHODOLOGY

This section presents the methodology of the approach we propose to identify the golden hours and golden spots for EV charging/discharging.

A. *Problem Formulation*

In this study, we aim to let the EV charging station operators maximize their revenue in a period by selecting the appropriate charging/discharging time and charger locations. The problem costs and revenues involved in the proposed approach are summarized in Fig. 1. The cost for the EV charging station operators includes the electricity cost and the facility cost. The electricity cost includes the electricity bill based on the energy usage for charging and a monthly demand charge. The facility cost includes the operations and maintenance costs of the charging station. The benefits for EV charging station operators are the rewards from the VDER program, including LBMP, ICAP, and DRV revenues.

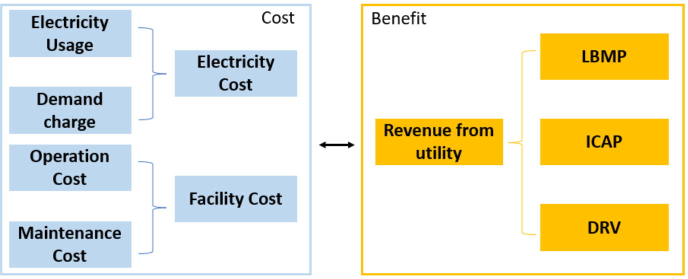

Fig. 1. Costs and revenues considered in the proposed approach

B. *Golden Hour and Golden Spot Identification*

In this study, we aim to identify the golden hours and golden spots for EV charging station operators to maximize their net revenue. These terms are defined as follows:

- *Golden hours*: Events or call windows provided by the utility operator that have the highest benefits for grid exports.
- *Golden spots*: Bidirectional, vehicle-to-grid-enabled EV charging stations that provide significant technical benefits to the local electric distribution grid.

We formulated the objective function as:

$$\max \sum_{t\in T}(B_t - C_t) \tag{1}$$

where B_t is the total benefit at time step t, and C_t is the total cost at time step t. The total benefit can be expressed as:

$$B_t = B_t^{LBMP} * P_t^{discharge} + s_t^{ICAP} * B_t^{ICAP} * P_t^{discharge} + s_t^{DRV} * B_t^{DRV} * P_t^{discharge} \quad (2)$$

where $P_t^{discharge}$ is the discharging power at time step t; and B_t^{LBMP}, B_t^{ICAP}, and B_t^{DRV} are the rewards from LBMP, ICAP, and DRV, respectively. s_t^{ICAP} and s_t^{DRV} are indicators of whether time step t has ICAP and DRV revenue, which is determined by the electric utility.

The total cost formulation can be expressed as:

$$C_t = C_t^{utility} + C_t^{facility} \quad (3)$$

$$C_t^{utility} = C_t^{electricity} * P_t^{charge} + s_t^{demand} * C_t^{demand} \quad (4)$$

$$C_t^{facility} = C_t^{operation} + C_t^{maintenance} \quad (5)$$

where $C_t^{utility}$ is the cost from the utility at time step t, $C_t^{facility}$ is the facility cost at time step t, P_t^{charge} is the charging power at time step t, $C_t^{electricity}$ is the electricity price at time step t, C_t^{demand} is the demand charge, s_t^{demand} is the demand charge indicator, $C_t^{operation}$ is the operational cost at time step t, and $C_t^{maintenance}$ is the maintenance cost at time step t.

In this study, the charging station for the EV charging station operator is located in a parking garage. The corresponding charging station constraint can be expressed as:

$$P_t^{charge} = \min\left(N_t^{vehicle}, N^{charger}\right) * P_{charger}^{charge} \quad (6)$$

$$P_t^{discharge} = \min\left(N_t^{vehicle}, N^{charger}\right) * P_{charger}^{discharge} \quad (7)$$

$$N_t^{vehicle} = N_t^{parking} * \alpha \quad (8)$$

Where $N_t^{vehicle}$ is the number of vehicles that can be charged or discharged at time step t, $N^{charger}$ is the number of chargers at the charging station, $P_{charger}^{charge}$ is the charging power for the charger, $P_{charger}^{discharge}$ is the discharging power for the charger, $N_t^{parking}$ is the number of vehicles parked in the garage at time step t, and α is a coefficient that determines the possibility that a vehicle parked in the garage will charge or discharge.

