Battery Management for Grid-Connected PV Systems with a Battery

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ABSTRACT

Photovoltaic (PV) power generation systems are one of the most promising renewable power sources to reduce the greenhouse gases. Grid-connected PV power systems do not generally have a battery to store the excess charge. However, due to severe imbalance between the peak level of PV power generation and peak load demand, battery-less Grid-connected PV systems are much less effective for the purpose of power generation and demand mismatch mitigation. Grid-connected PV systems equipped with a battery require elaborate management. This is the first paper that introduces a systematic battery management method that accommodates arbitrary electricity billing policies. More precisely, an optimization problem is formulated to determine the battery charging current from the Grid and the PV array taking into account the limited battery capacity, power converter efficiency, battery's internal resistance and rate capacity effect, and the maximum power tracking point of the PV array. Experimental results show that the proposed algorithm effectively reduces the electricity bill by as much as 28% when compared with previous state-of-the-art battery management policies.

Categories and Subject Descriptors

J.6 [**Computer-aided Engineering**]: Computer-aided design (CAD)

General Terms

Algorithms, Design

Keywords

Battery management, Grid-connected systems, Photovoltaic power, Electricity bill

1. INTRODUCTION

The number and capacity of photovoltaic (PV) power system installations are increasing rapidly. Cumulative installations of these systems, which are mainly Grid-connected, have reached 2.15 GW_{DC} in the US alone. Residential PV installations increased at a year-over-year rate of 64% and accounted for 29% of all PV installations in 2010 [1]. However, the growth rate is still slower than desired despite the many advantages of PV systems. This is because of the long break-even time for such systems (the time that is needed for customers to save enough money with lower monthly electricity bills to compensate the initial cost of purchasing and installing the PV system). Maximizing the benefit from the PV system, which is lower electricity bill, is equally important to reducing the installation cost to shorten the break-even time.

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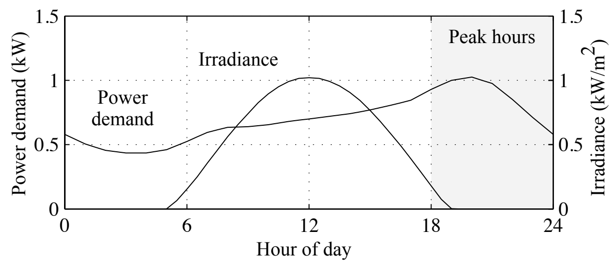

Figure 1: PV array output power and hourly average residential load profile (Southern California Edison territory) [7].

Many previous studies on solar powered systems focused on enhancing the efficiency of the PV system components such as the PV array and PV inverters. The mainstream research is related to maximum power point tracking (MPPT) methods that ensure maximum PV output power in spite of variable solar irradiance [2]. Recent work has presented a maximum power transfer tracking (MPTT) method to maximize the actual energy delivered from a PV array into an energy storage device, considering the power conversion losses [3].

Grid-connected PV systems without a battery do not require elaborate management. Simply performing MPPT or MPTT, and consuming the PV power first and the Grid power second has been sufficient for cases where the PV power is smaller than the load power. Similarly, standalone PV systems equipped with a battery [4, 5] can use a simple policy in which the battery is charged during the day and discharged during the night. In contrast, Grid-connected PV systems should consider complex scenarios such as using the electrical energy stored in the battery when the electricity price is high, i.e., during peak power consumption hours. However, one of the major hurdles in reducing the electricity bill is the mismatch among the PV power generation, load demand, and electricity prices. Figure 1 shows that the peak solar irradiance occurs at noon while the peak residential load demand is at 8pm. Many electricity providers sell the electricity at higher price during the peak hours to control the peak power demand. For example, unit electricity price in the greater Los Angeles are during the peak hours is as much as three times that during the off-peak hours [6]. Grid-connected PV systems without a battery can hardly cope with the peak-hour load demand.

