OPTIMIZATION ROUTINE FOR ENERGY STORAGE DISPATCH SCHEDULING IN GRID-CONNECTED, COMBINED PHOTOVOLTAIC-STORAGE SYSTEMS

Anders Nottrott, Jan Kleissl, Ph.D., and Byron Washom

University of California San Diego, Department of Mechanical and Aerospace Engineering,
La Jolla, CA, USA

Ongoing advances in electrochemical battery technologies have dramatically increased the energy density, reliability, and product lifetime of batteries. These improvements have translated to significant cost reductions in kilowatt (kW)-scale batteries, making battery energy storage an attractive option to regulate the variable power output of photovoltaic (PV) systems. If a battery is connected to the PV system behind the grid interconnect, the energy stored in the battery can be dispatched "on demand" to modulate the net output of the combined PV-storage system (hereafter PVS system) to the grid.

We considered a simplified PVS system, in which a PV array and a battery are connected to the electricity grid via a lossless DC-AC inverter (see Figure 1). The goal is to determine the optimal energy dispatch schedule for the battery to achieve load peak shaving, such that the net PVS system power output meets or exceeds the customer load peak. The optimization algorithm leverages day-ahead PV power output and load forecasts (with 15-minute resolution and 3-hour updates) to ensure that the customer load peak is eliminated or reduced as much as possible, subject to electrical performance constraints of the battery array. ***Our model provides a convenient framework to quantify the financial value of solar forecasts. In this paper we simulated the optimal storage dispatch schedule for a typical commercial-scale PVS system during one year, and compared the optimal scenario to a simple off-peak/on-peak, charge/discharge dispatch schedule that was generated without any knowledge of future PV power output or customer load (Figure 2). Our analysis shows that the application of solar forecasting to the energy storage dispatch problem results in significant financial savings when compared with a simple off-peak/on-peak scenario (Table 1). Financial savings are realized from a combination of demand charge reduction, time-of-use price arbitrage and reduced battery cycling, which results in extended battery lifetime.***

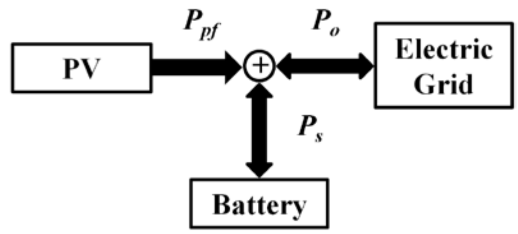


Fig. 1. Schematic of the model system illustrating the important components and power flows. All power electronics and wired connections are assumed to be 100% efficient and the battery output response is nearly instantaneous (i.e., the response time of lithium (Li)-ion type batteries is on the order of milliseconds while energy dispatch is modeled on 15-minute intervals). Because we have assumed the inverter to be lossless it is not shown in this diagram. The battery management system is included in the battery, which allows "black box" treatment of complex electrical dynamics and transients within the battery.

We applied a nonlinear, mathematical programming routine with receding horizon optimization to compute the optimum dispatch schedule for the energy stored in the battery. Equations 1, 2a-c, and 3a-c are the objective function, system dynamics, and battery performance constraints, respectively.

$$min\left\{f(P_{lf}^n, P_o^n) = \sum_{k=1}^{N} (P_{lf}^k - P_o^k)\Delta t \,, while\ P_{lf}^k \geq 0\ and\ P_{lf}^k > P_{pf}^k \right. \tag{1}$$

$s.t.$

$$P_{pf}^n + P_s^n = P_o^n \tag{2a}$$

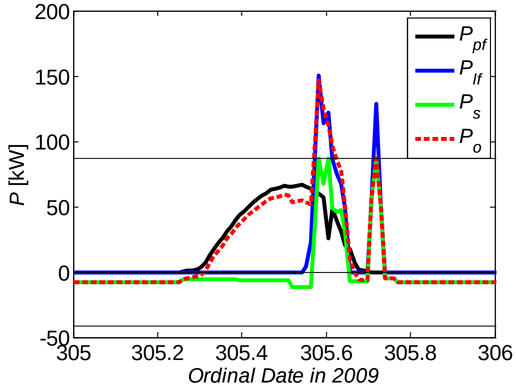
$$\frac{E^{n+1} - E^n}{\Delta t} = P^n \tag{2b}$$

$$\frac{P^{n+1} - P^n}{\Delta t} = R^n \tag{2c}$$

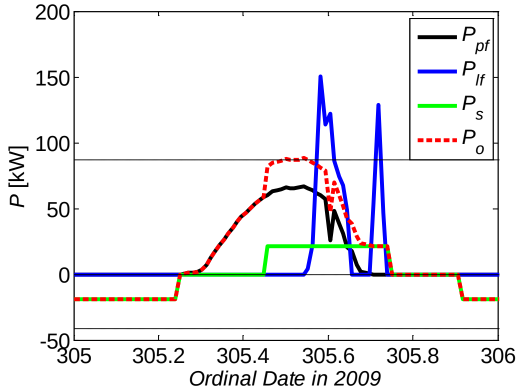
$$E_s^{min} \leq \sum_{k=1}^{n} P_s^k + E_0 \leq E_s^{max} \tag{3a}$$

$$P_s^{min} \leq P_s^n \leq P_s^{max} \tag{3b}$$

$$R_s^{min} \leq \frac{P_s^{n+1} - P_s^n}{\Delta t} \leq R_s^{max} \tag{3c}$$



(a)



(b)

Fig. 2. Typical PVs power flows on October 31, 2009. (a) The optimal storage dispatch schedule from the model described in Equations 1, 2, and 3; (b) the simple off-peak/on-peak, charge/discharge schedule that does not use solar or load forecasts. The PVS output (dashed red line) closely follows the customer peak load curve (blue line) in (a) but the PVS output falls short of the customer peak load in (b). This example indicates superior performance of the optimal scenario and demonstrates the advantages of applying the solar forecast to determine the stored energy dispatch schedule. Dashed lines show the limits of the battery charge/discharge power.