For the golden hour identification, we choose time step t that has the highest revenue $((B_t - C_t))$ compared to other hours.

For the golden spot identification, we consider two aspects including 1) total revenue and 2) grid impact. Here we choose the location that has the highest revenue during a period of time compared to other locations. In addition to the revenue, we consider the grid impacts from charging and discharging because the charging and discharging activities at different locations will cause different changes to the nodal voltages. The voltage-load sensitivity matrix (VLSM), proposed in [16], [17], is used to estimate how the charging/discharging load will impact the voltages of the distribution system. The VLSM can be expressed as:

$$|\delta V| = |VLSM_P||\delta P| \quad (9)$$

i.e.:

$$\begin{vmatrix} \delta V(1) \\ \vdots \\ \delta V(n) \end{vmatrix} = \begin{vmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{vmatrix} \begin{vmatrix} \delta P(1) \\ \vdots \\ \delta P(n) \end{vmatrix} \quad (10)$$

where $\delta V(i)$ is the voltage change at node *I*, and $\delta P(i)$ is the power change at node *i*. It is noted that the VLSM in (10) includes all the load spots in the distribution feeder. If the charging station operator has already had some spots as potential charging station location, we only need to calculate the VLSM for these spots. The following can be derived from (9) and (10):

$$\delta V(i) = \sum_{j=1}^{n} p_{ij}\, \delta P(j) \quad (11)$$

where p_{ij} represents the real power sensitivity factors at bus *i* with respect to bus *j*.

The detailed VLSM calculations can be found in [16]. In this paper, the voltage constraints for each node are set to 0.95 p.u.–1.05 p.u., which can be expressed as:

$$0.95 < V(i) + \sum_{j=1}^{n} p_{ij}\, \delta P(j) < 1.05 \quad (12)$$

where $V(i)$ is the original voltage at node *i* before the charging and discharging activity. The calculated $\delta P(j)$ range for each node will be another constraint to the maximum allowable charging and discharging power.

IV. SIMULATION RESULTS

This section presents the distribution system model, the parameters used for the case study, and the golden hour and golden spot identification results.

A. *Distribution System Model*

One distribution feeder from the SMART-DS data sets [14] is selected in this study, and the topology is presented in Fig. 2. The black dot on the bottom right is the location of the substation. This feeder has 8,340 buses, 16,166 nodes, and 10,059 loads. There is a three-phase capacitor bank with 450-kVAR rated power in the middle of the feeder (marked as yellow) for reactive power support. The loads are marked in red. Each load has a yearly load profile and the model is developed in OpenDSS [18], [19]. The VLSM is calculated for all the loads in this model and is used to estimate the maximum allowable charging/discharging power based on (12).

B. *Parameters*

In this study, we use one month of hourly data in July to identify the golden hours and golden spots. Based on the information the EV charging station operator provided, the discharging window is 2 p.m.–6 p.m. every workday, and the charging window is 10 p.m.–8 a.m. every workday. The discharging and charging powers for each charger are 15 kW and 5 kW, respectively.

The EV charging station is located in ConEdison's territory, so its summertime-of-use electricity price for small business is used [20]. The electricity price for on-peak hours (8 a.m.–

midnight) is 25.5 cents/kWh, and the electricity price for off-peak hours is 1.8 cents/kWh. It is noted that this only includes the 'delivery' charges, and the 'supply' costs are not considered in this study. There is also a $17 charge once per month. The VDER revenue parameters are downloaded from the VDER calculator. The LBMP price in July is shown in Fig. 3, the ICAP revenue is $0.015/kWh, and the DRV revenue is $0.854/kWh. The EV charging station operator will receive the ICAP and DRV revenue if the EVs are discharged from 4 p.m.–8 p.m. on a summer workday.

