Impacts of Dispatch Strategies and Forecast Errors on the Economics of Behind-the-Meter PV-Battery Systems

Preprint

Brian T. Mirletz and Nicholas D. Laws

1 National Renewable Energy Laboratory
2 The University of Texas at Austin

Presented at the 50th IEEE Photovoltaic Specialists Conference
San Juan, Puerto Rico
June 11-16, 2023

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-7A40-86194
July 2023

Impacts of Dispatch Strategies and Forecast Errors on the Economics of Behind-the-Meter PV-Battery Systems

Preprint

Brian T. Mirletz and Nicholas D. Laws

1 National Renewable Energy Laboratory
2 The University of Texas at Austin

Suggested Citation
Mirletz, Brian T. and Nicholas D. Laws. 2023. *Impacts of Dispatch Strategies and Forecast Errors on the Economics of Behind-the-Meter PV-Battery Systems: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-7A40-86194. https://www.nrel.gov/docs/fy23osti/86194.pdf.

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-7A40-86194
July 2023

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 the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office Award Number 38407. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

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

Impacts of Dispatch Strategies and Forecast Errors on the Economics of Behind-the-Meter PV-Battery Systems

Brian T. Mirletz
National Renewable Energy Laboratory
Golden, Colorado, USA
Email: brian.mirletz@nrel.gov

Nicholas D. Laws
Walker Department of Mechanical Engineering
The University of Texas at Austin
Austin, TX, USA Email: nlaws@utexas.edu

***Abstract*—To assess the economic value of batteries in hybrid PV-battery systems, one must create a dispatch profile for the battery. Many analyses of battery value assume perfect forecasts of PV generation and load, determining an upper limit on the value of the battery. Prior work that accounts for forecast uncertainty often does so in the context of a single dispatch algorithm, which does not provide a baseline for comparison. Furthermore, when multiple dispatch algorithms are assessed with uncertainty, the benefits considered are for diesel generation in a microgrid, not retail rate savings. This work addresses the gaps in the literature by comparing the performance of both heuristic and optimal dispatch algorithms for retail rate savings under forecast uncertainty, and provides comparisons of the robustness of these algorithms and their associated estimates of economic value. We find that using a perfect forecast can overestimate the value of hybrid PV-battery systems between 1% and 8% compared to the reality of using a day-ahead forecast, depending on the dispatch algorithm used. Thus, accounting for forecast uncertainty in system design and analysis will significantly improve the accuracy of modeled system values.**

***Keywords*—solar plus storage, batteries, battery dispatch, System Advisor Model, SAM, behind-the-meter**

I. INTRODUCTION

Pairing behind-the-meter (BTM) batteries with solar photovoltaic systems (PV) can provide numerous benefits to the customer, including bill reductions, increased PV self-consumption, and backup power [1]. However, the value of these benefits is highly dependent on the local conditions, such as the customer's utility rate, the battery control method, and forecast errors [2, 3, 4, 5]. Therefore, accurate estimation of system value is important for driving adoption.

A key component of system value is the choice of dispatch algorithm. Mirletz and Guittet 2021 explores the trade-offs of these dispatch strategies when varying utility rates, with estimated net present value (NPV) varying by factors of 2.3 or more for the same system design [4]. Dispatch strategies can vary by the use case, and both heuristic and optimal algorithms have been evaluated in the literature [6, 7]. However, these assume perfect forecasts; day-ahead weather forecasts include PV production errors ranging from 3% to 14% [8, 9], and forecasts of peak load have average error rates of 4 to 7% [10]. These forecast errors can cause reductions in system value. For example, Vedullapalli and Hadidi observed 1.3 to 7.8 percentage point reductions in system profit in demand charge reduction with optimal dispatch depending on the forecast used [11]. Mazzola et al. studied the effect of forecast errors on dispatch strategies, including load following, cycle charging, and optimization with a rolling forecast, finding forecast errors could increase the cost of diesel generation in a microgrid case between 1.2% and 6.6% [5]. Sahoo et al. accounted for forecast uncertainty for residential batteries with a sliding window method and a swarm intelligence-based optimization algorithm, but only compared their proposed algorithm to a manual schedule, and no heuristic algorithms that used a forecast were evaluated [12]. This paper provides the additional analysis of the financial impact of forecast uncertainty on grid connected systems, including comparisons between heuristic and optimal dispatch algorithms that utilize forecasts.

