Heuristic Dispatch Based on Price Signals for Behind-the-Meter PV-Battery Systems in the System Advisor Model

Preprint

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National Renewable Energy Laboratory

Presented at the 48th IEEE Photovoltaic Specialists Conference (PVSC 48)
June 20-25, 2020

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Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-7A40-79575
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Suggested Citation
Mirletz, Brian T. and Darice L. Guittet. 2021. *Heuristic Dispatch Based on Price Signals for Behind-the-Meter PV-Battery Systems in the System Advisor Model: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-7A40-79575. https://www.nrel.gov/docs/fy21osti/79575.pdf.

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Heuristic Dispatch Based on Price Signals for Behind-the-Meter PV-Battery Systems in the System Advisor Model

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***Abstract*—The economic potential of a behind-the-meter (BTM) PV-battery system depends greatly on how the battery is dispatched. Different utility rates, system sizes, generation and load profiles can all require different dispatch strategies. This paper presents price signals dispatch, a new algorithm for automated economic dispatch of BTM PV-battery systems, which utilizes 24-hour PV and load forecasts, degradation data, and utility rates. The algorithm is integrated with the System Advisor Model (SAM) tool and is tested with a nonlinear generic electrochemical battery model. Price signals dispatch outperforms SAM's existing algorithms in cases requiring a balance between demand charge management and energy arbitrage, and in cases where battery degradation imposes a significant cost.**

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

I. Introduction

Storage deployment is a promising method of supporting the electricity grid's transition to a more dynamic, flexible, reliable and sustainable system, with applications across the entire electricity value chain. Even though the cost of batteries is decreasing significantly, making storage systems viable in a broader range of use cases, the economic viability of a given storage project is nevertheless highly dependent on operating it to maximize multiple potential value streams [1] while managing important cost factors such as degradation and replacement [2]. In the behind-the-meter (BTM) space, storage is often added to photovoltaic (PV) systems to provide services beyond backup power such as increasing PV self-consumption, energy shifting, demand management, and frequency regulation, which can lead to increased revenue or electricity bill savings.

Studies of the economic impact of PV + battery analyze system design, operation, market and regulation factors that could support greater deployment in cost-effective and reliable ways for BTM [3]–[7], front-of-meter (FTM) [8]–[13] and combined application systems [14]. Authors may focus on different value streams, whether by comparing or stacking them [4]–[6]. Various dispatch optimization algorithms are used including derivative-free search methods [4], linear, convex [7], [9], mixed-integer programming [7], [10], [13], [15], and heuristic-based dispatch [3], [6], [11]. Studies also focus on improving battery modeling features, particularly around degradation, which has a complex, nonlinear relationship with operational characteristics and a potentially dramatic effect on project economics [6]–[8], [10], [12]. In addition, battery dispatch and technoeconomic performance research has generated a breadth of modeling tools such as those found in StorageVET [16], Battery Lifetime Analysis and Simulation Tool (BLAST) [17], HOMER [18], System Advisor Model (SAM) [19], and REopt Lite [15], among many others.

This work presents a heuristic dispatch algorithm that has been incorporated into the SAM software and uses a forecast of the electricity cost from the utility rate at each time step and projected battery degradation costs to plan dispatch. Prior to this, BTM battery systems in SAM included two dispatch options, one based on manually specified schedules for energy arbitrage (manual) and the other an automatic dispatch algorithm which considers load and PV generation forecasts to reduce peak grid power (peak shaving) [3]. Users could also specify custom time-series dispatch schedules. However, none of these algorithms consider the price of energy at each time step, meaning that some systems may have been missing value by dispatching based solely on PV, load, or time without associated price information. In addition, the algorithms did not consider a penalty for battery cycling, missing the longer-term implications of decreased capacity and increased replacement costs as they pertain to dispatch decisions. This new heuristic algorithm, price signals, considers time of use (TOU) tariffs for energy and demand more closely during its dispatch by computing marginal costs while penalizing battery degradation.

