A Dynamic Programming Approach to Estimate the Capacity Value of Energy Storage

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***Abstract*—We present a method to estimate the capacity value of storage. Our method uses a dynamic program to model the effect of power system outages on the operation and state of charge of storage in subsequent periods. We combine the optimized dispatch from the dynamic program with estimated system loss of load probabilities to compute a probability distribution for the state of charge of storage in each period. This probability distribution can be used as a forced outage rate for storage in standard reliability-based capacity value estimation methods. Our proposed method has the advantage over existing approximations that it explicitly captures the effect of system shortage events on the state of charge of storage in subsequent periods. We also use a numerical case study, based on five utility systems in the U.S., to demonstrate our technique and compare it to existing approximation methods.**

***Index Terms*—Capacity value, reliability theory, approximation techniques, energy storage**

NOMENCLATURE

A. Capacity Value Estimate Parameters and Variables

T number of time periods in planning horizon.
T' subset of periods used in capacity factor-based approximation
G_t time-t generating capacity available.
G_t^g time-t generating capacity available from generator g.
B_t time-t generating capacity available from benchmark unit in equivalent conventional power (ECP) calculation.
d_t^μ maximum potential time-t output from storage device.
$\xi_t(l_t)$ probability that beginning time-t storage level is l_t.
L_t time-t load.
$\bar{L}$ constant load added in each period in effective load-carrying capability (ELCC) calculation.
p_t time-t loss of load probability.
e loss of load expectation (LOLE) of base system.
e^L LOLE with g and loads added in ELCC calculation.
e^g LOLE with g added in ECP calculation.
e^B LOLE with benchmark unit added in ECP calculation.
w_t time-t weight used in capacity factor-based approximation.

B. Storage Optimization Model Parameters

π_t time-t energy price.
η roundtrip efficiency of storage device.
$\bar{R}$ power capacity of storage device.
$\bar{h}$ energy capacity, as a multiple of power capacity, of storage device.
$\bar{l}_1$ starting time-1 storage level.

C. Storage Optimization Model Variables

l_t beginning time-t storage level.
s_t energy stored in period t.
d_t energy discharged in period t.

I. INTRODUCTION

An important issue in long-run power system planning is the contribution of installed resources to reliably meeting demand. Generator outages, which can occur due to mechanical failures or planned maintenance, may leave the system with insufficient generating capacity to meet load. Renewable generators have the added complication of variable real-time resource availability affecting their contribution to serving load. Capacity value is the metric typically used to quantify a resource's effect on system reliability and for long-run resource adequacy planning [1]–[3]. Capacity value is often estimated using reliability-based methods. Such methods model resource outages probabilistically, *e.g.*, using an effective forced outage rate (EFOR). EFORs are used to compute the likelihood of a system capacity shortfall in each time period, which is typically measured by the loss of load probability (LOLP). A resource's capacity value is determined by its effect on LOLPs.

Energy storage also contributes capacity to the system. This is recognized in a 1976 EPRI study [4], which focuses on charging pumped hydroelectric storage (PHS) with baseload generation overnight to reduce the need to build peaking generation. Based in part on its ability to provide capacity, more than 20 GW of PHS capacity was built in the United States in the 1970s [5]. More recent analyses focus on the interplay between storage and variable renewables, suggesting that storage can provide flexibility to ease renewable integration [6]–[10]. Implicit in these analyses is the assumption that storage provides capacity value, reducing the need for conventional generation. Even more recently, the California Public Utilities

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Commission opened a rulemaking process to set policy for California utilities and load-serving entities to procure energy storage systems.[1] The assigned commissioner's ruling lists capacity among the benefits that storage can provide.

Despite recognition of this role that storage can play, methods to robustly estimate storage's capacity value are essentially non-existent in the literature. A difficulty in estimating storage's capacity value is that it is an energy-limited and time-dependent resource. Thus, its ability to serve load at time t depends on its prior operation. Moreover, one must consider both the planned operation of the device at time t and the amount of energy in storage. This is because if the system experiences a capacity shortfall at time t, stored energy that would otherwise not be discharged could be used to serve load.