II. METHODOLOGY

This work combines two state-of-the-art techno-economic decision support tools developed at the National Renewable Energy Laboratory (NREL). The System Advisor Model (SAM) contains technology performance models, including PV+battery systems, and allows for techno-economic analysis of systems in multiple financial contexts. The Renewable Energy Integration and Optimization (REopt) platform is used to evaluate optimal dispatch strategies, as well as determine the cost-optimal PV and battery capacities.

The SAM battery model utilizes subcomponent models, including voltage, lifetime, and thermal models for multiple battery chemistries [13]. SAM includes several choices for heuristic dispatch algorithms, including time-based manually specified schedules [14], automated dispatch for peak shaving based on forecasted generation and load (peak shaving dispatch) [15], and price signals dispatch, which considers utility rates in addition to those factors [4].

The peak shaving dispatch algorithm in SAM uses forecasts of generation and load to set a target for power drawn from the grid at each step, referred to as the grid power target [15]. If the power from the grid at a step is forecast to be greater than the target, the battery will discharge. Similarly, the battery will charge if grid use is forecast to be less than the target. Prior to this work, the peak shaving and price signals dispatch algorithms in SAM used the forecast both for the grid power target and to determine charge and discharge power at each step. For this paper, the battery is able to observe the actual load and PV generation at each time step and charge or discharge based on the difference between the grid usage and the target in real time. This does not change the performance of perfect forecasts, but improved the financial performance of the look-behind method by a factor of 6 for peak shaving[1].

To evaluate the performance of optimal dispatch, we used REopt's model predictive control module (MPC). REopt uses mixed integer linear programming to determine cost-optimal sizing and dispatch for distributed energy resources, including behind-the-meter batteries with PV [16]. The MPC module re-uses some of the core functionality from the REopt sizing and dispatch optimization to determine optimal dispatch strategies for use in real-time controls. It should be noted that the stability of model predictive control relies on only implementing the first interval of the optimal control plan. However, for this work only day-ahead forecasts were available so the entire 24 hour optimal dispatch from the REopt MPC module was used for each day in the simulated year [17]. For this work, the MPC module re-planned dispatch each hour, with the actual load and PV generation in the first step of each forecast.

We conducted a case study using actual day-ahead forecasts of weather from locations in Puerto Rico for 2018 from the Puerto Rico Grid Resilience and Transitions to 100% Renewable Energy study. Code and data used in the case study are available on GitHub[2]. Load profiles were generated for a hospital using EnergyPlus, using the day-ahead weather forecast to generate a day-ahead load forecast in addition to the actual weather and load [18]. The resulting load profile uses 6,800 MWh of electricity annually, with a peak load of 1,267 kW. The utility rate is the time-of-use at primary distribution voltage rate[3], which includes both time-of-use rates and demand charges. We assumed excess net metering credits would be compensated at $0.075/kWh at the end of June each year [19]. Costs for the system is based on the 2022 NREL benchmark [20], which are default parameters in SAM version 2022.11.21r2. The analysis period for the system is 25 years, with a 6.4% real discount rate. We assume that the project can receive a 30% ITC through direct pay and that the battery can charge from the grid. As of writing, direct pay requirements are still not published, so if the system was not eligible, it would uniformly decrease the net present value of the systems (NPVs). Batteries are replaced when they reach 80% of their nameplate capacity. Additional defaults (such as AC to DC and DC to AC efficiencies of 96%) are also used.

III. Results

A. System Sizing

System sizing was determined by REopt. Optimal sizing without considering resilience led to 3.63 MW-ac of PV, 151 kW of battery power, and 280.8 kWh of battery energy. However, given the building model is a hospital, resilience is a key consideration, so we re-sized the system with 50% critical load for a 24-hour outage. This resulted in 3.66 MW-ac of PV, 514 kW of battery power, and 4,884 kWh of battery energy. When testing with this size, the SAM battery dispatch algorithms were unable to meet the critical load during the outage, since the SAM grid outage dispatch algorithm does not currently have foresight of the outage. In order to meet the critical load, we restricted the economic dispatch of the battery to a minimum state of charge of 70%. With this constraint, the optimal system size was 3.66 MW-ac of PV, 506 kW of battery power, and 6,574 kWh of battery energy. We assumed that batteries would be available in 50-kW increments, so rounded up to 550 kW of battery power and 6,500 kWh of battery energy for the remainder of the analysis. Note that the rated battery power is based on the nominal voltage, the actual maximum power is higher at timesteps with a high state of charge, and therefore a high voltage. This allows up to 600 kW of discharge power.

