Practical Strategies for Storage Operation in Energy Systems: Design and Evaluation

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***Abstract*—Motivated by the increase in small-scale solar installations used for powering homes and small businesses, we consider the design of rule-based strategies for operating an energy storage device connected to a self-use solar generation system to minimize payments to the grid. This problem is inherently challenging, since strategies depend greatly on the choice of the tariff structure and forecasts of future generation and load. We propose an optimization framework for finding optimal operation strategies and use it to evaluate the performance of an existing operating strategy that we modified to not use forecasts, in the context of differential pricing. We also use our framework to propose a new practical operating strategy for peak-demand pricing. We simulate the two rule-based strategies using real data for solar generation and building load, and find that they are able to achieve near-optimal performance without requiring forecasts.**

I. Introduction

Given the proliferation of photovoltaic (PV) systems and storage devices and the widespread use of differential grid tariffs, the use of storage to minimize the payments made by a home or business owner to the grid is likely to be common in the near future. In this work, we study practical schemes to operate storage, that is, decide when to charge or discharge it, in the context of a home or business owner who would like to reduce their electricity bill by installing a small-scale solar PV system.

Three pricing trends are driving the evolution of such systems towards self-use: 1) the reduction of Feed-in Tariff (FIT) rates, sometimes below the cost of grid electricity [19] due to the decline in PV prices; 2) an increase in the cost of grid electricity (in several jurisdictions) [19], [2]; 3) a decrease in the price of Lithium-ion batteries [15].

Designing practical strategies for storage operation is a complex task [20]. An operating strategy has to decide whether loads should be met from storage or the grid, and when to make purchases from the grid to top up storage at just the right times, depending on the expected future loads, the expected PV generation, and the tariff structure to minimize the electricity bill of the system owner. PV generation could also be sold to the grid for profit, reducing the total electricity bill, and the amount sold would depend on the price and structure of the FIT.

Although some approaches for storage operation that balance these conflicting requirements exist today (these are discussed in detail in Section 2), they often depend on fine-grained predictions of future load and PV generation. Furthermore, they have not been rigorously evaluated, making it difficult to ascertain if better strategies are needed. We therefore propose an offline optimal oracle that can be used as a benchmark to evaluate online operating strategies. Specifically, given the pricing scheme and the past measured data for load and PV generation, the oracle algorithm can compute the minimum overall electricity bill the system owner could have paid, as well as the corresponding non-causal optimal storage operation strategy yielding that bill. This oracle can be used to evaluate existing operating strategies or to design new practical (causal) and efficient operation strategies.

We have used this oracle approach to analyze an existing strategy for storage operation to reduce electricity costs with time-of-use tariffs [20] and find that it exhibits near-optimal performance. We have also used our approach to propose a practical operating strategy for a tariff structure based on peak demands.

Our contributions are:

- The formulation and solution of an offline optimal integer linear program for the operation of a PV system with a storage device in the context of self-use that can find the non-causal optimal operation strategy for two very generic pricing schemes.
- A performance evaluation of the operating strategy for time-of-use pricing proposed by Zhu et al. [20] that we modified to avoid using forecasts.
- The design and evaluation of a practical operating strategy for peak-demand pricing.
- An investigation into the need for forecasting to obtain efficient operating strategies for time-of-use and peak-demand pricing.

II. Related Work

While there is some work on the operation of storage in the context of a renewable generation system for micro-grids and localized production systems, almost all work has presented various optimization-based strategies that require fine-grained predictions of load and renewable generation.

Ross et al. [16] consider a stand-alone micro-grid with wind turbine and diesel generator energy sources. They use hour-ahead predictions for wind and load to optimize the operation of storage over these predictions for the purpose of reducing the cost of running the diesel generator. Stand-alone systems are very different from the system that we consider. The biggest difference is that there is no pricing

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strategy associated with the alternative sources that are used to make up for deficits in renewable generation, since the cost of running a diesel generator is treated as a constant per unit of energy produced. As a result, storage operation strategies suited for stand-alone systems are not easily extendable to grid-connected systems where pricing is a major factor.

Optimal operation of storage typically takes advantage of price differences in order to minimize the cost paid to the grid. Chen et al. [5] propose an energy management system that optimizes the economic operation of a micro-grid. They propose a day-ahead power forecasting module as well as a genetic algorithm optimization module to take advantage of these forecasts and grid price structures. When their forecasting module fails to produce an accurate forecast, the performance of their system can suffer greatly. Li and Dong [12], [13] consider a system very similar to ours, and tackle the problem of minimizing the user's electricity payments. They consider the cost associated with charging/discharging the battery, with arbitrary grid pricing structures. They formulate an optimization problem, and apply Lyapunov optimization techniques in an online control policy that relies on predictions of future generation and load. Banos et al. [3] provide a review of optimization for renewable energy systems.

Dusonchet et al. [10] consider an optimal strategy for storage operation in the context of differential pricing with a renewable energy source. They come up with a strategy that takes advantage of the scheduled pricing and do energy arbitrage, but do not consider the effects of selling solar power to the grid and treat renewable generation as "negative load" rather than a source of power that can be stored in the battery. Zhu, Mishra et al. [20] also consider operating a PV system with storage under differential pricing to reduce the users grid payment. They propose a rule-based control algorithm that uses aggregate predictions for load and PV generation, which in practice are more accurate than predicting the load and PV curves, and evaluate this operating strategy using a number of real-world data sets, although they have no notion on a lower bound on grid payments with which to compare their strategy. In our work, we evaluate their strategy.