We test the three heuristic dispatch algorithms in SAM (manual, peak shaving, and price signals) in a case study for a PV + battery system at a San Diego Hospital and a San Francisco shopping center using utility rates with complex TOU structures and demand charges. We then expand on these results with a sensitivity analysis, testing the algorithms on a range of energy and demand prices. Our analysis of the dispatch behavior and performance reveals that although the heuristic dispatch algorithms are suboptimal compared to upper-bound, perfect forecast optimization algorithms, they still show in many cases that batteries offer additional economic value to solar. The fact that a battery can be economically viable with suboptimal operation is promising for real systems that operate with greater uncertainty and lack of control in design and operation than simulations [20]. The

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office Award Number 34221.

sensitivity analysis provides insight into which strategies are beneficial for what types of rates and can help clarify how to deploy batteries as demand and opportunities continue to increase.

II. Dispatch Algorithm

A. Overview

The price signals dispatch algorithm uses the following inputs:

- Monthly totals of forecasted load and PV generation over the analysis period
- Time step resolution forecasts for the next 24 hours of load and PV generation
- The utility rate
- Battery state of charge and battery capacity
- Projected battery degradation per cycle

These inputs are used to generate a forecast of the utility bill for each time step. That forecast is then used to plan 13 possible dispatch profiles for discharge from 0 to 12 hours, and the lowest-cost plan is selected for execution. Regardless of the simulation time step, computations are repeated each hour using a rolling 24-hour horizon.

B. Forecasting utility bill cost

SAM represents the utility bill's demand and energy charges with both flat and TOU rates, where prices vary with time period and usage tier. The utility bill forecast function uses the monthly forecasted load and generation data to determine the tier in which the electricity is purchased and uses that tier's pricing level to compute the anticipated costs of each time step. The tier must be forecast to ensure that any load shifting during hours at the beginning of a month are treated the same as hours at the end of the month, because compensation mechanisms such as net metering frequently compute tier usage based on a full month's energy use. Simply using the lower tiers at the beginning of the month could understate the value of shifting load on those days. The algorithm assumes that any cost differences from changing the tier because of dispatch will be negligible, given that differences in monthly energy use because of dispatch are approximately 3%.

For net billing utility rates, where excess generation is credited on an hourly basis, the energy charges can be determined hour by hour. For net metering, the total change in cost incurred in each TOU period between the start and end of the forecast is used to estimate the energy charges. This means if credits are earned during a forecast, the energy charge can be negative. Regardless of whether the rate allows selling the credits at the end of the year, the algorithm does not assign a monetary value to accumulated credits. If the required grid power is covered by excess credits during a forecast period, the estimated energy charge is $0.

For demand charges, the monthly average load, before PV generation, is used to anticipate a minimum demand charge. Any charges above this are assigned to the time step where the peak load is first observed. If a subsequent hour reaches a higher peak, then the subsequent cost increase in demand charges is assigned to that time step.

The highest cost time steps are used to estimate the best time to discharge. To determine the best time to charge the battery, the marginal cost of charging is calculated by running a 1 kilowatt (kW) load per time step through the forecast function.

C. Dispatch planning

Within each 24-hour forecast period, the planning function receives data from the forecast about each time step's load, generation, total additional electricity cost, and marginal electricity cost. Thirteen possible plans are generated with a period of discharge that ranges from 0 to 12 hours, where 0 represents not cycling the battery at all. The planner first schedules the battery to discharge at the highest cost time steps, assuming one full discharge cycle during the forecast period, subject to any provided dispatch limits. SAM's dispatch constraints are described in detail in DiOrio, Freeman, and Blair 2018 [21]. The discharge time steps are sorted by cost from highest to lowest, $t \in (0, ..., p)$, and the discharge power for each time step is distributed in order according to:

$$P_{discharge,t} = \frac{E_{remaining,t} * C_t}{(\sum_{i=t}^{p} C_i) * dt} \tag{1}$$

Where $P_{discharge,t}$ is the power discharged in kW, subject to the battery's power constraints; $E_{remaining,t}$ is the remaining battery energy available after power consumption in higher-cost time steps; C_t is the total cost of the time step in dollars, C_i is the cost of each unscheduled discharge time step in dollars, and dt is the length of the time step in hours. Discharge power is limited to load minus PV. As of the current version, SAM assumes that BTM batteries cannot export power to the grid. Equation 1 results in the most battery power being dispatched during the highest cost time steps.