Fig. 2. Topology of the selected distribution system

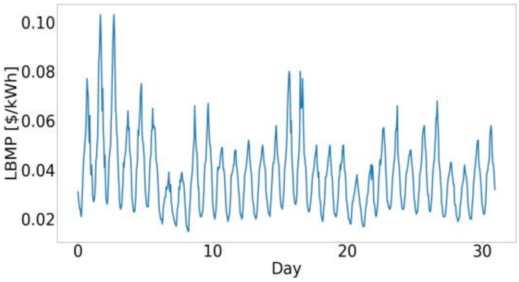

Fig. 3. LBMP price in July

The number of vehicles available for charging and discharging is randomly generated following some rules. For example, there will be more vehicles in the garage during the daytime if it is close to an office, and there will be more vehicles in the garage during the evening if it is close to a shopping mall. If the maximum number of available vehicles in the evening is approximately 40 but there are only 10 chargers present in the garage, the largest number of vehicles that can charge or discharge at the same time is 10 for this garage.

C. Golden Hour Identification

The optimizations in (1)–(8) are solved to identify the golden hours of the charging station. The revenue is calculated for each hour in that month; Fig. 4 shows the results for an example day. As shown, the revenue is much higher from 4 p.m.–6 p.m. The reason is because this time slot is within the discharge window and also has ICaAP and DRV revenue. We selected one golden hour each workday and the golden hour counts for July are shown in Fig. 5. The identified golden hours are 4 p.m. for 13 days, 5 p.m. for 7 days, and 6 p.m. for 2 days; therefore, the golden hour for this charging station is identified to be 4 p.m. It is noted that because of the high DRV rate, the golden hours are all happening at the overlap of discharging window and hours with DRV revenue. Although there are some small revenue differences at each hour because of the different available vehicles that can be discharged, all these hours can be identified as golden hours.

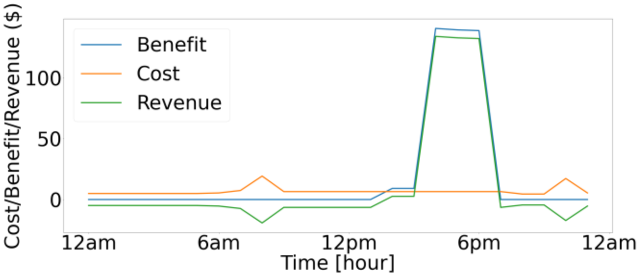

Fig. 4. Golden hour identification on an example day

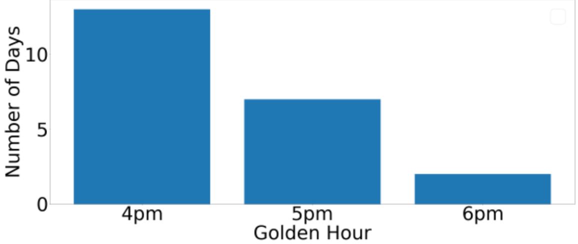

Fig. 5. Golden hour counts in July

D. Golden Spot Identification

All 10,059 loads in the feeder model are considered as golden spot candidates. The load locations are marked in red in Fig. 2. The size of the charging station is determined by the original rated load in the feeder model. If the original rated load is higher, the charging station will have more chargers. After solving the optimization in (1)–(12), we obtain the monthly revenue for all the golden spot candidates. Fig. 6 shows the revenue for 30 selected locations. The revenue for some spots can be as much as five times higher than the low revenue spots.