Tuohy and O'Malley [11], [12] propose a capacity value approximation technique, which we refer to as the maximum generation approximation, that overcomes these issues. This approximation first determines an optimal dispatch of the storage plant subject to technical constraints, assuming that no system shortages occur. While different objectives can be used, maximizing net profits from wholesale energy sales and purchases is commonly assumed. The approximation then determines, based on the dispatch, the maximum amount of energy that the storage device could feasibly generate (using stored energy) in each time period. This maximum potential generation is used to estimate the plant's capacity value.

An issue with this approximation is that it may overestimate storage's capacity value. To see this, consider two periods, $t < t'$, that are in quick succession and have high LOLPs. In real-time, there may be less stored energy available at time t' than the optimized dispatch suggests, since energy may be used to mitigate a time-t system shortage. Should a shortage occur, and since t and t' are in quick succession, there may be insufficient time for the storage device's state of charge to increase before t'.

In this paper we propose an approach to estimate storage's capacity value. We use a dynamic program to determine how storage operations are affected by system shortages. The resulting operational schedules are used to determine the probability that the storage device has energy available in each period, accounting for the probability of system shortages in previous periods. These estimated probabilities are used as EFORs to model storage availability in reliability-based models. Thus, these EFORs fully capture the effect of previous outages on storage's state of charge at any given time.

In addition to detailing this estimation technique, we demonstrate its use through a numerical case study of five utility systems in the U.S. We show that storage with one to 10 hours of discharging capability has capacity values ranging between 40% and 100% of nameplate capacity. We also demonstrate that there can be considerable interannual capacity value variability. We compare the capacity value estimates given by our technique to the maximum generation approximation, showing that the approximation overestimates capacity values for devices with small energy capacities. While the approximation is better for less energy-constrained storage, it is very sensitive to the subset of hours considered.

[1]Details are available from the California Public Utilities Commission's website http://www.cpuc.ca.gov/PUC/energy/electric/storage.htm.

The remainder of this paper is organized as follows: Section II discusses standard reliability-based and approximation methods used to estimate capacity values. Section III gives the formulation of our storage operation model. Section IV describes our proposed technique and further details the maximum generation approximation. Section V summarizes our numerical case study and the data used. We present our results in Section VI and Section VII concludes.

II. Capacity Value Estimation Techniques

A. Reliability-Based Methods for Generators

Reliability-based methods are among the most robust and widely accepted techniques to estimate generator capacity values [3], [13], [14]. These techniques use a standard reliability index, LOLP, to determine how a generator affects system reliability. LOLP is defined as the probability that outages leave the system with insufficient capacity to serve the load in a given time period. A related reliability index, loss of load expectation (LOLE), is defined as the sum of LOLPs over some planning horizon. LOLE gives a proportion of time within the planning horizon that capacity shortages occur. For instance, if the planning horizon is one year and the modeled time periods are hours, the LOLE can be interpreted as the sum of expected outage hours over the year. Reliability-based methods determine a generator's capacity value by how it affects the system's LOLE. Standard reliability-based metrics include the effective load-carrying capability (ELCC) and equivalent conventional power (ECP). We detail these established reliability-based methods [3] below.

Other reliability metrics, such as loss of energy probability or expected unserved energy, can also be used. It may also be desirable to place a cost on capacity shortages, for instance by weighting expected unserved energy by an assumed value of lost load (VOLL), which may be time- and customer class-variant. These metrics capture the severity of an outage, rather than treating all outages equivalently. These metrics are less common, however, and we focus on LOLE-based methods, to make our results directly comparable to previous works [11]–[22].

1) Effective Load-Carrying Capability: The ELCC of a generator, g, is defined as the amount by which the system's load can increase, when the generator is added, while maintaining the same LOLE. The ELCC is calculated by first computing the system's LOLPs without g as:

$$p_t = \text{Prob}\left\{G_t < L_t\right\}, \quad \forall\ t = 1, \ldots, T, \tag{1}$$

where the probability function accounts for the likelihood of generator or other failures and stochastic loads or renewable resource availability. The base system's LOLE is defined as:

$$e = \sum_{t=1}^{T} p_t. \tag{2}$$

Generator g is added to the system and a fixed load, $\bar{L}$, is added to each period, giving a new LOLE:

$$e^L = \sum_{t=1}^{T} \text{Prob}\left\{G_t + G_t^g < L_t + \bar{L}\right\}, \quad (3)$$

The value of $\bar{L}$ is iteratively adjusted until the LOLE of the system with g is the same as that of the base system, or until:

$$e = e^L. \quad (4)$$

Generator g's ELCC is defined as the value of $\bar{L}$ that achieves equality (4).