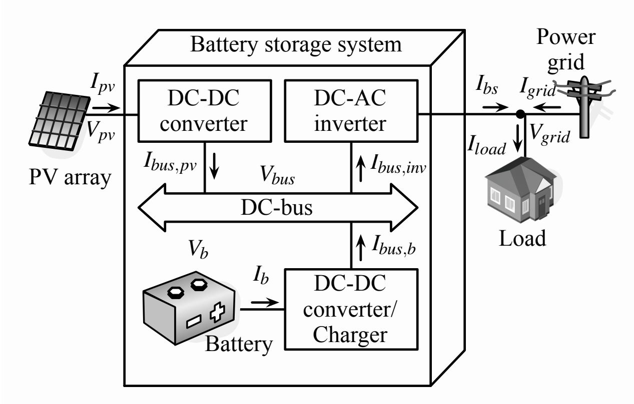

Figure 2: Architecture of the battery storage system for a Grid-connected PV system.

Grid-connected PV systems with a local battery are one way to significantly enhance the usefulness of the solar powered system because it can cope with the peak-hour load demand. Knowing when to charge and when to discharge the battery is the key to success of Grid-connected PV systems with a battery. However, most previous work performs battery management without employing systematic optimization and/or optimality consideration in spite of the significant amount of relevant work. For example, early work simply limits the battery current and considers reselling the excess energy from the PV system to the Grid [8]. *Power leveling*, which controls the power drawn from the Grid [9], and *peak shaving* [10] can mitigate the problem, but they do not provide systematic optimization of the system efficiency or the billing cost. There is a systematic optimization based on Lagrangian relaxation method, but it focuses on issues from the power distribution network such as locational marginal pricing (LMP) and transmission congestion problems [11]. Recent work provides an algorithm that determines when and how to charge and discharge the battery, but the method is ad-hoc without much reasoning about the optimality [12]. An electricity bill minimization algorithm similar to our work has been proposed in [13]. However, the work assumes a different electricity billing policy based on the peak power usage, which makes the proposed algorithm essentially a peak shaving algorithm. Moreover, this work does not consider the rate of PV power generation. In contrast, our work focuses on minimizing the mismatch between the PV power generation and the load demand in a grid-connected PV powered home to minimize the electricity bill.

This paper introduces a holistic optimization framework for residential Grid-connected PV power systems equipped with a battery. Unlike previous work, we develop a systematic optimization method for the battery management, which can effectively mitigate the electricity demand and supply mismatch. We devise an algorithm that determines when and how to store and retrieve energy from the battery to minimize the electricity billing cost. The proposed framework take into account the PV module impedance, converter loss, battery rate-capacity effect, and storage capacity limit for given solar irradiance, load profile, and billing policy. Experimental results show that our technique is capable of reducing 28% electricity bill when compared with previous battery management policies.

2. GRID-CONNECTED PV SYSTEM WITH A BATTERY

2.1 System Architecture

Figure 2 illustrates the overall system architecture considered in this paper. We consider household-scale power consumption as the load. The load is powered by the PV array, power grid, or both. It has an energy storage means to eliminate/reduce the mismatch between power generation and power demand. The energy storage means comprises a battery module to be charged from the Grid when the electricity price is low and from the PV array when the load power is lower than the PV generated power. Together with the Grid, the battery module supplies power to the load device during the peak hours.

The battery module consists of a DC-bus that delivers power to and from the power source, a battery bank, and the load devices. Charging and discharging processes are controlled by a DC–DC converter, a DC–AC inverter, and a charger. This architecture allows use of multiple energy storage banks, even heterogeneous banks, in order to enhance the performance metrics such as power and energy capacity, cycle efficiency, and lifetime [14]. In this paper, a single battery bank is installed.

2.2 Component Models

2.2.1 Photovoltaic array

Ideal power source can provide unlimited power capacity and constant voltage or current generation regardless of the environmental and load conditions. The PV array power capacity can be lower than its maximum value due to the environmental conditions such as solar irradiance and temperature. The output voltage of the PV array changes significantly as a function of the load current. We use a single-diode equivalent circuit model [15] and consider such characteristics to maximize the energy efficiency of the system. We keep the PV system efficiency at the maximum, by performing the maximum power transfer tracking introduced in [3].