We classified all the spots as low revenue spots, medium revenue spots, and high revenue spots, and they are marked in purple, yellow, and red, respectively, in Fig. 7. As shown, most low revenue spots are located closer to the feeder head. The reason is because the voltages for the nodes at the feeder head are usually higher, which can limit the discharging flexibility because the discharge will cause a voltage rise that may violate the voltage upper limit. Similar results also happen in the area close to the capacitor location. The higher voltage in that area caused more mid revenue spots than high revenue spots. Most high revenue spots are located at the end of the feeder because of their low voltages leading to higher discharge flexibility. However, there exists spots with short distance from the feeder head but high revenue. That's because the charging station sizes for these spots are large. The identified golden spot is marked as a big black dot at the top left of Fig. 7. This spot has relatively low voltage and a large charging station. It is noted that these results are based on the current VDER program and the voltage constraints from utility. In future scenarios, if the compensation program has changed or the distribution systems have voltage regulators integrated, EV charging station operators can still use this framework and the outcomes may differ.

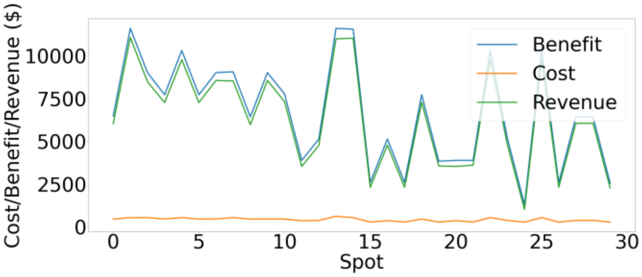

Fig. 6. Revenue for 30 example locations

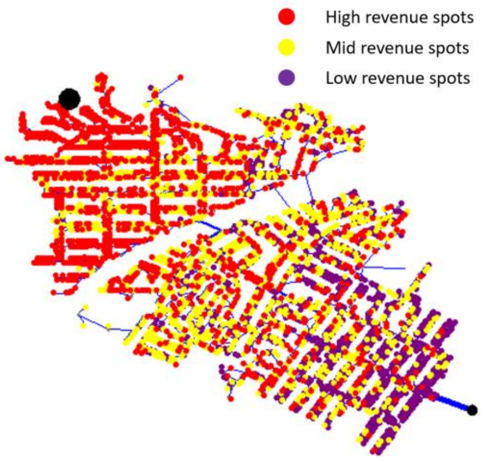

Fig. 7. Spots marked by revenue

V. Conclusion and Future Work

This paper presents a method to determine an EV charging station operator's charging and discharging strategies under New York State's VDER program. The benefits from different revenue streams such as the LBMP, the ICAP, and the DRV are calculated to determine the golden hours and golden spots. The grid impact is also considered for the golden spot identification based on the VLSM. The actual charging station parameters and a realistic distribution feeder model are used to evaluate the proposed method. The identification process can be used by the EV charging station operators to design their charging/discharging strategy and determine the location of the charging station. Future work in this study will test the proposed method on more distribution feeders and validate the actual operation in the field.

VI. Acknowledgement

The authors would like to thank the Wells Fargo Foundation Innovation Incubator (IN2) program for supporting this research.

References

[1] Kumar, Rajeev Ranjan, and Kumar Alok. "Adoption of electric vehicle: A literature review and prospects for sustainability." *Journal of Cleaner Production* 253 (2020): 119911.

[2] Tan, Kang Miao, Vigna K. Ramachandaramurthy, and Jia Ying Yong. "Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques." *Renewable and Sustainable Energy Reviews* 53 (2016): 720-732.

[3] Gough, Rebecca, et al. "Vehicle-to-grid feasibility: A techno-economic analysis of EV-based energy storage." *Applied energy* 192 (2017): 12-23.

[4] Schey, Stephen, Don Scoffield, and John Smart. "A first look at the impact of electric vehicle charging on the electric grid in the EV project." *World Electric Vehicle Journal* 5.3 (2012): 667-678.

[5] J. Wang, S. Huang, D. Wu and N. Lu, "Operating a Commercial Building HVAC Load as a Virtual Battery Through Airflow Control," in *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 158-168, Jan. 2021, doi: 10.1109/TSTE.2020.2988513.