2) Equivalent Conventional Power: The ECP of a generator, g, is defined to be the capacity of a benchmark unit that can replace g while maintaining the same LOLE. The benchmark unit is assumed to have a positive EFOR. The ECP is calculated by first computing the LOLE of the system when g is added as:

$$e^g = \sum_{t=1}^{T} \text{Prob}\left\{G_t + G_t^g < L_t\right\}. \quad (5)$$

The LOLE of the system when only the benchmark unit (*i.e.*, without g) is added is also computed as:

$$e^B = \sum_{t=1}^{T} \text{Prob}\left\{G_t + B_t < L_t\right\}. \quad (6)$$

The nameplate capacity of the benchmark unit is iteratively adjusted until the LOLE of the system with the benchmark unit is the same as that with g, or until:

$$e^g = e^B. \quad (7)$$

Generator g's ECP is defined as the nameplate capacity of the benchmark unit that achieves equality (7).

B. Capacity Factor Approximations

Approximations are also used to estimate capacity values. Traditionally, approximations were used due to the computational cost of iteratively computing LOLPs, although that is less of an issue today [18]. Approximations are still used due to reduced data needs or because they provide insights into the factors that affect capacity value [19]. One method, which is applied to wind [15], [16] and solar [17], [20]–[22], approximates the capacity value of a resource as its weighted capacity factor over a subset of periods during which the system has a high likelihood of experiencing a shortage. These approximations commonly focus on periods with the highest loads and use the base system's LOLPs, given by (1), as weights.

With this approximation, the weights are defined as:

$$w_t = \frac{p_t}{\sum_{\tau \in T'} p_\tau}, \quad \forall\, t \in T', \quad (8)$$

where $T' \subseteq \{1, \cdots, T\}$ is the subset of periods with the highest loads. The capacity value approximation for generator g is given by:

$$\sum_{t \in T'} w_t \cdot G_t^g. \quad (9)$$

An important question when applying these techniques is the number of periods to consider. Milligan and Parsons [15] show that when applied to wind, the approximation should consider the 10% of periods with the highest loads. Madaeni *et al.* [20] apply the approximation to a concentrating solar power (CSP) plant, showing that only the 10 highest-load hours of the year should be considered. The sensitivity of the approximation stems from different wind and solar generation patterns and the extent to which they are coincident with system loads.

III. Storage Operation Model

Models to optimize storage operations are abundant in the literature. Although storage can be put to a multitude of uses [23], most models focus on so-called energy arbitrage (*i.e.*, charging energy when the price or cost is low and discharging when high). This can either be done by an integrated utility or system operator minimizing total system costs [4], [12] or by a profit-maximizing firm reacting to prices [24]–[26].

A. Storage Operation Model Assumptions

For ease of exposition, we assume that storage is used by a profit-maximizing firm for energy arbitrage only. The firm is assumed to have perfect foresight of future energy prices and naïvely maximize energy profits, without considering the possibility of future system shortages or their effect on storage operations. Sioshansi *et al.* [26] show that this perfect foresight assumption has a relatively small effect on operational decisions, since prices tend to follow predictable diurnal and seasonal patterns. We, thus, use a deterministic profit-maximization to model storage operations. Our capacity value estimation method is agnostic to the objective function, however. We discuss the implications of this assumed optimization criterion on storage's capacity value in Sections VI and VII.

We further assume that the energy capacity parameter, $\bar{h}$, is integer and that the starting storage level, $\bar{l}_1$, is an integer multiple of $\bar{R}$.

B. Storage Operation Model Formulation

We formulate our model as a dynamic program, as it aids our capacity value estimation. This model is identical, however, to the linear program proposed by Sioshansi *et al.* [26]. We follow the notational conventions used by Powell [27].

1) Variables: Our model has one set of endogenous state variables, l_t, and two sets of action variables, s_t and d_t. We could also define the energy prices as exogenous state variables, but do not do so to simplify notation.