2.2.2 Converters and inverters

The target system consists of two switching power converters that connect the battery to a DC-bus: one for charging the bank and the other for discharging the bank. The PV array also connects to a DC–DC converter, which converts the DC voltage from the PV array to the DC-bus voltage. There also exists a DC–AC inverter and a rectifier for power delivery between the DC-bus and the Grid, respectively. *Efficiency* of a converter or inverter is defined as

$$\eta = \frac{P_{out}}{P_{in}} = \frac{P_{in} - P_{loss}}{P_{in}} = \frac{V_{in} \cdot I_{in} - P_{loss}}{V_{in} \cdot I_{in}}, \quad (1)$$

where P_{in} and P_{out} denote input and output power levels of the converter, respectively, and P_{loss} is the power loss in the converter/inverter. The power loss of a switching power converter comprises three components: conduction loss P_{cdct}, switching loss P_{sw} and controller loss P_{ctrl} [16] such that

$$P_{loss} = P_{cdct} + P_{sw} + P_{ctrl}. \quad (2)$$

The conversion efficiencies of the DC-AC inverter and rectifier can be modeled in a similar way as (2) except that there are additional components P_{trans}, and P_{filter}, which are the power losses from transformer and filters, respectively. The power loss for inverter is given as

$$P_{loss} = P_{cdct} + P_{sw} + P_{ctrl} + P_{trans} + P_{filter}. \quad (3)$$

The power loss components are strongly dependent on the input voltage V_{in}, output voltage V_{out}, output current I_{out}, and the circuit component properties. We derive a closed form expression for η as a function of V_{in}, V_{out}, and I_{out}. The details of power loss equations for each term in (2) can be obtained from [16], and that of inverters are from [17, 18]. We do curve fitting for the converter efficiency as a quadratic function, which can still accurately represent the power converter efficiency in terms of the input voltage V_{in}, output voltage

Table 1: Parameter values for converter/charger and inverter models.

	Converter / charger	Inverter
a_1	2.40E-1	1.78E-1
a_2	-6.63E-5	-3.96E-5
a_3	-5.45E-3	-5.97E-5
a_4	7.13E-4	7.00E-6
a_5	1.16E-2	6.07E-3
a_6	6.89E-3	1.03E-3
a_7	-3.6967E-2	-5.85E-3

V_{out}, output current I_{out} as shown in (4). We denote the equations for calculating efficiencies of the PV converter, battery converter, and inverter as η_{pv}^{out}, η_{b}^{out}, η_{inv}^{out}, respectively. Also, we can calculate the efficiency using the term of I_{in} instead of I_{out}. We denote the equations as η_{pv}^{in}, η_{b}^{in}, η_{inv}^{in}. The regression coefficient values for the quadratic equation are reported in Table 1.

$$\eta^{out} = a_1 V_{in}^2 + a_2 V_{out}^2 + a_3 I_{out}^2 + a_4 V_{in} + a_5 V_{out} + a_6 I_{out} + a_7. \quad (4)$$

2.2.3 Battery

Modeling the behavior of battery itself is a challenging task, which has been studied during the past few decades. Battery models from [19, 20] are mainly based on electrochemical process modeling and analysis. Despite the accuracy of the models, they are too complex for use during the system-level design of electronics. Instead we rely on a circuit based model, which captures the most important battery behavior, i.e., the rate capacity effect. The rate capacity effect of batteries is described by the Peukert's formula,

$$\eta_{rate}(I) = \frac{k}{I^{\alpha}}, \quad (5)$$

where k and α are constants.

3. ELECTRICITY BILL REDUCTION

3.1 Power Generation and Usage Models

Residential electrical load demand is fairly periodic although it fluctuates greatly according to time of day. The periodicity of the usage patterns is closely related to consumers' livening patterns, including space heating, cooling, hot water usage, cooking times, television watching hours, and so on. The hourly averaged residential load profile measured in Southern California shows that the peak value occurs at 8pm when residents come home from work [7]. The peak is 2.5 times higher than the minimum value. Many electricity providers sell electricity at different rates at different times of day to control the usage of electricity during peak hours. For example, unit electricity price in Los Angeles is 16.061 ¢/kWh during peak hours, and 4.655 ¢/kWh during off-peak hours [6].