[6] J. Wang, N. Lu, S. Huang and D. Wu, "A Data-driven Control Method for Operating the Commercial HVAC Load as a Virtual Battery," *2019 IEEE Power & Energy Society General Meeting (PESGM)*, Atlanta, GA, USA, 2019, pp. 1-5, doi: 10.1109/PESGM40551.2019.8973486.

[7] J. Wang *et al*., "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method," in *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 5396-5406, Nov. 2020, doi: 10.1109/TSG.2020.3008603.

[8] J. Wang *et al*., "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method," in *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 5396-5406, Nov. 2020, doi: 10.1109/TSG.2020.3008603.

[9] C. McEntee, D. Mulcahy, J. Wang, X. Zhu and N. Lu, "A VSM-Based DER Dispatch MINLP for Volt-VAR Control in Unbalanced Power Distribution Systems," *2019 IEEE Power & Energy Society General Meeting (PESGM)*, Atlanta, GA, USA, 2019, pp. 1-5, doi: 10.1109/PESGM40551.2019.8973721.

[10] Astoria, Ross. "On the radicality of New York's reforming the energy vision." *The Electricity Journal* 30.5 (2017): 54-58.

[11] Bowen, Thomas, Sam Koebrich, Kevin McCabe, and Ben Sigrin. "The locational value of distributed energy resources: A parcel-level evaluation of solar and wind potential in New York state." *Energy Policy* 166 (2022): 112744.

[12] Mendieta, Maria P., and Mushfiqur R. Sarker. "Gradient Boosting Algorithm to Identify Markets for Residential Solar: New York State Case Study." *In 2018 IEEE Power & Energy Society General Meeting (PESGM)*, pp. 1-5. IEEE, 2018.

[13] Headley, Alexander, Clifford Hansen, and Tu Nguyen. "Maximizing revenue from electrical energy storage paired with community solar projects in NYISO markets." *In 2019 North American Power Symposium (NAPS)*, pp. 1-6. IEEE, 2019.

[14] Krishnan, Venkat K., et al. Smart-ds: Synthetic models for advanced, realistic testing: Distribution systems and scenarios. No. NREL/PR-5D00-68764. National Renewable Energy Lab.(NREL), Golden, CO (United States), 2017.

[15] NYPSC, 2017. Order on net energy metering transition, phase one of value of distributed energy resources, and related matters. Mar. http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7B5B69628E-2928-44A9-B83E-65CEA 7326428%7D

[16] X. Zhu, J. Wang, N. Lu, N. Samaan, R. Huang, and X. Ke, "A hierarchical VLSM-based demand response strategy for coordinative voltage control between transmission and distribution systems," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 4838-4847, Sept. 2019.

[17] X. Zhu *et al*., "Voltage-load sensitivity matrix based demand response for voltage control in high solar penetration distribution feeders," *2017 IEEE Power & Energy Society General Meeting*, Chicago, IL, USA, 2017, pp. 1-5, doi: 10.1109/PESGM.2017.8273887.

[18] J. Wang *et al*., "A Machine Learning-based Method to Estimate Transformer Primary-Side Voltages with Limited Customer-Side AMI Measurements," *2021 IEEE Power & Energy Society General Meeting (PESGM)*, Washington, DC, USA, 2021, pp. 01-05, doi: 10.1109/PESGM46819.2021.9638064.

[19] H. Padullaparti *et al*., "Phase Identification in Real Distribution Networks with High PV Penetration Using Advanced Metering Infrastructure Data," *2022 IEEE Power & Energy Society General Meeting (PESGM)*, Denver, CO, USA, 2022, pp. 01-05, doi: 10.1109/PESGM48719.2022.9916986.

[20] https://www.coned.com/en/our-energy-future/electric-vehicles/electric-vehicle-drivers/electric-vehicles-and-your-bill