2) State-Transition Functions: The endogenous state variables evolve according to:

$$l_{t+1} = l_t + s_t - d_t, \qquad \forall\, t = 1, \cdots, T; \quad (10)$$

and

$$l_1 = \bar{l}_1. \quad (11)$$

3) Constraints: Gross charging and discharging are constrained to be within the storage device's power capacity:

$$0 \leq s_t \leq \bar{R}, \qquad \forall\, t = 1, \cdots, T; \tag{12}$$

and:

$$0 \leq d_t \leq \bar{R}, \qquad \forall\, t = 1, \cdots, T. \tag{13}$$

We also constrain the storage level to be within the device's energy capacity:

$$0 \leq l_t \leq \bar{h} \cdot \bar{R}, \qquad \forall\, t = 1, \cdots, T. \tag{14}$$

4) Objective Function: The time-t profit contribution is given by:

$$C_t(l_t; s_t, d_t) = \pi_t \cdot (\eta \cdot d_t - s_t). \tag{15}$$

The parameter, $\eta \in [0, 1]$, represents a constant roundtrip device efficiency. Let $\mathcal{A}$ denote the set of all feasible policies. A policy, $a_t(l_t)$, is a mapping between a time-t state, l_t, and a feasible time-t decision, (s_t, d_t). For each policy, $a \in \mathcal{A}$, we define the total profit from time t forward as:

$$G_t^a(l_t) = \sum_{\tau=t}^{T} C_t(l_\tau; a_\tau(l_\tau)). \tag{16}$$

The objective is to find an optimal policy, a^*, that satisfies:

$$G_t^{a^*}(l_t) = \sup_{a \in \mathcal{A}} G_t^a(l_t), \tag{17}$$

for all $0 \leq t \leq T$. We let $s_t^*(l_t)$ and $d_t^*(l_t)$ denote the charging and discharging decisions given by such an optimal policy.

C. Properties of an Optimal Policy

It is straightforward to show that if the time-t energy price makes it optimal to charge or discharge at time t, it is optimal to charge or discharge until either the time-t power or energy capacity is exhausted. This is due to the linearity of the dynamic program's objective and constraints. Since we assume that $\bar{h}$ is integer and $\bar{l}_1$ is an integer multiple of $\bar{R}$, it is straightforward to show that there is an optimal policy in which the storage level in each period is an integer multiple of $\bar{R}$. We hereafter assume that storage is operated using such a policy.

This assumption also allows storage operations to be optimized using the dynamic program algorithm, since we can restrict ourselves to the finite state space:

$$l_t \in \{0, \bar{R}, 2 \cdot \bar{R}, \ldots, \bar{h} \cdot \bar{R}\}, \qquad \forall\, t = 1, \cdots, T; \tag{18}$$

and the finite action space:

$$s_t, d_t \in \{0, \bar{R}\}, \qquad \forall\, t = 1, \cdots, T. \tag{19}$$

IV. Capacity Value Estimation for Storage

We now detail the maximum generation approximation and our proposed estimation technique.

A. Maximum Generation Approximation

The maximum generation approximation uses the optimized storage dispatch policy to compute the maximum amount of energy that the storage device could feasibly provide in each period as:

$$d_t^\mu = \eta \cdot \min\{\bar{R}, l_{t-1}\}. \tag{20}$$

These d_t^μ values are intended to represent the maximum amount of energy the storage device could provide at time t, should a system shortage occur, and are used to estimate the capacity value. Tuohy and O'Malley [11], [12] approximate the capacity value of PHS that is operated by a utility using a capacity factor approximation (*i.e.*, by substituting $G_t^g = d_t^\mu$ in (9)). Madaeni *et al.* [22] apply the same method to a CSP plant with thermal energy storage (TES).

B. Proposed Storage Capacity Value Estimation Technique

A limitation of the maximum generation approximation is that it does not capture the effect of a time-t system shortage on the storage level in subsequent hours. Fig. 1 illustrates the effect of shortages on storage operations by showing the optimized hourly dispatch of a 100 MW storage device with 8 hours of storage capacity. The dashed line in the figure represents hourly energy prices and the unmarked solid line represents an optimized dispatch policy if no shortages occur. The remaining marked solid lines represent optimal dispatch policies after some combination of shortages. A shortage results in a lower state of charge, since the storage device provides energy it otherwise wouldn't to mitigate the shortage. For instance, the solid line marked with 'x's represents the resulting storage policy if a shortage occurs during hour 2. This reduces the ending hour-2 storage level from 200 MWh to 0 MWh, since the storage device does not charge during hour 2 and instead discharges stored energy to mitigate the shortage.