When the total energy used for discharging in all time steps is known, the algorithm schedules charging. If the battery is DC-connected, hours where the forecast anticipates clipped power are scheduled for charging. After that, remaining charging occurs during the hours with the lowest marginal cost. If the battery is only allowed to charge from the PV system, then for AC-connected batteries charging is limited to PV minus load for each time step. DC-connected batteries are permitted to charge up to the total PV generation. With either PV or grid charging, the total power from the grid is limited to the 25th percentile of net grid use, to avoid creating new peaks.

Finally, the algorithm considers a basic energy balance, starting with the state-of-charge (SOC) of the battery at the beginning of the forecast period. If an hour is found to be outside the battery's state of charge limits, planned charging or discharging (respectively) is reduced to maintain those limits.

D. Plan selection

The forecast function then calculates the cost of the 13 dispatch plans based on their estimated grid use. The lowest

cost dispatch plan is chosen, where cost in dollars is computed as:

$$C_{total} = C_{utility\_bill} + C_{cycle} * n_{cycles} - E_{remaining} * C_{marginal} \quad (2)$$

Where $C_{utility\_bill}$ is the anticipated additional utility bill costs in dollars for the forecast period. C_{cycle}, in units of $\$/cycle$, is multiplied by n_{cycles} to estimate the cost of the expected degradation of the battery over the planned cycles. C_{cycle} can be automatically computed by multiplying the battery's replacement costs by the expected degradation per cycle (computed via the battery lifetime models in SAM), or input manually. Note that the automatically computed cost does not change based on replacement strategy. $E_{remaining}$ is the kWh of energy remaining in the battery at the end of dispatch, multiplied by the DC to AC efficiency, and $C_{marginal}$ is the highest $\$/kWh$ cost of energy from the grid during the dispatch period. Including $E_{remaining}$ allows the algorithm to value energy stored in the battery for discharge outside of the forecast period.

III. Case Study

A. SAM Battery Model

The SAM battery model is composed of complementary voltage, thermal, lifetime, and efficiency models. Detailed equations for the model are described in DiOrio, Dobos, and Janzou 2015 [22]. The systems in these case studies used the default parameters for a lithium ion battery with nickel manganese cobalt cells from SAM 2020.11.29, which are based on a fit of accelerated lifetime test data from Smith et al. 2017 [23]. We assumed that the AC to DC and DC to AC efficiency was 96%; the DC to DC efficiency is determined by the voltage model and specific cycling patterns. For the case study, the battery is replaced when it has degraded to 50% of its initial capacity. Both systems use an AC-connected battery, and we examined different options for charging in the results. Cost assumptions are the defaults from SAM 2020.11.29, which are summarized in Table I and are based on Augustine and Blair 2021 [24].

B. Location and Load

The case studies focus on two load profiles in different locations: a hospital in San Diego and a shopping center in San Francisco. Load profiles coincident with the weather files were generated using EnergyPlus, version 9.0.1 and 9.4.1, respectively [25]. Utility rates from San Diego Gas & Electric[1] (SDG&E) and Pacific Gas & Electric[2] (PG&E) were then selected for each load profile. The San Diego Gas & Electric includes a flat demand charge, a TOU demand charge from 4 p.m. through 8 p.m., and six TOU periods. Three TOU periods are active from November through May, with a peak energy charge of $0.299/kWh from 4 p.m. through 8 p.m.. The rates change from June through October, with a peak energy charge of $0.521/kWh during the same period. The Pacific Gas & Electric rate includes all of the same demand charge features, the TOU demand charges are active from 8 a.m. to 8 p.m., with two different periods in the summer. One set of TOU rates is active November through April, and has two periods with a peak energy charge of $0.113/kWh from 8 a.m. through 8 p.m.. The summer rates run May through October, with a peak energy charge of $0.371/kWh from 12 p.m. through 5 p.m..

A PV plus battery system was sized for each location using REopt Lite [15]. The size of the hospital system exceeded SDG&E's net metering limit, so we assumed any electricity exported to the grid was not compensated. The shopping center received net metering. The resulting systems are shown in Table II. REopt Lite also provides an optimal dispatch profile based on a one-year perfect forecast, so we ran the systems with this dispatch as well for comparison.