3.2 Battery Management for Electricity Bill Reduction

We minimize the electricity bill, which is the summation of Grid power usage multiplied by the unit cost. We consider two sources of power generation to demonstrate the proposed idea: a PV array and Grid. The optimal policy for the Grid-connected PV system without battery storage is to do maximum energy harvesting. For such systems, simply performing MPPT or MPTT will suffice [3]. On the other hand, achieving the goal of electricity bill reduction in a Grid-connected PV-powered homes with battery storage involves optimization from many aspects. Depending on the ratio between the peak hour and off-peak hour electricity prices, the in-home PV system may either supply power to the load or charge the battery during off-peak hours. Also, we charge the battery when the electricity is cheap and the PV power is not enough to fully charge the battery, preparing to use the battery to perform load shaving during the peak hours. However, charging the battery is less efficient than supplying power to the load due to the battery's internal resistance and charger power losses. Furthermore, high-current charging and discharging result in severe charging and discharging efficiency degradation due to the rate-capacity loss in the battery. We prohibit the case where the battery becomes fully charged and the PV power generation is higher than the load power consumption because we do not consider selling the PV power to the utility company not to lose generality. Not all the electricity companies buy PV power from individual residences.

3.3 Problem Formulation

The electricity bill minimization problem for Grid-connected residential PV power systems is formulated as follows.

Objective:

Minimize electricity bill for a day, that is,

$$cost_{day} = \sum_{n=1}^{N} C[n] p_{Grid}[n], \quad (6)$$

where $C[n]$ is the unit price of the Grid electricity ($/kWh), $p_{Grid}[n]$ is the power drawn from the Grid (W) at time slot n, and N is the number of time slots per day.

Given:

- Solar irradiance profile for a day $G[n]$.
- Residential load demand profile for a day $I_{load}[n]$.
- Unit price of the Grid electricity $C[n]$.

Control variables:

- DC-bus voltage $v_{bus}[n]$.
- PV operating point $V_{pv}[n]$, $I_{pv}[n]$.
- Battery current $I_b[n]$, where $I_b > 0$ if discharging, and $I_b < 0$ if charging.

The control variables not only determine when to charge or discharge the battery storage, but also set the optimal operating conditions for charging and discharging.

4. ELECTRICITY BILL OPTIMIZATION ALGORITHM

The following observations are the bases of the proposed offline optimization algorithm.

Observation 1: It is beneficial to charge the battery when the electricity is the cheapest, that is, time slot $n_{min} = \arg\min_n(C[n])$, and discharge the battery when the electricity is the most expensive, that is, $n_{max} = \arg\max_n(C[n])$.

Observation 2: Increasing the charging and discharging current of battery storage reduces the charging and discharging efficiency, respectively, due to the battery IR loss and the rate capacity effect.

From the aforesaid observations, it is beneficial to discharge the battery storage at time slot $n_{max} = \arg\max_n(C[n])$, but too much discharging would lower the benefit. We define the variable $C_{com}[n]$, that is the *compensated cost* for effectively determining the time and magnitude of charge/discharge current. Due to the non-ideal characteristics of the power converters and battery storage, charging and discharging efficiency is less than 100%. We reflect the non-ideal characteristics in the variable, $C_{com}[n]$, as follows. The value of $C_{com}[n]$ is initialized to $C[n]$ at the beginning of the algorithm, and it is updated according to the following equation in each iteration.

$$C_{com}[n] = \begin{cases} \dfrac{E_{supplied}}{E_{charge} - E_{loss}} \cdot C[n], & \text{when charging,} \\ \dfrac{E_{extracted}}{E_{extracted} + E_{loss}} \cdot C[n], & \text{when discharging,} \end{cases} \tag{7}$$

where $E_{supplied}$ and $E_{extracted}$ denote the amounts of electrical energy that is supplied to and extracted from the terminal of the battery. E_{loss} is the loss due to the battery IR loss and the rate capacity effect. Higher charging or discharging current makes E_{loss} higher. For example, suppose charging the battery from the Grid at time slot $n_{min} = \arg\max_n(C_{com}[n])$. As our iterative algorithm increases the charging current gradually, $C_{com}[n_{min}]$ increases. As the charging current becomes too high, the compensated cost C_{com} will also become high, and thus further increasing the charging current is avoided. The same approach applies to discharging vice versa when the electricity price is high.