B. Forecast Error

The root mean squared error (RMSE) in direct normal irradiance between the actual weather data and the forecast weather data is 140 W/m^2, and the mean absolute error (MAE) is 75 W/m^2, or around 13.6% of the maximum DNI. This is in line with typical errors in day-ahead forecasts [9]. The RMSE for the PV production data was 493 kW, with MAE of 249 kW, corresponding to 13.6% of the maximum generation. The RMSE for the load data was 33.4 kW, with MAE of 25.2 kW, or around 2.6% of the peak load.

C. Dispatch Results

For this system, we tested the battery with both perfect forecasts and actual day-ahead forecasts using the following dispatch methods:

- Peak shaving dispatch with a rolling 24-hour forecast (peak shaving).
- Price signals dispatch with a rolling 24-hour forecast (price signals).
- Optimal dispatch with a rolling 24-hour forecast (MPC 24 hour).
- Optimal dispatch with a full-year forecast horizon (Full-year horizon).
- A time-based schedule with no forecast (Manual dispatch).

The SAM dispatch models and the REopt dispatch models have different underlying models for the underlying battery and utility rate structures, and the battery power and utility rate calculations presented here were performed in SAM. Price signals dispatch is able to account for surplus or consumed kWh by time of use period during each month, whereas the MPC algorithm does not track net metering credits over the course of the month. The full-year horizon forecast does not have information about the real-time PV and load values, and is not able to re-plan given the forecast errors. Therefore, we will not focus on specific NPV values, rather the differences within each algorithm's performance when run with and without forecast errors.

The algorithms respond differently to forecast errors. Peak shaving will perform charging and discharging according to its grid power target, but forecast errors may introduce differences in the target. For example, on the day when the peak occurs in

[1]https://github.com/NREL/ssc/pull/683, https://github.com/NREL/ssc/pull/1031
[2]https://github.com/NREL/SAM-analyses/tree/main/2023/mirletz_laws_pvsc
[3]https://apps.openei.org/IURDB/rate/view/5bfdc7925457a33744146c53

TABLE I. NPV REDUCTIONS FROM USING DAY-AHEAD FORECASTS.

Dispatch	Peak shaving	Price Signals	MPC 24 hour	Full-year horizon	Manual Dispatch
Perfect Forecast NPV	$8,119k	$8,840k	$8,433k	$8,519k	$7,639k
Day-ahead Forecast NPV	$8,045k	$8,732k	$7,739k	$7,605k	N/A
NPV Reduction %	0.91%	1.23%	8.23%	10.7%	N/A

TABLE II. CHANGES IN ELECTRICITY BILL COMPONENTS FROM FORECAST ERRORS.

Dispatch	Peak shaving	Price Signals	MPC 24 hour	Full-year horizon
Increase in demand charge	$8.0k	$5.3k	$49.7k	$102.1k
Percent change versus perfect forecast	9.4%	9.4%	52.4%	117.8%
Increase in energy charge %	$4.0k	$7.1k	$32.3k	$5.1k
Percent change versus perfect forecast %	0.3%	0.5%	2.3%	0.5%

June, the actual weather and load data produces a grid power target of 722.4 kW, whereas the grid power target based on the day-ahead forecast data was 649.5 kW. This tighter grid power target meant that the battery using the day-ahead forecast data fully discharged before the peak, resulting in a higher peak demand charge. The other dispatch algorithms specify power to or from the battery in each time step, meaning that if there is not as much PV production as expected, the batteries will charge from the grid instead. Batteries are allowed to discharge when load does not exceed PV output, which could allow the discharge to push PV power to the grid, but the batteries are not allowed to discharge to the grid by SAM's powerflow code.

The differences in NPV for each dispatch algorithm are reported in Table I. Peak shaving dispatch shows the smallest reduction in system value, followed by price signals dispatch, MPC, and then full year horizon. Manual dispatch results are provided for reference, but would be the same regardless of forecast.