Our work differs from the existing research in that we present an approach for designing efficient rule-based operating strategies with a focus on avoiding the need for forecasts, rather than relying on more complex operating methods such as stochastic model predictive control [8]. This allows us to avoid additional costs, and makes the system operation very predictable for the user. We demonstrate our approach on two pricing schemes, show that there exists an efficient practical strategy for differential pricing, and design a new strategy for peak-demand pricing.

III. System Description and Mathematical Model

We consider a typical small solar installation consisting of (a) a set of PV panels along with associated inverters and power electronics; the PV output is assumed large enough to significantly reduce grid use, (b) a Lithium-ion energy storage device (ESD) along with an associated battery management system that can either store energy or discharge it, (c) a bi-directional grid connection that allows load to be met from the grid, the ESD to be charged from it, and for power to be sold to it, (d) a control component that operates the system in real time. A Lithium-ion ESD has desirable properties such as low maintenance and high energy/power density [6], making it a good fit for the application at hand. Figure 1 illustrates our system.

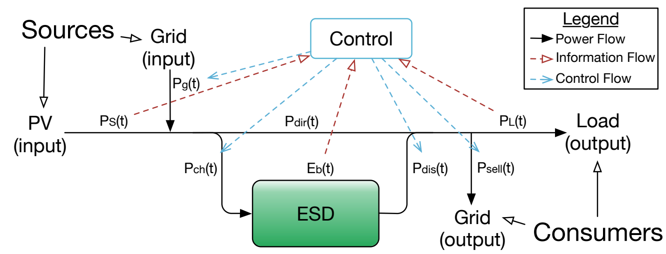


Fig. 1: System model

The PV system and ESD are assumed to be owned and operated by a home or small-business owner. The grid is assumed to charge for any electricity that is supplied, with the price depending on the pricing scheme being considered. The grid also purchases any electricity that the system sells. Importantly, we assume that the cost of buying from the grid is always higher than the payment for selling to the grid.

TABLE I: Notation

Name	*Description (units)*
System parameters and variables	
$p'(t)$	Price per unit of energy sold at time t (\$/kWh)
$P_S(t)$	Power generated by solar panels at time t (kW)
$P_L(t)$	Load at time t (kW)
B	Capacity of ESD (kWh)
MD, MC	ESD maximum discharge and charge fractions
$\alpha_c(\alpha_d)$	Charge (discharge) rate limits per unit of storage (kW/kWh)
$\eta_c(\eta_d)$	Charge (discharge) efficiency. Both are ≤ 1
$P_g(t)$	Power drawn from the grid at time t (kW)
$P_{sell}(t)$	Power sold to the grid at time t (kW)
$P_c(t)$	Power used to charge the ESD at time t (kW)
$P_{dir}(t)$	Power flowing directly from PV and grid to meet the load or be sold at time t (kW)
$P_d(t)$	Power from the ESD at time t (kW)
$E_{ESD}(t)$	Energy content of the ESD at time t (kWh)
T_u, T_h	Time slot duration, time horizon (hours)
Differential pricing variables	
$p(t)$	Price per unit of energy purchased at time t (\$/kWh)
Peak-demand pricing variables	
Γ	Threshold above which the demand price is paid (kW)
π_b	Base price per unit of energy purchased (\$/kWh)
π_d	Demand price penalty per unit of energy purchased with power demand exceeding Γ (\$/kWh)

We assume a discrete time model, with T_u being the length of each time slot. For simplicity, we define t to represent the time interval $[t \times T_u, (t+1) \times T_u)$, and use the phrase 'at time t' to mean 'during the time interval $[t \times T_u, (t+1) \times T_u)$'. All the variables are assumed to be constant within a time slot. The available output power of the PV panels at time t is equal to $P_S(t)$. The PV output power may be used to meet the load directly, to charge the ESD provided that there is room, or it can be sold to the grid. The grid can also be used to meet the load and/or charge the ESD, with $P_g(t)$ being the power bought from the grid at time t. The load at time t is equal to $P_L(t)$, and can be met using a combination of PV, grid, and ESD output. The power sold by the system is denoted as $P_{sell}(t)$.[1] $P_{dir}(t)$ is the constant power from PV and grid sources that is used to meet the load directly or sold to the grid at time t, $P_c(t)$ is the power from the sources used to charge the ESD, and $P_d(t)$ is the power from the ESD used to serve the load at time t. The system is subject to some constraints that we discuss next.

There are some natural constraints on the flow of power through the system. We require the load to be met at all times, and the energy being sold comes from either the battery or the direct link from the grid and PV sources. Thus

$$P_{dir}(t) + P_d(t) = P_L(t) + P_{sell}(t), \forall t \in [1, T_h]. \quad (1)$$

In addition, $P_c(t)$ and $P_{dir}(t)$ cannot exceed the input power of the system, therefore

$$0 \leq P_c(t) + P_{dir}(t) \leq P_S(t) + P_g(t), \forall t \in [1, T_h]. \quad (2)$$