The solution to electricity bill minimization is composed of two parts. The first part of the solution involves solving the electricity bill minimization problem without the maximum battery capacity constraint as shown in Algorithm 1. It assumes that the battery capacity is unlimited. For practical cases, the size of battery is limited, often much smaller than the total load energy consumption throughout a day. Thus, the second part of the solution involves solving the problem with the battery capacity limit constraint based on the solution of the first part as shown in Algorithm 2.

- Operating condition $\tau : (v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$ pair that describes the operating condition of the system. The terms correspond to the voltage of the DC-bus, PV converter output power, input/output power to/from the battery charger/converter, and input/output powers of the inverter/rectifier, respectively.
- `VBUS_LUT_1`: lookup table of optimal v_{bus} for given G and I_{load} values constructed at offline.
- `VBUS_LUT_2`: lookup table of optimal v_{bus} for given discharging $P_{bus,b} > 0$ and I_{load} values constructed at offline.
- `VBUS_LUT_3`: lookup table of optimal v_{bus} for given charging $P_{bus,b} < 0$ and I_{load} values constructed at offline.
- `MPTT`: optimal PV operating point (V_{pv}, I_{pv}) for given G and v_{bus}.
- $P^{max}_{bus,pv}(G)$: the PV converter output power for given solar irradiance G and the optimal v_{bus}.
- $P^{min}_{bus,inv}(I_{load})$: the inverter input power when the I_{load} is supplied wholly by the inverter output for the optimal v_{bus}.
- n_s, n_e: the beginning of *active management period* defined by the time when $P^{max}_{bus,pv}$ becomes greater than $P^{min}_{bus,inv}(I_{load})$, and the end of *active management period* defined by 24 hours plus n_s.

Algorithm 1 determines the operating condition τ for every time slot. The power values $P_{bus,pv}$, $P_{bus,b}$, $P_{bus,inv}$ are defined on the DC-bus side of the converter. Three lookup tables `VBUS_LUT_1`, `VBUS_LUT_2`, and `VBUS_LUT_3` are built offline. They contain optimal values of v_{bus} that maximizes the actual power delivered from the source to destination considering the conversion losses. We obtain converter losses from the converter model, and thus, $V_{pv}[n]$, $I_{pv}[n]$, $I_b[n]$, etc. The key idea of Algorithm 1 is to

Algorithm 1: Electricity bill minimzation algorithm without battery capacity limit.

Input: G: irradiance, I_{load}: load current

Output: Operating condition $\tau = (v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$

for $\forall n,\ P^{max}_{bus,pv}(G[n]) > P^{min}_{bus,inv}(I_{load}[n])$ **do**
    $v_{bus}[n] \leftarrow$ `VBUS_LUT_1`$(G[n], I_{load}[n])$
    $(V_{pv}[n], I_{pv}[n]) \leftarrow$ `MPTT`$(G[n], v_{bus}[n])$
    $P_{bus,pv}[n] \leftarrow V_{pv} \cdot I_{pv} \cdot \eta^{in}_{pv}(V_{pv}[n], v_{bus}[n], I_{pv}[n])$
    $P_{bus,inv}[n] \leftarrow \dfrac{V_{load} \cdot I_{load}[n]}{\eta^{out}_{inv}(v_{bus}[n], V_{load}, I_{load}[n])}$
    $P_{bus,b}[n] \leftarrow P_{bus,inv}[n] - P_{bus,pv}[n]$
    $P_b[n] \leftarrow \eta^{in}_b(V_{bus}[n], V_b, -P_{bus,b}[n]/V_{bus}[n])$
    $SOC_b \leftarrow charge(P_b, SOC_b)$