While demand charges only make up 9.6% of the bill without system, in all cases they make up the majority of the difference between the bill savings with the perfect forecast and the day-ahead forecast. Table II summarizes these changes. Changes in energy savings are smaller, given that all systems have the same PV production.

Figure 1 shows how the forecast errors reduce peak shaving. The peak demand for June occurs at 11 am, and with the actual forecast every algorithm except manual dispatch is discharging at that time. However, the forecast expects the highest PV production of the day at that time, so the algorithms using the forecast schedule a charge. The algorithms with real-time information (peak shaving, price signals, and MPC) stop charging, while the full-year forecast charges anyway. This increases the peak demand charge for the hour.

For additional metrics, Table III shows battery throughput (energy discharged in year 1), round trip efficiency, and percent of energy charged from PV. The main trend in these data is that the cases using the day-ahead forecast for dispatch tend to have a lower percentage of energy charged from PV. This is another potential source of the cost increases in Table II, as energy from the grid is more expensive.

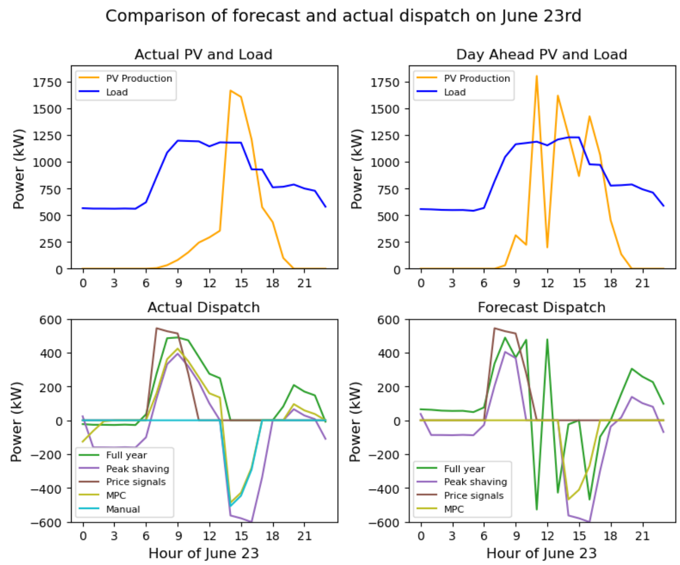

Fig. 1. A comparison of dispatch using a day-ahead forecast versus perfect forecast on June 23, the day of peak grid demand. Negative numbers for battery power indicate charging, while positive numbers indicate discharging. The perfect forecast allows the algorithms to plan to discharge at 11 am and reduce the peak, whereas the expected PV production at that time in the day-ahead forecast discourages discharging.

TABLE III. BATTERY METRICS. MOST ALGORITHMS DISCHARGE LESS WITH FORECAST ERRORS. ALL ALGORITHMS CHARGE FROM THE GRID MORE WITH FORECAST ERRORS.

Dispatch and forecast	Energy Discharged Year 1	Round Trip Efficiency	Charge Percent from PV
Peak shaving - perfect	398 MWh	90.28%	89.6%
Peak shaving - day ahead	311 MWh	90.36%	83.7%
Price signals - perfect	546 MWh	89.62%	99.6%
Price signals - day ahead	546 MWh	89.52%	99.4%
MPC - perfect	715 MWh	90.08%	99.8%
MPC - day ahead	588 MWh	89.60%	99.9%
Full-year - perfect	802 MWh	90.72%	99.2%
Full-year - day ahead	471 MWh	90.99%	97.3%
Manual	470 MWh	90.50%	100.0%

Due to the 70% state of charge restriction for resilience, the depth of discharge is low for all cases, and SAM's battery degradation models predict that the battery will last for the entire 25-year lifetime of the system. This is likely to be an optimistic assumption, but it is consistent between all dispatch algorithms so we did not examine the costs of battery replacement in this analysis.

IV. Conclusions

We find that using a perfect forecast can overestimate the value of hybrid PV-battery systems between 1% and 8% compared to the reality of using a day-ahead forecast, depending on the dispatch algorithm used. For large systems such as those studied here, this can be $674,000 of value. Given the impact to project value, accounting for forecast uncertainty in system design and analysis will significantly improve the accuracy of modeled system values.