We consider the ESD to be a Lithium-Ion battery, with imperfections modeled as in [7]. The charging and discharging power for each unit of ESD capacity cannot exceed limits α_c and α_d kW/kWh respectively. These limits scale linearly with the size of the battery. Another constraint is that the battery must not be charged and discharged at the same time, so we add a binary variable $I(t)$ to ensure that this constraint is met:

$$0 \leq P_c(t) \leq I(t) B \alpha_c, \forall t \in [1, T_h] \quad (3)$$
$$0 \leq P_d(t) \leq (1 - I(t)) B \alpha_d, \forall t \in [1, T_h] \quad (4)$$
$$I(t) \in \{0, 1\}, \forall t \in [1, T_h] \quad (5)$$

where B is the capacity of the ESD. In order to prolong the lifetime of the ESD, maximum discharge and charge limits MD and MC are enforced:

$$B \cdot MD \leq E_{ESD}(t) \leq B \cdot MC, \forall t \in [1, T_h], \quad (6)$$

where $E_{ESD}(t)$ is the energy content of the ESD at the beginning of interval t. MD and MC are interpreted as fractions of the total capacity. The ESD loses a fraction of charging/discharging power due to energy conversion losses, with the efficiency of the charging/discharging process denoted as η_c and $1/\eta_d$ respectively. [2] If $P_c(t)T_u$ kWh is used to charge the battery, only a fraction η_c is stored and the rest is lost. Likewise, to supply $P_d(t)T_u$ kWh to the load, the amount of energy that must be removed from the battery is $P_d(t)T_u/\eta_d$. The resulting recursive equation expresses the state of charge:

$$E_{ESD}(1) = U \quad (7)$$
$$E_{ESD}(t+1) = E_{ESD}(t) + \eta_c P_c(t) T_u - \frac{P_d(t)}{\eta_d} T_u, \quad (8)$$

where U is the initial energy content.

[1] The system does not prohibit the immediate selling of power bought from the grid. In our work, we assume that the pricing structure prevents this from being a profitable operation, i.e., the cost of buying from the grid is assumed to always be greater than the cost of selling to the grid.

[2] In general, η_c and η_d are not equal [9].

A simple operating strategy is to charge the ESD if there is an excess in PV energy ($P_S(t) > P_L(t)$) and discharge it when there is not enough PV to meet the load ($P_S(t) < P_L(t)$). This strategy was used to maximize self-consumption of PV generation in [4], and we use it as a simple benchmark below. Note that this strategy ignores pricing.

We denote $p'(t)$ to be the cost per unit of energy sold to the grid at time t. We consider the electricity payment to be the sum of grid payments minus the sum of the Feed-in Tariff we receive from the grid for selling energy.

We consider two pricing schemes:

Differential Pricing (also called real-time pricing): Let $p(t)$ be the cost per unit of grid energy at time t. The electricity payment over the time horizon is thus

$$\sum_{t=1}^{T_h} (p(t)P_g(t) - p'(t)P_{sell}(t))T_u, \quad (9)$$

Peak-demand Pricing: The price increases if we are purchasing more than some power threshold Γ from the grid; the grid charges π_b for every unit of energy purchased, with an additional π_d demand price for the power demand that exceeds Γ. We denote $P_{over}(t)$ to be the purchased power that exceeds Γ at time t, thus

$$P_{over}(t) = max(0, P_g(t) - \Gamma) \quad (10)$$

The electricity payment over the time horizon is then

$$\sum_{t=1}^{T_h} (\pi_b P_g(t) + \pi_d P_{over}(t) - p'(t)P_{sell}(t))T_u \quad (11)$$

In the next section, we formulate the problem of minimizing the payment made by the system. We will use the results to determine if the simple strategy suffices.

IV. Problem Formulations and Optimal Operation

A. Problem Formulation

In order to obtain the offline optimal operational strategy (i.e., the oracle), we first assume that our system has complete knowledge of load and PV generation over the entire time horizon. This is done only to obtain a benchmark against which we measure realistic (online) operating strategies. Note that the oracle does not take the price of the system into consideration, and focuses only on optimizing the operation of a given system.

Combining our system constraints, we formulate the problem of minimizing the electricity payment of the system owner as an integer linear program (ILP) for the two pricing schemes.

Differential Pricing: Given $(P_S(t))$, $(P_L(t))$, B, MD, MC, α_c, α_d, η_c, η_d, U, $(p(t))$, $(p'(t))$, T_u, T_h:

$$\min_{\substack{P_{dir}(t), P_c(t), P_d(t),\\ P_g(t), P_{sell}(t), I(t)}} \sum_{t=1}^{T_h} (p(t)P_g(t) - p'(t)P_{sell}(t))T_u \quad (12)$$

subject to

$$0 \le P_g(t), P_{dir}(t), P_{sell}(t) \quad \forall t \quad (13)$$
$$P_{dir}(t) + P_d(t) = P_L(t) + P_{sell}(t) \quad \forall t \quad (14)$$
$$E_{ESD}(1) = U \quad (15)$$
$$E_{ESD}(t+1) = E_{ESD}(t) + \eta_c P_c(t) T_u - \frac{P_d(t)}{\eta_d} T_u \quad \forall t \quad (16)$$
$$0 \le P_c(t) + P_{dir}(t) \le P_S(t) + P_g(t) \quad \forall t \quad (17)$$
$$0 \le P_c(t) \le I(t) B \alpha_c \quad \forall t \quad (18)$$
$$0 \le P_d(t) \le (1 - I(t)) B \alpha_d \quad \forall t \quad (19)$$
$$I(t) \in \{0, 1\} \quad \forall t \quad (20)$$
$$B \cdot MD \le E_{ESD}(t) \le B \cdot MC \quad \forall t \quad (21)$$

Peak-demand Pricing: Given $(P_S(t))$, $(P_L(t))$, B, MD, MC, α_c, α_d, η_c, η_d, U, π_b, π_d, Γ, T_u, T_h:

$$\min_{\substack{P_{dir}(t), P_c(t), \\ P_d(t), P_g(t), \\ P_{sell}(t), P_{over}(t), \\ I(t)}} \sum_{t=1}^{T_h} (\pi_b P_g(t) + \pi_d P_{over}(t) - p'(t) P_{sell}(t)) T_u \quad (22)$$

subject to
Constraints (13-21)

$$0 \le P_{over}(t) \quad \forall t \quad (23)$$
$$P_g(t) - \Gamma \le P_{over}(t) \quad \forall t \quad (24)$$

Note that we do not define $P_{over}(t)$ to be the equality in Eq. 10, and instead use two linear constraints to get the same effect.