C. Case Study Results

The net present value (NPV) of each system by dispatch algorithm for the case with only PV charging for the ITC [26] versus the case allowing grid charging is shown in Table III. The price signals dispatch algorithm uses the automatically calculated cycle degradation penalty for these results. In both cases, for the systems with batteries that only charge from PV, REopt Lite's mixed-integer linear optimization generates the dispatch plan that results in the highest NPV, because of its perfect forecast of a full year's data. Within SAM's heuristic algorithms, price signals dispatch performs best in the San Diego Hospital case, both with and without grid charging. Peak shaving performs best in the San Francisco Shopping

[1] https://en.openei.org/apps/IURDB/rate/view/5cb743065457a321559b6ec4
[2] https://openei.org/apps/IURDB/rate/view/5e0b93695457a39434fa5c5f

TABLE I
Cost and financial assumptions used in the analysis

Variable	Value
PV System Cost	$1.67/Wdc
Battery Power Cost	$629.47/kW
Battery Capacity Cost	$206.67/kWh
Analysis Period	25 years
Inflation Rate	2.5%
Nominal Discount Rate	6.4%
Federal Tax Rate	21%

TABLE II
PV and battery sizing for each system and load data for each location

System	PV Capacity	Battery Power	Battery Capacity	Peak Load	Annual Energy Consumption
San Francisco Shopping Center	1000 kWac	169 kW	711 kWh	747 kW	4,444 MWh
San Diego Hospital	1,500 kWac	974 kW	7,356 kWh	1,186 kW	5,475 MWh

TABLE III
NPV RESULTS FOR EACH OF THE DISPATCH ALGORITHMS, IN THOUSANDS OF DOLLARS.

System	Price signals dispatch	Peak shaving	Manual dispatch	REopt Lite	PV only
San Francisco Shopping Center w/ ITC	$2,039k	$2,098k	$1,492k	$2,155k	$2,060k
San Diego Hospital w/ ITC	$3,614k	$2,774k	$3,614k	$4,363k	$2,701k
San Francisco Shopping Center Grid Charging	$1,593k	$1,746k	$1,454k	$1,627k	N/A
San Diego Hospital Grid Charging	$2,973k	$1,369k	$2,037k	$3,238k	N/A

Center case. The most economic algorithm changes for the San Francisco shopping center when grid charging is allowed; in that case, peak shaving delays a battery replacement relative to REopt Lite, resulting in a higher NPV. However, both cases have a lower NPV when grid charging is allowed in addition to PV charging.

Figure 1 shows heat maps of the three dispatch strategies for the San Diego Hospital case when the battery can only charge from PV. Manual dispatch discharges strictly in the high cost period of 4 pm to 9 pm. Peak shaving aligns its dispatch with the peak grid use in mornings and evenings, when PV is not available to offset load. The peak shaving algorithm also frequently discharges more in early days of the month, since the grid power target is reset to zero at the beginning of each month and climbs over the course of high load or low resource days. The price signals dispatch algorithm utilizes both of these strategies: with much of its dispatch concentrated in the high cost period but occasional discharge outside those hours to shave peak demand.

An hourly dispatch profile for each algorithm on April 2 is shown in Figure 2, which demonstrates these strategies in more detail. The peak shaving algorithm is able to limit demand to 401 kW, but the low grid power target means that peak shaving is discharging after 9 pm, which provides relatively little value. Manual dispatch allows a peak of 726 kW. Price signals provides a balance between these two strategies: it avoids discharging overnight, it reduces load during the evening high energy cost period, and it shaves the peak for demand charges to 579 kW, below the average monthly load of 587 kW. This shows the ability of the price signals dispatch algorithm to dispatch against the peak shaving and energy arbitrage value streams simultaneously.