while $c_{th,low} < c_{th,high}$ && $!endCond$ **do**
    for $\forall n,\ C_{com}[n] = c_{th,high}$ **do**
        if $n = \phi$ **then**
            $c_{th,high} \leftarrow max(C_{com})$
            continue
        $P_{bus,b}[n] = min(P_{bus,b}[n] + P_{inc,d}, \dfrac{P_{load}[n]}{\eta^{out}_{inv}})$
        $v_{bus}[n] \leftarrow$ `VBUS_LUT_2`$(P_{bus,b}[n], I_{load}[n])$
        $(V_{pv}[n], I_{pv}[n]) \leftarrow$ `MPTT`$(G[n], v_{bus}[n])$
        $P_{bus,pv}[n] \leftarrow V_{pv} \cdot I_{pv} \cdot \eta^{in}_{pv}(V_{pv}[n], v_{bus}[n], I_{pv}[n])$
        $P_{bus,inv}[n] \leftarrow P_{bus,pv}[n] + P_{bus,b}$
        $P_b[n] \leftarrow \eta^{out}_b(V_b, V_{bus}[n], P_{bus,b}[n]/V_{bus}[n])$
        $SOC_b \leftarrow discharge(P_b, SOC_b)$
        $C_{com}[n] \leftarrow decreaseCost(P_{bus,b}$
        if $SOC_b = 0$ **then**
            break
    for $\forall n,\ C_{com}[n] = c_{th,low}$ **do**
        if $n = \phi$ **then**
            $c_{th,low} \leftarrow min(C_{com})$
            continue
        $P_{bus,b}[n] \leftarrow P_{bus,b}[n] - P_{inc,c}$
        $v_{bus}[n] \leftarrow$ `VBUS_LUT_3`$(P_{bus,b}[n], I_{load}[n])$
        $(V_{pv}[n], I_{pv}[n]) \leftarrow$ `MPTT`$(G[n], v_{bus}[n])$
        $P_{bus,pv}[n] \leftarrow V_{pv} \cdot I_{pv} \cdot \eta^{in}_{pv}(V_{pv}[n], v_{bus}[n], I_{pv}[n])$
        $P_{bus,inv}[n] \leftarrow P_{bus,pv}[n] + P_{bus,b}$
        $P_b[n] \leftarrow \eta^{in}_b(V_{bus}[n], V_b, -P_{bus,b}[n]/V_{bus}[n])$
        $SOC_b \leftarrow charge(P_b, SOC_b)$
        $C_{com} \leftarrow increaseCost(P_{bus,b})$

return $\tau \leftarrow (v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$

use two threshold values, $c_{th,low}$ and $c_{th,high}$. We initialize the low threshold value to $min(C_{com}[n])$. If we pick all the time slots n with $C_{com}[n] = c_{th,low}$, these are the slots with minimum electricity cost, and thus, are suitable candidates for battery charging. Throughout the algorithm, $c_{th,low}$ gradually increases, as C_{com} increases. We initialize $c_{th,high}$ to $max(C_{com}[n])$, and find all the time slots n with $C_{com}[n] = c_{th,high}$, which are suitable for discharging the battery. We store the cheapest electricity in the battery and use it when the electricity price is the highest. Power from the PV array is free, and always cheaper than the Grid electricity price. The algorithm considers charging the battery with PV power first, and the electricity from the Grid next. Algorithm 1 is optimal if the battery capacity is unlimited and the initial state of charge (SOC) of battery is sufficient.

Algorithm 2: Electricity bill minimzation algorithm with battery capacity limit $SOC_{b,max}$.

Input: G: irradiance, I_{load}: load current, $SOC_{b,init}$: initial SOC at n_s, $\tau = (v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$: result of Algorithm 1

Output: Operating condition $(v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$

$n_{mark,s} \leftarrow n_s$
$n_{mark,e} \leftarrow n_s$
$SOC_{mark} \leftarrow SOC_{b,init}$
for $n = n_s$ *to* n_e **do**
  $SOC_b \leftarrow updateSOC(P_{bus,b}[n], SOC_b)$
  if $SOC_b > SOC_{b,max}$ **then**
    $n_{mark,e} \leftarrow nextDischarge(P_{bus,b}, n)$
    $\tau[n] \leftarrow reschedule1(SOC_{mark}, SOC_{b,max}, n_{mark,s}, n_{mark,e})$
    $n_{mark,s} \leftarrow n_{mark,e}$
    $SOC_{mark} \leftarrow SOC_{b,max}$
    continue
  else if $SOC_b < 0$ **then**
    $n_{mark,e} \leftarrow nextCharge(P_{bus,b}, n)$
    $\tau[n] \leftarrow reschedule2(SOC_{mark}, 0, n_{mark,s}, n_{mark,e})$
    $n_{mark,s} \leftarrow n_{mark,e}$
    $SOC_{mark} \leftarrow 0$
    continue
return $\tau \leftarrow (v_{bus}, P_{bus,pv}, P_{bus,b}, P_{bus,inv})$