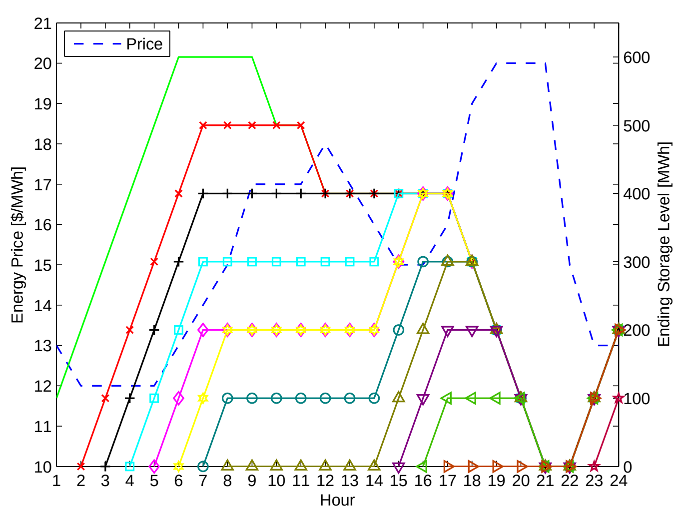

Fig. 1. Optimized storage dispatch with different beginning storage levels.

The remaining marked lines in Fig. 1 represent the resulting storage level after some combination of shortages. For instance, if a shortage occurs during hour 2, the line marked with 'x's tells us that the ending hour-2 storage level is 0 MWh. Suppose no other shortages occur until hour 7. The state of charge would follow the line marked with 'x's, until hour 7, when the state of charge falls to 300 MWh (since storage would not be charged during hour 7 and would instead discharge 100 MWh to mitigate the shortage). Thus, the state of charge would thereafter follow the line marked with squares.

The maximum generation approximation uses the unmarked solid line to estimate the capacity value. For instance, since the optimized policy results in 200 MWh of energy being stored at the end of hour 2, the storage device is modeled as contributing 100 MW (less efficiency losses) to mitigating an hour-3 shortage. The solid line marked with 'x's shows, however, that if a shortage occurs during hour 2, the storage device is completely depleted at the beginning of hour 3 and contributes 0 MW to system reliability. Thus, to accurately determine the time-t reliability impact of storage, one must account for the effect of earlier shortages on the expected time-t storage level.

Consideration of these shortages is the contribution of our proposed capacity value estimation technique, which we now detail. We proceed by discussing two additional assumptions regarding shortage events and then show how optimal policies derived from the dynamic program are combined with system LOLPs to compute the probability that the storage device can provide energy if a shortage is to occur in each period.

1) System Shortage Assumptions: We assume that if a system shortage occurs at time t, any planned (based on the operational policy) time-t charging does not take place. Moreover, if there is any energy available in storage at the beginning of time t, the storage plant discharges up to its physical capacity limits. Since we noted in Section III-C that the values of l_t in an optimal policy are integer multiples of $\bar{R}$, the amount discharged if $l_t > 0$ must equal $\bar{R}$. Thus, when accounting for system shortages, l_t transitions according to:

$$l_{t+1} = \begin{cases} \max\{0, l_t - \bar{R}\}, & \text{if a time-}t\text{ shortage occurs,} \\ l_t + s_t^*(l_t) - d_t^*(l_t), & \text{otherwise.} \end{cases} \quad (21)$$

Although we model the effect of shortages on the storage level, the storage operator is assumed to follow the same arbitrage profit-maximization given by the dynamic program in Section III, which neglects shortages. If a shortage occurs at time t, resulting in the time-$(t+1)$ storage level being $l_{t+1} = \max\{0, l_t - \bar{R}\}$, the storage device is assumed to follow a new storage policy that is optimal from time $t+1$ forward based on the new storage level.

Note, however, that when a time-t shortage occurs, the resulting storage level, l_{t+1}, takes on a value that is in the same finite state space, given by (18), of the original dynamic program. Thus, if the original dynamic program is solved using the dynamic programming algorithm, one knows how the future operation of the storage plant changes if a shortage occurs at time t. Namely, the new time-$(t+1)$ storage decisions are given by $s_{t+1}^*(\max\{0, l_t - \bar{R}\})$ and $d_{t+1}^*(\max\{0, l_t - \bar{R}\})$, where the new time-$(t+1)$ storage level resulting from the time-t shortage is substituted in the policy.