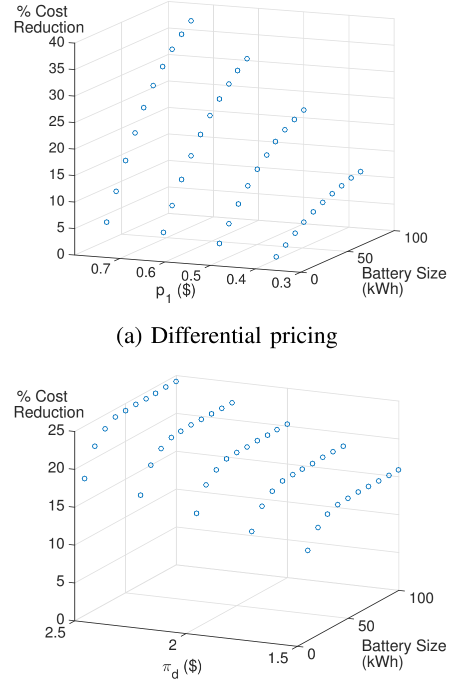
B. Parameter values

We solve the ILPs using the following values for the parameters. $P_S(t)$ and $P_L(t)$ are real traces from Hochschule Landshut University of Applied Sciences in Germany for nine months, April through December in 2014, with measurements every five minutes ($T_u = 1/12$ hours). The maximum observed load is ≈24kW, while the maximum observed PV output is ≈25kW. The ESD is set to mimic a Lithium-Ion battery with $MD = 0.1$, $MC = 0.9$, $\alpha_c = 0.33$, $\alpha_d = 1.67$, $\eta_c = 0.85$, and $\eta_d = 1$ [18]. We assume that the battery has minimal charge at $t = 0$, i.e., $U = B \cdot MD$. The capacity of the battery B ranges from 10 to 100kWh.

To mimic the fixed-rate contracts for buying solar power that are seen in practice, we set the selling price $p'(t)$ to be a constant p' equal to \$0.12 per kWh, the approximate FIT in Germany as of August 2015.

Differential Pricing: Our formulation obtains the optimal strategy for any real-time pricing scheme. For the numerical results, we consider a common type of differential pricing called time-of-use (ToU) pricing. We set a high price p_1 during the day [8am, 8pm) and low price p_2 during the night [8pm, 8am), resulting in a pricing that follows the typical demand shape for user electricity load. We fix p_2 to be \$0.25 per kWh, a typical spot-price in Germany during the night [14], and vary p_1 from \$0.375 to \$0.75.

Peak-demand Pricing: We set $\Gamma = 9.06kW$, corresponding to the 80th percentile of load measurements over the nine month period. The base price π_b is set to \$0.25, and the demand price π_d is varied from \$1.50 to \$2.50.



(a) Differential pricing

(b) Peak-demand pricing

Fig. 2: Cost reduction percentage from using the optimal strategy over the simple strategy.

Note that for both pricing schemes, the lowest price for purchasing power from the grid is less than the payment obtained by selling power to the grid, effectively preventing grid arbitrage.

C. Optimal Operation

In Figure 2, we compare the cost savings from using the optimal strategy instead of using the simple strategy, which we simulated on our system using the same inputs that were used to solve the ILP. We see significant cost savings when the optimal strategy is used, indicating the need for a better operating strategy than the simple price-agnostic one. These savings increase with increasing the pricing free variable, and increasing battery size, although there is a critical battery size beyond which we see no increase in cost reduction for a finite time horizon.

To realize these gains, the optimal strategy takes advantage of the precise knowledge of the future, both in terms of load and PV generation. We are aware that a deployment of this optimal approach on a real system would require accurate forecasts, and it is unclear how forecasting errors affect the performance of the system. However, the non-causal optimal strategy provides us valuable insights on which to base the design of a practical strategy.

D. Insights

To gain insights into the operation of the ILP, we visualize the optimal charging and discharging patterns over time

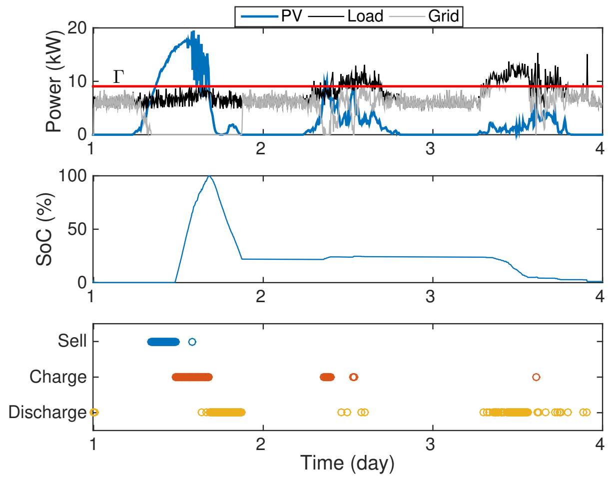


Fig. 3: Visualization of the optimal strategy for peak-demand pricing over three days. PV, Load, and battery SoC are shown. Selling, charging, and discharging events (but not quantities) are also depicted.