Algorithm 2 reschedules the battery charging and discharging operations so that the battery SOC does not exceed the maximum value or becomes below zero. The charging and discharging schedule from Algorithm 1 might violate both the maximum and minimum battery capacity constraint. Algorithm 2 starts at the beginning of a *active management period*, n_s. Algorithm 2 charges and discharges the battery according to the scheduling result of Algorithm 1 as time passes until the battery capacity constraint is violated. Functions $nextDischarge(P_{bus,b}, n)$ and $nextCharge(P_{bus,b}, n)$ find the timeslot next to n where the closest discharge or charge begins. The functions $reschedule1()$ and $reschedule2()$ derive an operating condition τ schedule that makes SOC_b from SOC_{mark} to $SOC_{b,max}$ and from SOC_{mark} to 0 during time interval $[n_{mark,s}\ n_{mark,e}]$, respectively, while meeting the battery capacity constraints. This rescheduling problem is much simpler than the original problem since the start and end SOC values are given, and the capacity limit is met for the interval $[n_{mark,s}\ n_{mark,e}]$. Function $reschedule1()$ works as follows. It fixes the discharging schedule as derived in Algorithm 1. The next step is to perform initial charging to avoid depletion by the discharging schedule fixed in the previous step. This initial charging is always feasible from the definition of the interval $[n_{mark,s}\ n_{mark,e}]$. Finally, $reschedule1()$ determines the rest of the charging schedule using $c_{th,low}$ and C_{com} to minimize the charging cost until the total accumulated charge at $n_{mark,e}$ becomes $SOC_{b,max}$. Function $reschedule2()$ is defined in a complementary manner. Algorithm 2 is based on Algorithm 1 and ensures the solution quality of the capacity limited problem because Algorithm 1 gives the optimal results for the unconstrained case.

5. EXPERIMENTAL RESULTS

We compare the efficacy of the proposed algorithm with two baseline algorithms. Both baseline algorithms charge the battery from the PV array and Grid during off-peak hours and discharge the battery during the peak hours. For the first baseline, charging and discharging current from the Grid is fixed to 1C to maximize cycle efficiency of the battery, and it performs MPTT to determine the operating point of the PV array and DC-bus voltage. For the second baseline, the charging current from the Grid is fixed to 1C and discharging current is determined greedily during the peak hours, and it also performs MPTT.

We use an actual profile of residential load demand and Grid electricity price from Southern California [6, 7]. The peak load demand is 1.025 kW at 8pm as shown in Figure 1. The unit price of the Grid electricity is 4.679 ¢/kWh during peak hours and 1.879 ¢/kWh during off-peak hours. The PV array used for our experiment out-