2) Storage Energy Availability Probability: We define:

$$I_{t+1}(y) = \{l_t : l_t + s_t^*(l_t) - d_t^*(l_t) = y\}, \quad (22)$$

as the set of time-t storage levels that yield optimal time-t storage policies which give a time-$(t+1)$ storage level of y. If there is not a time-t shortage, any time-t storage level contained in the set $I_{t+1}(y)$ results in a time-$(t+1)$ storage level equal to y. Otherwise, if a shortage occurs at time t, we know from (21) that the time-$(t+1)$ storage level equals y only if $l_t = y + \bar{R}$. We further know that the probabilities of the random transitions in (21) are given by the system LOLPs, computed using (1). Thus, a time-t shortage does and does not occur with probabilities p_t and $1 - p_t$, respectively. We can, thus, compute the distribution of the time-t storage level recursively as:

$$\xi_1(y) = \begin{cases} 1, & \text{if } y = \bar{l}_1, \\ 0, & \text{otherwise,} \end{cases} \quad (23)$$

and:

$$\xi_{t+1}(y) = p_t \cdot \xi_t(y + \bar{R}) + (1 - p_t) \cdot \sum_{\lambda \in I_{t+1}(y)} \xi_t(\lambda). \quad (24)$$

We finally know that by the assumptions discussed in Section IV-B1, if a shortage occurs at time t and $l_t > 0$, the storage device provides $\eta \cdot \bar{R}$ MW (in net) to help mitigate the shortfall. Otherwise, if a shortage occurs and $l_t = 0$, the storage device provides 0 MW. Since $\xi_t(y)$ gives the distribution of the time-t storage level, we know that $l_t = 0$ with probability $\xi_t(0)$ and that $l_t > 0$ with probability $1 - \xi_t(0)$. Thus, we can model the storage device in any capacity value estimation technique, including the reliability-based methods outlined in Section II-A, as a resource with a a $\eta \cdot \bar{R}$ MW capacity and a time-t EFOR of $\xi_t(0)$.

V. Case Study and Data

We estimate the capacity value of storage in five utility systems—Pacific Gas and Electric (PG&E), Southern California Edison (SCE), NV Energy (NE), Public Service Company of New Mexico (PNM), and FirstEnergy (FE). We use both our proposed method and the maximum generation approximation to estimate the capacity values. We model LOLPs and storage operations at hourly timesteps and estimate capacity values for each year independently. Our analysis considers a small device with a $\bar{R} = 100$ MW power capacity, an $\eta = 0.8$ roundtrip storage efficiency, between $\bar{h} = 1$ and $\bar{h} = 10$ hours of storage capacity, and a starting storage level (at the beginning of each year) of $\bar{l}_1 = 0$.

Our analysis uses eight years of hourly historical conventional generator, load, and price data from 1998 to 2005. Table I provides summary data regarding each utility, including the range of annual load factors, installed generation capacity, and capacity-weighted fleet-average EFORs. We model generator outages using a simple two-state (up/down) model. LOLPs are estimated by computing the system's capacity outage table, which assumes that generator outages follow serially and jointly independent Bernoulli distributions [3]. Data requirements and sources used for our analysis are detailed below.

TABLE I
UTILITIES STUDIED (DATA FROM 1998 TO 2005)

Utility	Load Factor [%]	Installed Generator Fleet Capacity [GW]	Average EFOR [%]
PG&E	52.1–56.7	6.0–6.0	3–5
SCE	52.3–60.1	5.0–5.0	3–5
NE	44.3–48.0	1.6–2.3	8–11
PNM	64.1–69.5	2.0–2.3	7–11
FE	58.5–65.2	9.9–9.9	6–7

A. Conventional Generators

We model each conventional generator owned by each utility, as reported in Form 860 data filed with the U.S. Department of Energy's Energy Information Administration. Form 860 also provides rated winter and summer capacity data for each generator.

We estimate generator EFORs using the North American Electric Reliability Corporation's Generating Availability Data System (GADS). The GADS specifies historical annual average generator EFORs based on generating capacity and technology. We combine these with Form 860 data, which specify generator prime mover and generating fuel, to estimate EFORs. The EFORs used range between 2.2% and 13.3%. We use a natural gas-fired combustion turbine as the benchmark unit in ECP calculations, since such generators are often built for peak-capacity purposes. We assume a 7% EFOR for the combustion turbine, based on the GADS.