Improving the performance of dispatch while using a forecast could come from real-time controls, improved forecasts, or algorithmic improvements. Batteries in the field would run controls sub-hourly, allowing for real-time correction decisions while facing forecast errors and sub-hourly variability. When we added real-time information to the price signals dispatch forecast processing, the NPV increased by 2.9%. Hour-ahead forecasts of PV generation and load may be more accurate than day-ahead forecasts.

The most robust algorithm to forecast errors was also the simplest: peak shaving dispatch. This algorithm's use of grid power targets allows for flexible adaptation to changes in actual load and generation. However, it does not account for load shifting in its dispatch, which is a major source of value for the other algorithms. Therefore, future work could develop different grid power targets for different time of use periods, allowing for load shifting using this method. Future work could also examine additional utility rate structures and locations, ensuring the robustness of the results.

Acknowledgment

The authors would like to acknowledge Janine Keith and Nate Blair for comments and suggestions on drafts, and Liz Breazeale for editing support. 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 the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office Award Number 38407. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

References

[1] G. Fitzgerald, J. Mandel, and J. Morris. (). The economics of battery energy storage, RMI, [Online]. Available: https://rmi.org/insight/economics-battery-energy-storage/ (visited on 12/28/2022).

[2] J. McLaren, N. Laws, K. Anderson, N. DiOrio, and H. Miller, "Solar-plus-storage economics: What works where, and why?" *The Electricity Journal*, vol. 32, no. 1, pp. 28–46, Jan. 1, 2019, ISSN: 1040-6190. DOI: 10.1016/j.tej.2019.01.006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1040619018302744 (visited on 12/28/2022).

[3] A. Prasanna, K. McCabe, B. Sigrin, and N. Blair, "Storage futures study: Distributed solar and storage outlook: Methodology and scenarios," NREL/TP-7A40-79790, 1811650, MainId:37010, Jul. 27, 2021, NREL/TP–7A40–79 790, 1811650, MainId:37010. DOI: 10.2172/1811650. [Online]. Available: https://www.osti.gov/servlets/purl/1811650/ (visited on 12/28/2022).

[4] B. T. Mirletz and D. L. Guittet, "Heuristic dispatch based on price signals for behind-the-meter PV-battery systems in the system advisor model," in *2021 IEEE 48th Photovoltaic Specialists Conference (PVSC)*, ISSN: 0160-8371, Jun. 2021, pp. 1393–1400. DOI: 10.1109/PVSC43889.2021.9519013.

[5] S. Mazzola, C. Vergara, M. Astolfi, V. Li, I. Perez-Arriaga, and E. Macchi, "Assessing the value of forecast-based dispatch in the operation of off-grid rural microgrids," *Renewable Energy*, vol. 108, pp. 116–125, Aug. 1, 2017, ISSN: 0960-1481. DOI: 10.1016/j.renene.2017.02.040. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S096014811730126X (visited on 06/21/2021).

[6] P. P. Mishra, A. Latif, M. Emmanuel, Y. Shi, K. McKenna, K. Smith, and A. Nagarajan, "Analysis of degradation in residential battery energy storage systems for rate-based use-cases," *Applied Energy*, vol. 264, p. 114 632, Apr. 15, 2020, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2020.114632. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261920301446 (visited on 01/13/2023).

[7] J. Cai, H. Zhang, and X. Jin, "Aging-aware predictive control of PV-battery assets in buildings," *Applied Energy*, vol. 236, pp. 478–488, Feb. 15, 2019, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.12.003. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918318208 (visited on 01/13/2023).

[8] S. Theocharides, G. Tziolis, J. Lopez-Lorente, G. Makrides, and G. E. Georghiou, "Impact of data quality on day-ahead photovoltaic power production forecasting," in *2021 IEEE 48th Photovoltaic Specialists Conference (PVSC)*, ISSN: 0160-8371, Jun. 2021, pp. 0918–0922. DOI: 10.1109/PVSC43889.2021.9518471.

[9] Y. Wang, D. Millstein, A. D. Mills, S. Jeong, and A. Ancell, "The cost of day-ahead solar forecasting errors in the united states," *Solar Energy*, vol. 231, pp. 846–856, Jan. 1, 2022, ISSN: 0038-092X. DOI: 10.1016/j.solener.2021.12.012. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0038092X21010616 (visited on 04/24/2023).