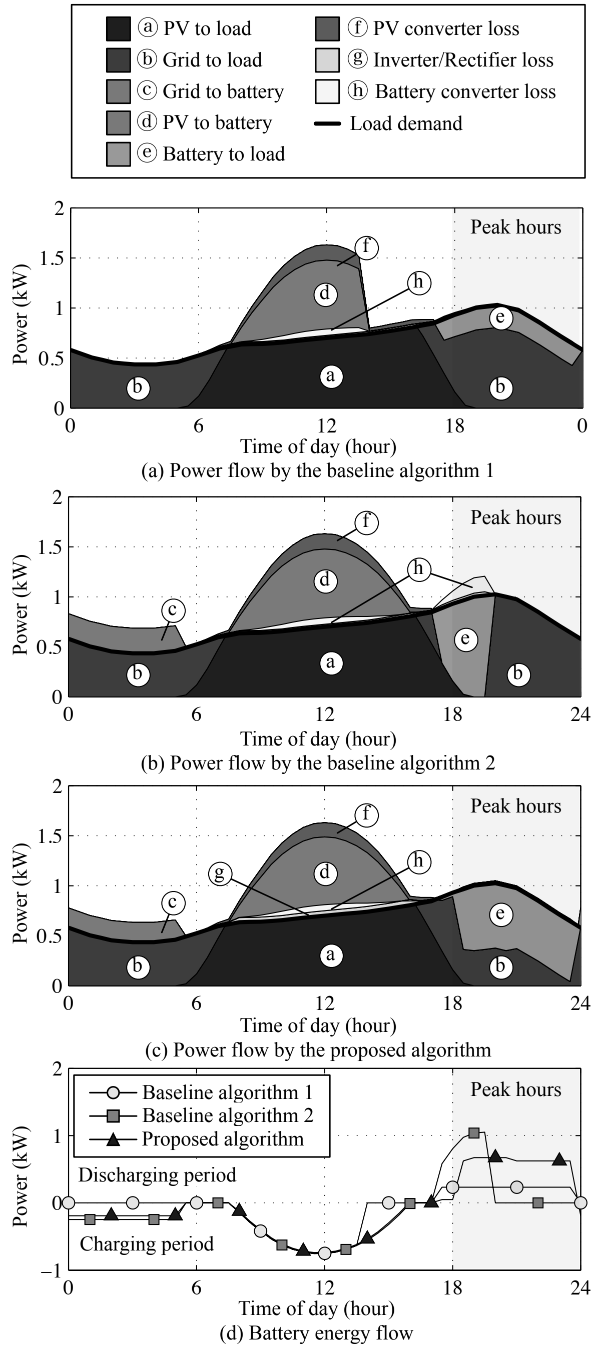

Figure 3: Power input and output variation with time.

puts 1,000 W/m^2 and the maximum power point voltage and current is 67.8 V and 23.6 A. The capacity of battery bank is 0.864 kWh rated at 5 A output current with the output voltage of 48 V. The result of the proposed algorithm is shown in Figure 3.

The resulting battery management policy shows different charging and discharging patterns. The first baseline has fixed charge and discharge current and thus it loses the potential for further gain. Figure 3(a) shows that the first baseline does not fully utilize the PV power even though the battery is not full because the total amount of energy discharged during the peak hours is limited. If the PV power keeps charging the battery during daytime, the net energy throughout the day become positive. Figure 3(d) shows the same results. Baseline 1 does not charge from the Grid during off-peak hours, since it cannot utilize it. Battery current is kept at 1C during the peak hours. This minimizes the rate capacity loss, but it also poses limits on the gain. The second baseline greedily supplies the load during the peak hours, which results in severe inefficiency due to the rate capacity effect. Baseline 2 fully utilizes the battery by charging the battery both from the PV array and Grid as shown in Figure 3(b). Charging from Grid is temporarily disabled at around 6 o'clock in the morning, and it prevents the battery becoming fully charged while the PV power is still available. By the end of daytime, the battery becomes fully charged and is ready for discharging during peak hours. Baseline 2 greedily discharges the battery during peak hours as shown in Figure 3(d), and thus it soon becomes fully depleted. There is no other choice but to use expensive Grid electricity beyond that point, which increases the electricity bill. The proposed algorithm determines the charging and discharging schedule while considering both the loss due to large charge/discharge current and utilization of the Grid price fluctuation. The proposed algorithm fully charges the battery by the end of daytime, just like Baseline 2. To fully utilize the price differences between the peak hours and off-peak hours, the proposed algorithm sets the discharging current to a value between Baselines 1 and 2 as shown in Figure 3(d). Discharging the battery at higher current than Baseline 1 increases the rate capacity loss, but it is beneficial due to the price difference between the peak and off-peak hours. The proposed algorithm reduces the electricity bill during a day to 18.73 ¢ while two baselines give 26.14 ¢ and 25.38 ¢ , respectively.

6. CONCLUSION

PV power generation is promising but not very effective to mitigate demand and supply mismatch of electricity. Grid-connected PV systems with a battery has great potential to resolve the mismatch as long as elaborated battery management ensures optimal charge and discharge policies. This paper is the first work to address holistic optimization of battery management for Grid-connected PV systems. We devise an offline algorithm that schedules battery charge and discharge for solar given solar irradiance and load profile. Our framework allows for arbitrary Grid electricity price function, and all the lossy components, such as converter loss, and rate capacity loss of batteries, in the Grid-connected PV powered system with electrical energy storage. Experimental results show that the electricity price is reduced by up to 28% when compared with baseline policies.

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