against the PV generation, load, ESD state of charge (SoC), and grid price curves. In the interest of space, in the rest of the paper we discuss peak-demand pricing results in greater detail than differential pricing results. Figure 3 is an example for three days with the peak-demand pricing scheme. Some key observations from visualizing the strategy in this way are:

Observation 1: If there is an upcoming period where PV output is not enough to meet the load and the difference between them is greater than Γ, then the battery discharged only to make up for the remaining load so that grid use does not exceed Γ. If there is no such period in the near future, then the battery is discharged whenever PV output is not enough to meet the entire load, with the grid being used as a last resort.

Observation 2: The grid is used to charge the battery on some days if PV output in the near future is going to be low and the battery does not have enough charge to keep grid use from exceeding Γ during that time. The charge level depends on the severity of the PV deficit in the high-price period; less PV generation or more load increases the amount of charging that is done. If the grid is used to charge the battery, it is done when the resulting grid use would not exceed Γ.

Observation 3: The system sells power to the grid only when the storage is full and load has been met. Only PV power is sold, since it is not profitable to sell grid power because of the negative price difference, and discharging the ESD to sell power is also non-optimal due to efficiency losses incurred when the ESD is charged again. This means that the selling price has no effect on the optimal strategy, as long as it is less than the low grid price.

Observation 4: The optimal strategy is the same as long as the grid price ratio (p_1/p_2) is above a threshold where grid charging is profitable, which is determined by the round-trip efficiency of the battery. This is not evident from Figure 3, and was discovered by varying the price ratio and comparing optimal strategies for each ratio.

In effect, the optimal strategy for peak-demand pricing is trying to balance two competing risks:

1) **The risk of grid use exceeding Γ.** We can avoid paying the high demand price by using the battery as a back-up to keep the grid usage below Γ. This risk is minimized if the ESD is charged fully at all times except for when it is needed to prevent grid use from exceeding Γ
2) **The risk of wasting PV output.** If PV generation exceeds the load and the ESD is fully charged, then the excess generation is sold to the grid for a low price rather than being stored and used to offset. purchasing grid power at a later time. This can be avoided by discharging the battery whenever PV generation is not enough to meet the load, in order to make room for storing excess PV generation in the future. This risk is minimized by having the ESD be empty as often as possible.

A similar visualization of the optimal strategy can be used for the ToU pricing scheme. After doing so, we have observed that the optimal strategy for ToU pricing balances two competing risks that are similar to the ones observed for peak-demand pricing. They are:

1) **The risk of using the grid during the day.** We can avoid paying high prices during the day by charging the ESD from the grid at night when prices are low, and using that energy during the day. This risk is minimized if the ESD is charged fully at the start of the high-price period.
2) **The risk of wasting PV output during the day.** This can be avoided by discharging the battery at night (to meet the load at night) to make room for excess PV generation during the day. This risk is minimized by having the ESD be empty at the start of the high-price period.

Using these insights, we next look at practical strategies that improve on the simple strategy.

V. Operating Strategies

We assume that the system control knows at time t, $P_S(t)$, $P_L(t)$, and $E_{ESD}(t)$, and is responsible for computing $P_g(t)$, $P_c(t)$, and $P_d(t)$. It also has knowledge of the pricing scheme. Our goal is to come up with an algorithm, i.e., a set of rules for the controller that uses the available limited information to reduce the grid payments of the PV and storage system owner. A practical strategy decides the operation of the system at any time by relying on easily-obtained information to make decisions. The algorithms that we describe in this section rely on measurements and (possibly) predictions, make feasible control decisions, and have very low time complexity; thus they can be easily implemented on a real system. In the following, we describe an existing strategy [20] for two-period ToU pricing that makes decisions based on a parameter X_j, that refers to the amount of energy in the ESD at the start of the jth high-price period. We also present a new strategy for the peak-demand pricing case which uses a single parameter Y that refers to the amount of energy in the ESD that we maintain to use as a back-up to avoid paying the demand price.

A. Strategy for ToU Pricing

We interpret the pseudo-code given by Zhu et al. [20] and apply it to our system with some minor modifications as

Algorithm 1. We use the notation $[z]_+$ to represent $max(0, z)$. In a nutshell, their algorithm has two main cases, depending on the price period. During the high price period, the algorithm behaves like the simple strategy, charging only with excess solar and discharging whenever needed to avoid using the grid. During the low price period, the algorithm is effectively preparing to avoid using the grid in the next high price period. The battery is charged if its energy content is below X_j , and allowed to be discharged if it is above X_j . The modifications are:

Modification 1: The algorithm in [20] was not designed to consider the opportunity to sell power to the grid, and instead curtails the PV power if it cannot be used or stored. In the optimal strategy, only the excess solar power is sold, so we modify the algorithm to do the same, i.e., $P_{sell}(t) = [P_S(t) - P_L(t) - P_c(t)]_+$.

Modification 2: The algorithm in [20] charges the battery (if needed) as soon as possible using PV and grid sources once a decision is made for it to be charged, in order to have enough energy to meet the demands of the upcoming high-price period. We modify the algorithm to charge at the latest possible time, i.e., right before the start of the high-price period. This is done to give the battery a chance to be charged with excess PV power before the high-price period starts in order to minimize grid use.