Variables *E*, *P*, and *R* are energy, power, and ramp rate. Variables with subscript *s* are related to the battery array, subscript *pf* refers to the PV power output forecast, subscript *lf* is the load forecast, subscript *o* denotes power flows to and from the grid, and *0* indicates an initial condition. Superscript *n* is the current timestep and *N* denotes the maximum number of timesteps over the forecast horizon (i.e., *N* = 96 for a 24-hour forecast horizon at a 15-minute sampling rate). Superscripts *min* and *max* indicate performance limits of the battery.

An idealized PV output forecast was obtained from one year of 15-minute DC power output data from the EBU2 rooftop PV array on the University of California, San Diego (UCSD) campus. The PV array has a DC nameplate rating of 75 kW DC. A load forecast was generated from UCSD campus historical load data. Uncertainty in the load forecast was simulated by incorporating random, normally distributed fluctuations with a standard deviation of 5% of the magnitude of the peak load at any given time. To simplify the analysis, weekend and holiday loads were not considered in this paper. The desired amount of customer peak load reduction (based on the load forecast) is a parameter in the model and was set to 150 kW for the results presented herein. The energy storage device was a Sanyo DCB-102 Li-ion type battery array consisting of 120 DCB-102 batteries. A single Sanyo DCB-102 is specified to have an energy storage capacity of 1.59 kW a lifetime of 3000 cycles at 80% depth of discharge (DoD). The retail cost was assumed to be \$1000/kWh. The battery array has a total energy storage capacity of E_s^{total} = 190 kWh and a maximum charging power P_s^{min} = 41.2 kW and discharging power P_s^{max} = 86.6 kW. To avoid overcharging or overdrawing of the battery array, the model parameters E_s^{max} and E_s^{min} are set to $0.2E_s^{total}$ and $0.99E_s^{total}$, respectively. Power requirements for active cooling of the battery array are not considered in the model.

Utilities assess time-of-use (TOU) energy pricing and demand charges for industrial customers. We performed a basic cost analysis to compare relative benefits of the optimal dispatch scenario and the off-peak/on-peak dispatch scenario. The customer's monthly energy bill was calculated for one year using the San Diego Gas & Electric (SDGE) AL-TOU rate schedule for industrial customers. The AL-TOU schedule includes basic service fees, seasonal and peak demand charges, and TOU energy pricing. Table 1 shows the results of the cost analysis and illustrates significant advantages of the application of solar forecasting in peak-shaving applications. The financial value of the solar forecast can be quantified in terms of the difference between profits to the PVS system owner at the end of the system lifetime under the two scenarios. For this case the value of the solar forecast was approximately \$116,000.

Table 1. Cost analysis comparison of optimized dispatch schedule with the PV power output forecast and simple off-peak/on-peak dispatch schedule without the PV power output forecast. The value of the solar forecast is about $116,000 based on the difference between the profits associated with each scenario. The battery lifetime increased by 173% under the optimized dispatch scenario relative to the simple off-peak/on-peak scenario.

	Optimization *with* PV Power Output and Load Forecast	**Off-Peak/On-Peak *without* PV Power Output and Load Forecast**
Annual Energy Bill Cost Reduction [$]	33,200	29,200
Number of Cycles at 80% DoD [cyc/yr]	420	730
Battery Lifetime [yr]	7.1	4.1
Fixed Cost Simple Payback Time [yr]	5.7	6.5
Total Profit at End of Battery Lifetime (Annual Energy Bill Savings x Battery Lifetime – Fixed Costs) [$]	45,300	– 70,700

BIOGRAPHICAL NOTE

Conference presenter: Byron Washom is the University of California at San Diego’s (UCSD’s) new Director of Strategic Energy Initiatives and is responsible for energy management policy to achieve the campus' goals for quantum improvements in energy management and greenhouse gas reductions. Before UCSD, Mr. Washom was the CEO for 20 years of a due diligence firm that specialized in CleanTech, and he served as Senior International Advisor to the World Bank and the Department of Energy. He is a four-time Rockefeller Foundation Grantee and a former Heinz Endowment Grantee for early commercialization of CleanTech into developing countries. Mr. Washom was also Founder and President of Advanco Corporation, which in 1984 set the long-standing world records for solar electric conversion efficiency at 29.4% and subsequently achieved an IR100 Award. He was the 2008 Recipient of UCSD’s Citizen of the Year Award for Sustainability, and he was a Visiting Faculty Member at the Rady School of Management while teaching the graduate-level course, The Business of Renewable Energy. Fast Company magazine named him to their June 2010 cover story, “100 Most Creative Persons in Business, 2010.”