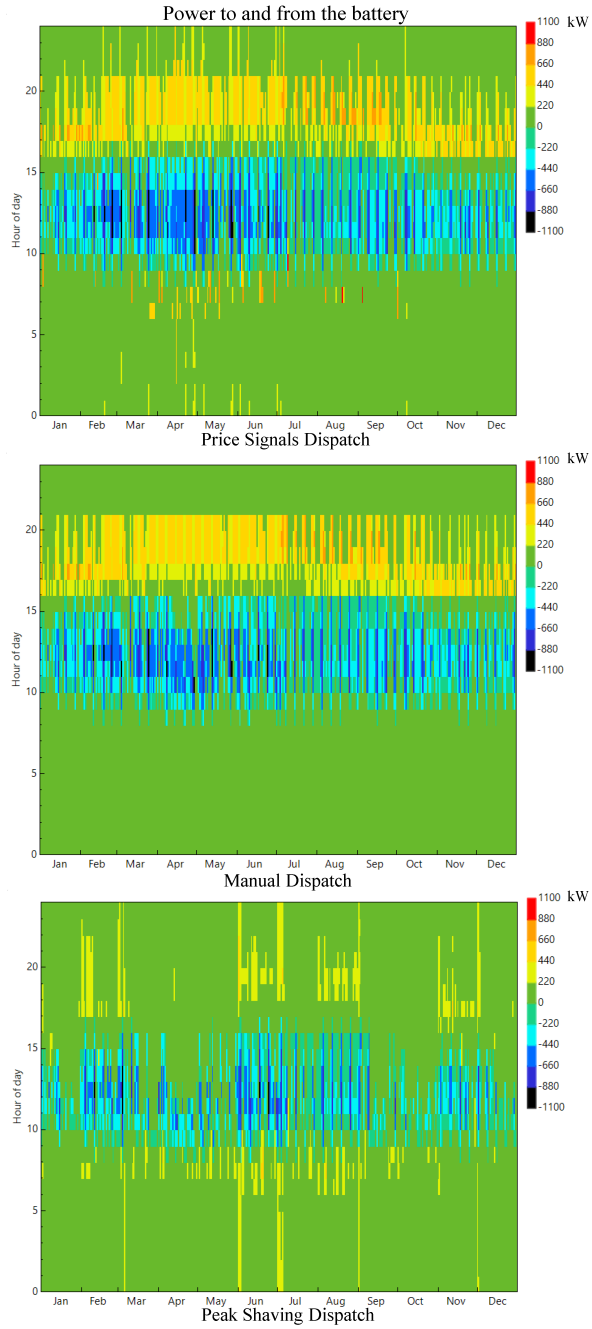

Fig. 1. Heat maps of the three SAM dispatch strategies executed over year 1 for the San Diego Hospital case. Negative numbers indicate battery charging; positive numbers indicate discharging; units are kW. The high energy cost period is from hour 16 to 21 each day.

IV. Sensitivity Analysis

A. Methodology

We conducted a sensitivity analysis to further assess the impact of the utility rate parameters and battery replacement strategy on dispatch results. We varied four parameters to generate 625 rates, all of which used the TOU periods of