Algorithm 1 Storage operation at any time t

if t is in a low-price period **then**
  if $E_{ESD}(t) < X_j$ and $t_{jstart} - t \leq \frac{X_j - E_{ESD}(t)}{B\alpha_c\eta_c}$ **then**
    $P_c(t) = min\Big(\frac{X_j - E_{ESD}(t)}{\eta_c T_u}, B\alpha_c\Big),$
    $P_d(t) = 0,$
    $P_g(t) = [P_L(t) - P_S(t) + P_c(t)]_+$
  else
    $P_c(t) = min\Big([P_S(t) - P_L(t)]_+, B\alpha_c, \frac{BMC - E_{ESD}(t)}{\eta_c T_u}\Big),$
    $P_d(t) = min\Big(\frac{(E_{ESD}(t) - X_j)\eta_d}{T_u}, B\alpha_d, [P_L(t) - P_S(t)]_+\Big),$
    $P_g(t) = [P_L(t) - P_S(t) - P_d(t)]_+$
  end if
else if t is in a high-price period **then**
  $P_c(t) = min\Big([P_S(t) - P_L(t)]_+, B\alpha_c, \frac{BMC - E_{ESD}(t)}{\eta_c T_u}\Big),$
  $P_d(t) = min\Big(\frac{E_{ESD}(t)\eta_d}{T_u}, B\alpha_d, [P_L(t) - P_S(t)]_+\Big),$
  $P_g(t) = [P_L(t) - P_S(t) - P_d(t)]_+,$
end if
$P_{sell}(t) = [P_S(t) - P_L(t) - P_c(t)]_+$

The algorithm is critically dependent on the parameters X_j. A well chosen X_j value balances the risks of having to sell PV generation for a low selling price and using the grid during the high-price period that were discussed in the previous section. Zhu et al. propose that X_j should be dynamic, with the controller predicting the PV generation and load for the high-price period of the upcoming day and setting X_j to be the difference, i.e.:

$$X_j = min(B \cdot MD, \; max\Big(B \cdot MC, \sum_{t=t_{jstart}}^{t_{jend}} ((P_L(t) - P_S(t))T_u\Big) \tag{25}$$

where t_{jstart} and t_{jend} are the start and end times of the high-price period of day j. We will refer to this as the 'day-ahead X' strategy, and consider this to be a practical approach because the required predictions are only for aggregate values, rather than fine-grained load and PV generation curves. As it turns out, this method of choosing X_j is very close to what is done in the optimal strategy, as shown in Figure 4. In the case where predictions for day-ahead PV and load are unavailable or unreliable, or if we wish to avoid predictions altogether, we propose to simplify the problem of selecting the X_j's by forcing $X_j = X$ for all j's. We will refer to this as the 'static X' strategy. Note that, in practice, the controller would choose the value of X based on data sets measured in the past at the premises and use the best value of X for the given grid prices and the given battery size. It is possible that the best X for a given location, grid prices, and ESD size is seasonally dependent; we defer this analysis to future work. In our evaluation, we evaluate the performance of the static and day-ahead X strategies separately.

B. Strategy for Peak-demand Pricing

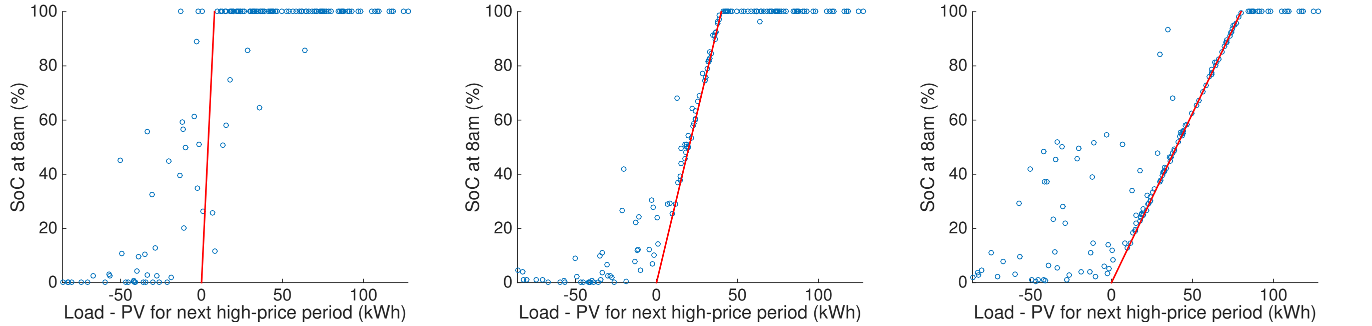
Our operating strategy for peak-demand pricing is developed using our observations on the optimal strategy. Our strategy uses a static parameter Y, which is the amount of energy we try to have stored to act as a backup when the load exceeds Γ. We will refer to this strategy as 'static Y'. The strategy is split into two operating modes, depending on whether the energy content of the battery is above or below Y kWh. The mathematical expressions for defining each mode are more complex than those in Algorithm 1, so instead we describe the strategy as a sequence of priorities for the flow of power through the system:

Mode 1: if $E_{ESD}(t) \leq Y$

1) PV power is used first to meet the load that exceeds Γ, then to charge the battery to Y. PV is then used to meet the rest of the load, and then to charge the battery if all the load has been met; remaining power is sold.
2) The battery is then discharged only if needed to meet the load that exceeds Γ.
3) The grid is used to meet the remaining load, and then to charge the battery to Y as long as grid use does not exceed Γ.