[10] B. Yildiz, J. Bilbao, and A. Sproul, "A review and analysis of regression and machine learning models on commercial building electricity load forecasting," *Renewable and Sustainable Energy Reviews*, vol. 73, pp. 1104–1122, 2017. DOI: 10.1016/j.rser.2017.02.023.

[11] D. T. Vedullapalli and R. Hadidi, "Effect of forecaster performance on peak shaving in a university building by battery scheduling," in *2020 IEEE/IAS 56th Industrial and Commercial Power Systems Technical Conference (I CPS)*, ISSN: 2158-4907, Jun. 2020, pp. 1–6. DOI: 10.1109/ICPS48389.2020.9176774. [Online]. Available: https://ieeexplore.ieee.org/document/9176774.

[12] E. Oh and S.-Y. Son, "Theoretical energy storage system sizing method and performance analysis for wind power

forecast uncertainty management," *Renewable Energy*, vol. 155, pp. 1060–1069, Aug. 1, 2020, ISSN: 0960-1481. DOI: 10.1016/j.renene.2020.03.170. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148120305036 (visited on 12/27/2022).

[13] N. DiOrio, A. Dobos, S. Janzou, A. Nelson, and B. Lundstrom, "Technoeconomic modeling of battery energy storage in SAM," National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-64641, Sep. 1, 2015. DOI: https://doi.org/10.2172/1225314. [Online]. Available: https://www.osti.gov/biblio/1225314.

[14] N. DiOrio, A. Dobos, and S. Janzou, "Economic analysis case studies of battery energy storage with SAM," National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP–6A20-64987, 1226239, Nov. 1, 2015, NREL/TP–6A20–64 987, 1 226 239. DOI: 10.2172/1226239. [Online]. Available: http://www.osti.gov/servlets/purl/1226239/.

[15] N. A. DiOrio, "An overview of the automated dispatch controller algorithms in the system advisor model (SAM)," National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/TP-6A20-68614, Nov. 22, 2017. DOI: https://doi.org/10.2172/1410499. [Online]. Available: https://www.osti.gov/biblio/1410499.

[16] S. Mishra, J. Pohl, N. Laws, D. Cutler, T. Kwasnik, W. Becker, A. Zolan, K. Anderson, D. Olis, and E. Elgqvist, "Computational framework for behind-the-meter DER techno-economic modeling and optimization: REopt lite," *Energy Systems*, vol. 13, no. 2, pp. 509–537, May 1, 2022, ISSN: 1868-3975. DOI: 10.1007/s12667-021-00446-8. [Online]. Available: https://doi.org/10.1007/s12667-021-00446-8 (visited on 12/27/2022).

[17] J. Keith, B. Mirletz, M. Prilliman, N. Blair, D. Guittet, S. Janzou, and P. Gilman, "FY19-FY21 final technical report: Foundational open source solar system modeling through improvement and validation of the system advisor model and PVWatts," NREL/TP-7A40-82478, 1870820, MainId:83251, May 26, 2022, NREL/TP–7A40–82 478, 1870820, MainId:83251. DOI: 10.2172/1870820. [Online]. Available: https://www.osti.gov/servlets/purl/1870820/ (visited on 12/28/2022).

[18] "EnergyPlus™," National Renewable Energy Lab. (NREL), Golden, CO (United States); Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States), EnergyPlus™ (e+); 005462MLTPL00, Sep. 30, 2017. [Online]. Available: https://www.osti.gov/biblio/1395882 (visited on 01/12/2023).

[19] (). Puerto rico - net metering, Database of State Incentives for Renewables and Efficiency, [Online]. Available: https://programs.dsireusa.org/system/program/detail/2846/puerto-rico-net-metering (visited on 05/17/2023).

[20] V. Ramasamy, J. Zuboy, E. O'Shaughnessy, D. Feldman, J. Desai, M. Woodhouse, P. Basore, and R. Margolis, "U.s. solar photovoltaic system and energy storage cost benchmarks, with minimum sustainable price analysis: Q1 2022," NREL/TP-7A40-83586, 1891204, MainId:84359, Sep. 28, 2022, NREL/TP–7A40–83 586, 1891204, MainId:84359. DOI: 10.2172/1891204. [Online]. Available: https://www.osti.gov/servlets/purl/1891204/ (visited on 01/12/2023).