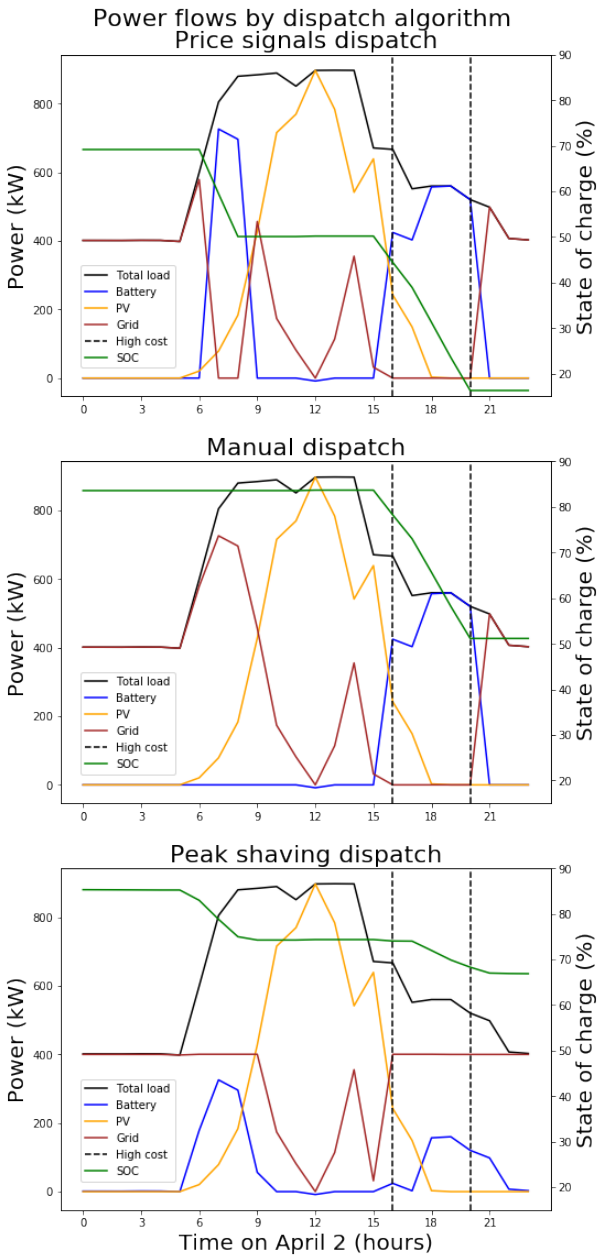

Fig. 2. Details of power flows on April 2 of year 1 for the San Diego Hospital system with PV only charging. Negative numbers for battery power indicate charging from PV. No power is sent to the grid during the period shown.

the San Diego Hospital case with net metering for excess generation. The parameters include:

- The energy charge in the highest cost TOU period, ranging from \$0.10 to \$0.50 per kWh
- The TOU ratio between charge in the highest cost period and the lowest cost period, ranging from 1 to 10
- The fixed demand charge, ranging from \$0 to \$59.05 per kW
- The TOU demand charge, ranging from \$0 to \$13.45 per kW

The energy charges within all six TOU periods scale with the highest cost TOU period and lowest cost TOU period rates. For example, the default rate had a TOU ratio of approximately 5 and maximum energy charge of \$0.521/kWh, with an intermediate rate of \$0.299/kWh and a minimum rate of \$0.102/kWh. If the maximum rate within the analysis case changes to \$0.30/kWh, then the intermediate rate will change to \$0.172/kWh, and the minimum rate will change to \$0.0591/kWh if the TOU ratio remains the same. These variations resulted in the demand charges ranging from 0% to 83.8% of the year 1 utility bill for the original load without the renewable energy system.

All three dispatch methods were tested on each rate and compared to a PV-only system. Four different battery replacement strategies were tested:

- No replacements
- Replace when capacity degrades to 50% of nameplate
- Replace when capacity degrades to 80% of nameplate
- Augment 20% of the capacity every five years

The price signals dispatch algorithm also varied the cycle degradation penalty, testing \$0, \$0.01, \$0.02 per cycle-kWh, as well as the automatically calculated penalty. Manually specified penalties were subject to the same inflation rate as the battery replacement costs and utility rates each year, which is specified in Table I. All cases used the same system size as specified in Table II, though the PV-only system does not include the battery and therefore has a lower total installed cost.

B. Analysis Results

In the 625 utility rates analyzed for this one system size and one load profile, the batteries dispatched by one of SAM's heuristic algorithms improve the NPV over a PV-only system in 240 cases, and cases dispatched by price signals dispatch have a positive NPC in 531 of the cases. The performance of the battery dispatch algorithms varies significantly with the battery replacement strategy; price signals dispatch is the only algorithm to outperform PV-only when the battery is replaced at 80% of nameplate capacity.

Table IV shows the relative performance of each algorithm across cases with different TOU ratios. Because TOU ratio was an input variable, cases are evenly distributed between the five TOU ratios. Neither manual dispatch nor price signals

TABLE IV
RESULTS OF THE SENSITIVITY ANALYSIS BY TOU RATIO. COLUMNS INDICATE THE NUMBER OF CASES WHEN THE ALGORITHM (OR PV-ONLY SYSTEM) ACHIEVED THE HIGHEST NPV FOR THAT CASE.