Mode 2: if $E_{ESD}(t) > Y$

1) PV power is used to meet the load, then to charge the battery. The remaining power is sold.
2) The battery is discharged to meet any load that exceeds Γ. The battery can then be further discharged, provided that the battery energy content doesn't go below Y.
3) The grid is used to meet any remaining load.



(a) $B = 10kWh$ (b) $B = 50kWh$ (c) $B = 100kWh$

Fig. 4: Optimal X_j plotted against the day-ahead difference in load and PV generation. The line represents the choice of day-ahead X_j as proposed by Zhu et al. [20].

Just like the static X strategy, the Y value does not require forecasting and can be chosen by training the algorithm on historical data. In our numerical examples, we compare all these strategies and observe their performance through a simulation campaign of the system.

VI. Results and Discussion

We simulate our system with a Lithium-Ion battery using our proposed operating strategies, as well as with the simple strategy for comparison. Our performance metric is the cost increase relative to the grid payments with the optimal strategy. Given a non-optimal strategy S, the relative cost increase is

$$\frac{Cost(S) - Cost^*}{Cost^*} \tag{26}$$

where $Cost^*$ is the cost given by the oracle. The battery size varies between 10 and 100kWh, which is a realistic range for the given PV and load traces. We look at differential (ToU) and peak-demand pricing with the same prices as in Section IV-B. For determining the X and Y parameters, we incorporate a training and test set. We use data from April, June, August, October, and December to learn the best static X and Y, and use them to test on May, July, September, and November data.

A. Differential Pricing Results

Figure 5 shows the cost reduction potential for each strategy. The day-ahead X strategy performs near-optimally for all the tested battery sizes and grid price values as long as we are able to perfectly predict the aggregate PV and load for the next high-price period. The static X strategy also provides significant improvement, and works best when the relative difference in day/night grid prices is large and/or battery size is small. A smaller battery benefits little from prediction, partly because there is less flexibility to decrease the electricity payments. Altogether, one might interpret these results as saying that there is no need for forecasting. The effects of varying the selling price were tested and were minimal because with our traces, very little energy is sold in all the strategies we consider. Indeed, our strategies are designed to use or store as much PV power as possible, with selling used as a last resort.

In order to test the robustness of the day-ahead strategy to prediction errors, we introduce errors into our simulation.

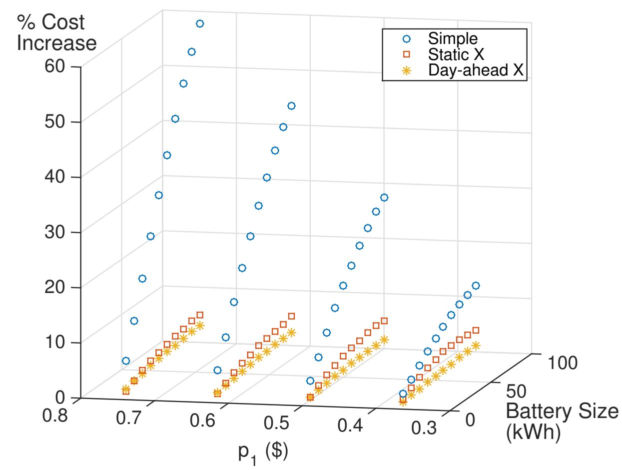


Fig. 5: Cost increase across different battery sizes and p_1 values for the three strategies for TOU pricing.

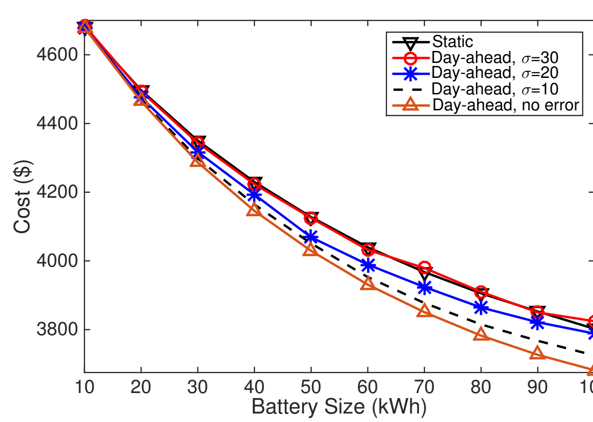


Fig. 6: The effect of prediction error on the day-ahead strategy performance. $p_1 = 0.50, p_2 = 0.25$.

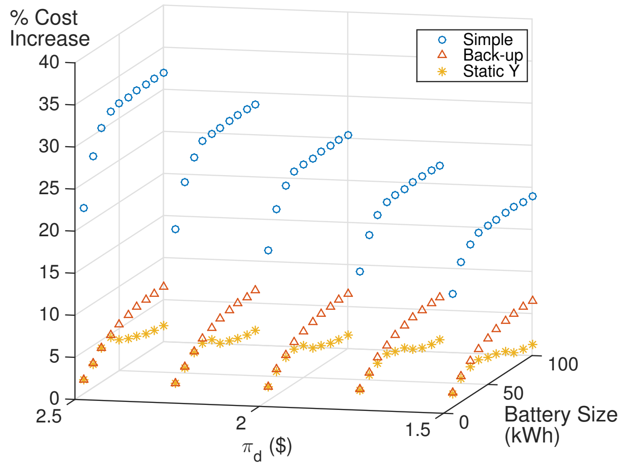


Fig. 7: Cost increase across different battery sizes and π_d values with peak-demand pricing of simple, static Y, and back-up strategies. $\pi_b = \$0.25$