B. Loads

Hourly historical load data for each utility in each year are obtained from Form 714 filings with the Federal Energy Regulatory Commission. We assume loads are fixed and deterministic based on these data. Most of the utilities had less generation installed during the study period than their peak loads. This is because the utilities are interconnected with larger balancing authorities, independent system operators, or regional transmission organizations that trade generation capacity among the constituent utilities. For example, PG&E and SCE purchase energy and capacity from merchant generators in the California ISO market and elsewhere in the Western Electricity Coordinating Council. Thus, these resources contribute to PG&E and SCE system reliability.

Since details of these transactions are not available, we instead account for the generation and load mismatch by adjusting the load profiles in each year so that the LOLPs of the base system in each year sum to 2.4. This corresponds to the standard planning target of one outage-day every 10 years [28]. This load adjustment is done by scaling all of the hourly loads by a fixed percentage, ranging between 32% and 71% in the different utilities and years. This load scaling can be thought of as accounting for the amount of capacity that each utility should contract to purchase in each hour to supplement its installed capacity and meet its reliability target.

C. Energy Prices

Storage operations are optimized to maximize net energy sales profits. Hourly day-ahead prices from the California ISO markets are used to optimize storage devices in the two California utility service territories. Specifically, prices for the SP15 zone are used for SCE and the NP15 zone for PG&E. Hourly day-ahead prices for the AEP GEN hub, obtained from PJM Interconnection, are used for FE. Hourly system lambda data, obtained from Form 714 filings by NE and PNM, are used for the other two locations.

VI. STORAGE CAPACITY VALUE

A. Dynamic Program-Based Method

Fig. 2 summarizes average annual ECPs of storage devices with different energy capacities in the five utility systems. The capacity values are reported as percentages of the assumed 80 MW net (of efficiency losses) discharging capacity. The figure also shows the minimum and maximum ECP estimates among the five utilities and eight study years. Storage's capacity value is closely tied to its energy capacity, however the relationship between energy prices and system LOLPs also plays an important role. This is because the capacity value is highly sensitive to storage dispatch decisions, which are governed by energy prices.

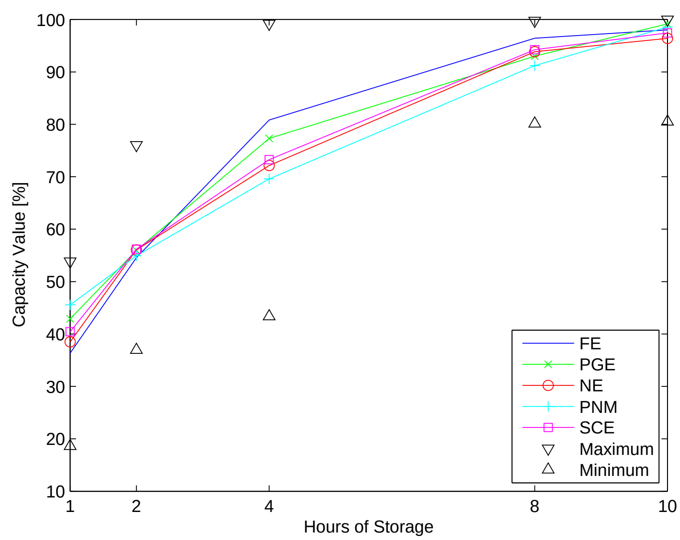

Fig. 2. Average annual ECP estimates for storage devices over the study years 1998–2005.

For instance, the ECP of storage with four hours of capacity in the PG&E system ranges from a low of 60% in 1999 to a high of 99% in 2004. Figs. 3 and 4 show hourly prices and storage dispatch on the day from each of these two years with the highest LOLPs. The figures show the beginning storage level in each hour if no outages occur and the $\xi_t(0)$ values computed from recursion (24). Energy prices on 12 July, 1999 peak in hours 12 through 16 whereas the highest LOLPs occur later in hours 17 and 18. Thus, a profit-maximizing storage operator opts to discharge the device in hours 12 through 16 to exploit the relatively high energy prices. This results in no stored energy being available in hours 17 and 18 and a modeled EFOR of $\xi_{17}(0) = \xi_{18}(0) = 1$ for the storage device when it is most needed to improve system reliability.