TOU Ratio	Total cases	Price signals	Peak shaving	Manual	PV-only
1	125	0	18	0	107
2.5	125	1	25	0	99
5	125	11	20	34	60
7.5	125	10	20	35	60
10	125	15	15	35	60

TABLE V
RESULTS OF THE SENSITIVITY ANALYSIS BY DEMAND CHARGE PERCENTAGE WITHOUT SYSTEM. COLUMNS INDICATE THE NUMBER OF CASES WHEN THE ALGORITHM (OR PV-ONLY SYSTEM) ACHIEVED THE HIGHEST NPV FOR THAT CASE.

Demand charge %	Total cases	Price signals	Peak shaving	Manual	PV-only
0% - 10%	166	0	0	41	125
10% - 20%	122	0	0	41	81
20% - 40%	173	17	13	22	121
40% - 70%	137	20	59	0	58
> 70%	27	0	26	0	1

dispatch achieves the highest NPV when the TOU ratio is 1; both algorithms improve their relative performance at higher ratios. Higher TOU ratio cases where PV-only had the highest NPV had smaller bills overall, meaning the reduced upfront capital cost of not purchasing a battery was of more value in those cases.

Table V sorts the results by the percentage of the utility bill for the load without solar and storage (demand charge % in the table). Peak shaving performs best in cases with high demand charges (at least 24% of the bill) whereas manual dispatch performs best when demand charges make up less than 32% of the utility bill. Price signals dispatch achieves the highest NPV in the middle ground, when the demand charge is between 21% and 57% of the bill.

Representative cases are shown in Figure 3 for two different TOU ratios and four different demand charge over total bill percentages. Peak shaving and manual dispatch have the best performance in three cases each; price signals dispatch in two. In the case with the 2.5 TOU ratio and 21% demand charge bill, the price signals dispatch algorithm is the only dispatch algorithm to achieve an NPV higher than PV-only.

Given that the battery may need to be replaced because of operational constraints, we analyzed the results of different replacement strategies. The cost of replacing the battery is assumed to be the nameplate capacity times the per kWh cost, or $1,520,322 in year 1 dollars. This cost can reduce the ability of the battery system to provide value above PV-only if the algorithm does not consider degradation. Table VI summarizes these results. While all three algorithms have positive NPVs in the majority of cases when the battery is replaced at 80% of nameplate capacity, only price signals dispatch achieves a higher NPV than PV-only. Price signals dispatch is able to delay or avoid battery replacements, while still creating sufficient additional utility bill savings for good performance. None of the SAM algorithms trigger a battery replacement in the 50% replacement strategy. Price signals dispatch outperforms PV-only in the most cases for this strategy as well. The strategy of replacing 20% of the battery every five years resulted in lower NPVs than the other replacement strategies in every case.

The best performing cycle degradation penalty depends on the choice of replacement strategy. For the 80% replacement strategy, the highest NPV was achieved by using the flat

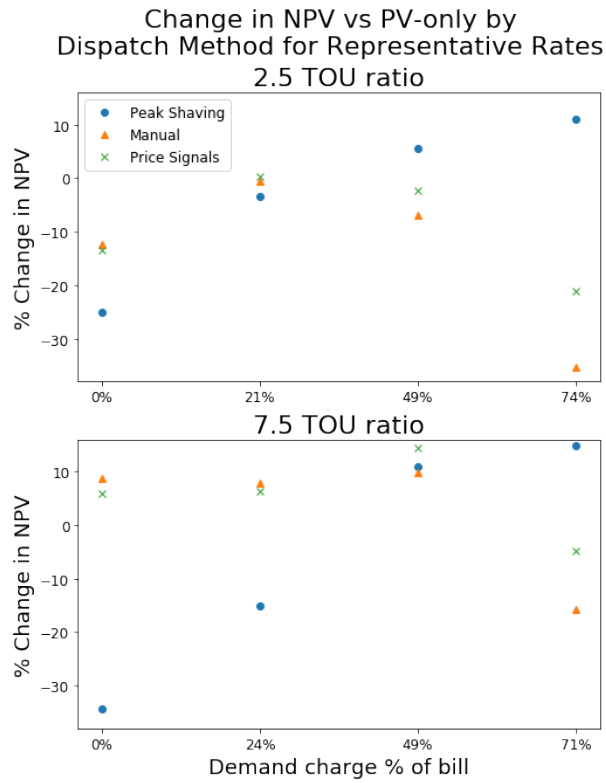

Fig. 3. The NPV of the SAM dispatch methods is compared for eight representative cases. The y-axis shows the ratio of the NPV with a battery dispatched by each algorithm versus the PV-only system.

penalty of $0.02, for 314 cases. The automatically calculated penalty had the best performance in 51 cases. For the 50% replacement strategy, a cycle degradation penalty of $0 had the best performance in 367 cases. This fits with the lack of battery replacements in that strategy overall.