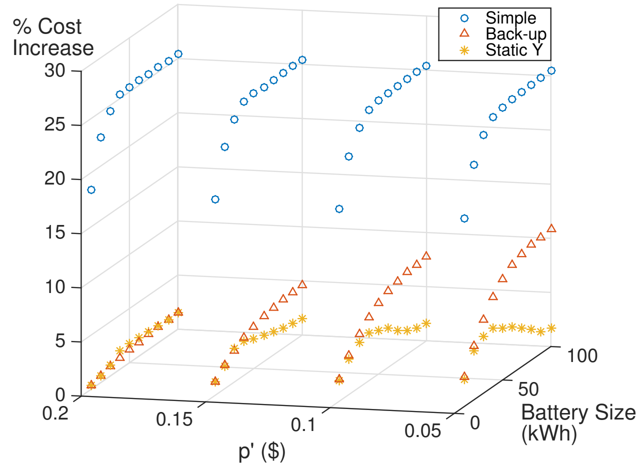


Fig. 8: Cost increase with varying selling price and battery size. $\pi_b = \$0.25$ and $\pi_d = \$2.00$.

Prediction errors, as a percentage of the actual value, are introduced by sampling a normal distribution with a mean of zero and applying it to the actual aggregate PV generation calculated for each day's high price period. This is a reasonable prediction error distribution according to results from [17]. Similarly, we apply errors to the aggregate load predictions. The standard deviation σ of the error distribution is the same for the two distributions, and is varied between 10% and 30%. We simulate the system with these prediction error distributions 5000 times to obtain an average grid cost of the system over the time horizon for each σ. Figure 6 shows the effect of error on the day-ahead strategy. Prediction errors further the conclusion that the day-ahead strategy is only marginally better than our static strategy. With substantial prediction errors ($\sigma = 30\%$) for both load and PV, the average performance is almost identical to the static strategy for all the battery sizes and price ratios we tested.

B. Peak-demand Pricing

For peak-demand pricing, a second existing operational strategy, in addition to what we refer to as the simple strategy, is currently in commercial use, for example by Stem [1], a company that provides energy storage and management services. This strategy is designed for peak-demand pricing but does not consider a PV power source. It aims to use storage solely to prevent grid use from exceeding the demand threshold. We refer to this strategy as the 'back-up' strategy (because it is used as a back-up power source), and model it as always being in Mode 1 of our static Y strategy, i.e., set $Y = B \cdot MC$, the upper limit on the battery capacity.

In Figure 7, we compare the relative cost increase of the simple, static Y, and back-up strategies. Our static Y strategy exhibits near-optimal performance. The back-up strategy also exhibits a noticeable improvement over the simple strategy, though not as good as the static Y strategy. This is not surprising, since the back-up strategy is a special case of the static Y strategy. The back-up strategy performance degrades when the selling price is decreased, as shown in Figure 8. This is because the battery is almost always kept full, and is unable to store excess PV generation. Once again, these results suggest that forecasting might not be necessary, as the potential decrease in grid payments is less than 5%.

C. Insights

Our work provides three key insights.

First, the role of storage in this system is two-fold. On the one hand, it is used to store energy during low-price periods to reduce grid use during high-price periods or periods of high demand. On the other hand, it is used to store excess solar production (over demand) to reduce grid use during times of low (or zero) solar production. These two roles are sometimes mutually opposed, where under some circumstances, it is better to have the store fully charged, whereas under other circumstances, it is best to have it fully discharged. This is why our heuristic strategies focus on X_j and Y as the critical tuning parameters, in an effort to find the best balance between the two uses.

Second, our design approach is based on two steps. In the first, we assume perfect knowledge of the future to find the offline optimal control strategy. Then, we use insights gained from this strategy to create online near-optimal strategies. We believe that this general approach can be used in many other problem domains.

Third, we proposed rule-based strategies that do not rely on forecasting. In the ToU pricing case, we found that adding some aggregate forecasting can result in slightly better performance, and it is questionable if this benefit is worth the cost of the additional complexity, given that our static strategies already exhibit near-optimal performance when trained on representative data. Our approach to designing operating strategies, with a focus on avoiding complexity (i.e., forecasting, online optimization), has shown promising results.

D. Limitations

Although our work has made what we believe to be significant contributions, it is not without its limitations, the main one being that our analysis does not consider the amortized cost of using the battery, which ought to be a cost applied to the discharge process of the battery. In our defence, Lithium-Ion batteries have a long lifetime, rated up to 15,000 charge-discharge cycles [11], and go through roughly only about 1.5 cycles per day on average[3] if the battery and PV system are sized to meet a significant portion of the load (as we do). This translates to a battery cycle lifetime of up to 30 years, so incorporating this into our analysis is not likely to significantly change the results.

Our operating strategies could also be augmented to take into account seasonal variations in PV production and load, which may result in additional performance improvements. Addressing these limitations opens up several interesting avenues for future work.

VII. Conclusion

Lower PV prices and the impending widespread deployment of Lithium-Ion storage, combined with rising utility prices and the reduction of Feed-in Tariffs, are likely to make self-use of PV generation much more widespread in the near future. We focus on evaluating and demonstrating how to come up with strategies of storage operation for a system with PV generation, using jurisdictions with differential or peak-demand prices as our examples. We have modified an existing algorithm for differential pricing and developed a novel algorithm for peak-pricing, both of which do not rely on forecasts to achieve near-optimal performance in real operating scenarios.

VIII. Acknowledgments

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