V. DISCUSSION

Our results show an improvement in NPV for PV-battery systems using the price signals dispatch algorithm described in this paper and quantifies the tradeoffs between three heuristic dispatch algorithms. For the San Diego hospital case, the price signals dispatch algorithm achieved additional utility

TABLE VI
RESULTS OF THE REPLACEMENT STRATEGY ANALYSIS BY ALGORITHM. % REPLACEMENT INDICATES THE PERCENT OF NAMEPLATE CAPACITY REMAINING WHEN THE BATTERY IS REPLACED.

Algorithm	Positive NPV 80% replacement	Outperforms PV 80% replacement	Positive NPV 50% replacement	Outperforms PV 50% replacement
Price signals dispatch	503	80	531	171
Peak shaving	478	0	517	118
Manual dispatch	482	0	531	150

bill savings over the peak shaving algorithm via savings on energy charges, even while allowing a higher average monthly demand charge. The SAM heuristic algorithms achieve 83% to 107% of NPV of the REopt Lite dispatch in the case study. These results show that dispatch accounting for degradation with a rolling 24-hour forecast can outperform a perfect 8760 forecast that does not adjust dispatch for degradation.

The particular structure of net metering credits and TOU periods used in the sensitivity analysis gave manual dispatch an advantage, because it was able to utilize the net metering credits earned from excess PV generation from 6 am to 3 pm to cover energy use from 9 pm to midnight. Only discharging during one TOU period allows manual dispatch to generate similar utility bill savings in this case with less energy throughput, when compared to price signals dispatch.

To maximize value for a system, the best choice of dispatch algorithm within SAM depends on the utility rate structure. If a high TOU ratio is present with minimal demand charges, manual dispatch is a good choice. Peak shaving performs well when reducing demand charges is the main source of utility bill savings. Price signals dispatch performs best in cases requiring a balance between these two revenue streams, or cases when battery replacements would be a significant cost.

All of the cases above represent perfect day-ahead forecasts of load and weather data, which may produce optimistic forecasts of value. Load forecasts can be accurate to within 2.5% for hourly forecasts and 7% for daily peaks over a year [27], giving confidence that the price signals dispatch algorithm could help inform battery management systems.

VI. Conclusions and Future Work

The price signals dispatch algorithm adds to SAM's suite of heuristic dispatch methods and shows that BTM PV + battery systems can be economically viable in more situations than the prior algorithms suggested. Future work could yield several possible improvements to price signals dispatch. In the case study, price signals dispatch tends to result in more energy throughput for the battery, which results in round-trip efficiency losses. The highest cost period often discharges the battery equal to the entire grid use in that time step. Peak shaving will allow a small amount of grid use based on the grid power target, which allows for more efficient dispatch in some cases. More explicitly controlling and varying the maximum discharge in price signals dispatch could improve performance, though possibly at the expense of runtime.

The efficacy of the manual dispatch in the sensitivity analysis suggests that assigning no value to accumulated net metering credits is a conservative assumption. This assumption biases the battery toward charging rather than utilizing credits. However, assuming that the credits will have their full value can bias the battery against charging, meaning the battery could have insufficient state of charge to shave a peak. A robust discount factor for accumulated net metering credits would improve the efficacy of the algorithm.

Finally, the cycle degradation penalty assumes an average amount of degradation for each cycle based on prior degradation, which may not match actual battery degradation for every cycle. The algorithm could predict a detailed cycling pattern based on the dispatch plan, so estimates of the cost of cycling could be calculated with additional detail.

Acknowledgment

The authors thank Janine Keith for support with conceptualization and editing.

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office Award Number 34221. A portion of this research was performed using computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory. This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

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