The energy price pattern is markedly different on 9 September, 2004. On this day, prices peak in hours 16 and 20

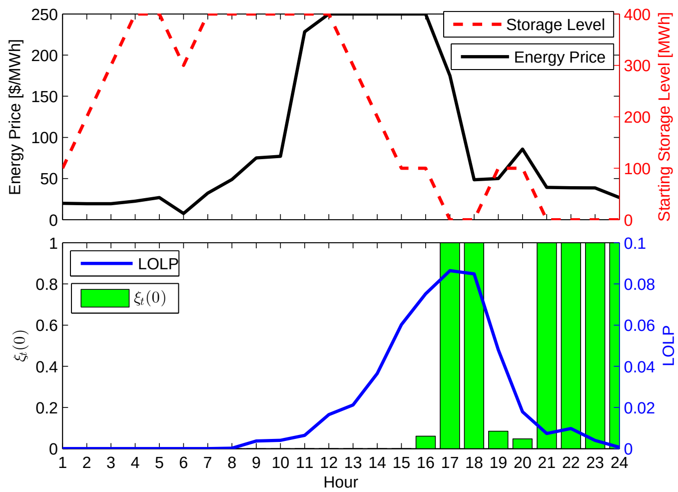

Fig. 3. Hourly energy prices, LOLPs, and storage dispatch in PG&E system on 12 July, 1999.

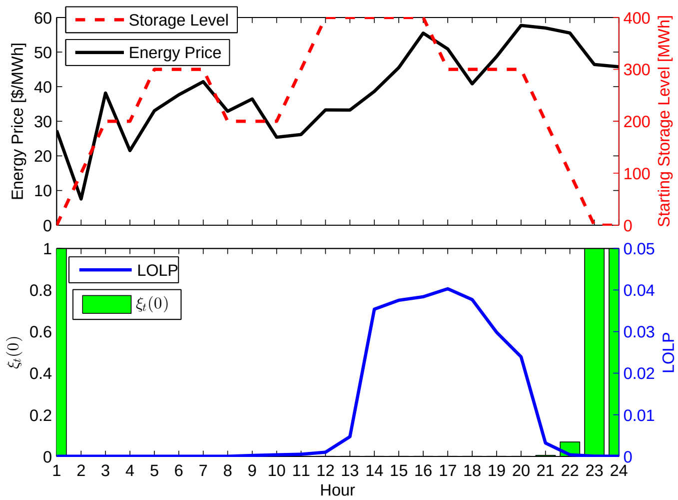

Fig. 4. Hourly energy prices, LOLPs, and storage dispatch in PG&E system on 9 September, 2004.

through 22 while LOLPs peak in hours 14 through 20. Although this price pattern results in the storage device discharging in hour 16, some energy is kept in storage during hours 17 through 22 to exploit future high prices. Thus, even when the LOLPs in the preceding hours are taken into account, $\xi_t(0)$ is nearly zero in hours 14 through 20, when the LOLPs are highest. This means that the storage device is able to provide nearly 100% of its capacity during these crucial hours.

These results point to a potential shortcoming of relying on energy prices only to signal the need for capacity in a system with storage. In theory, spot electricity prices increase as capacity becomes more scarce [29]. If prices are sufficiently high, meaning capacity is scarce, they signal generating capacity to enter the market. A cursory examination of the market data show that the energy prices roughly provide this signal, insomuch as energy prices and LOLPs are positively correlated. However, the capacity value of storage, especially highly energy-constrained devices, is sensitive to diurnal price peaks being coincident with LOLPs, with potentially large capacity value reductions without such coincidence.

Madaeni *et al.* [22] note the same issue with relying on energy prices to signal the operation of a CSP plant with TES for capacity purposes. They explore the use of a capacity payment [30] to provide stronger incentives for a CSP plant to have stored energy available during high-LOLP periods. This mechanism provides generators with supplemental payments that depend on their ability to provide generating capacity during system operator-designated shortage events. They demonstrate that a capacity payment reduces interannual variability in the capacity value of CSP relative to the energy-only case. They further show that a capacity payment increases the average capacity value of CSP plants with energy-constrained TES systems. A capacity payment is, thus, likely to have similar effects on the capacity value of pure storage devices. Moreover, our proposed capacity value estimation technique can be adapted to include a supplemental capacity payment. Doing so simply requires profit contribution function (15) to be changed to include the capacity payment. Madaeni *et al.* [22] show how their mixed-integer programming model of a CSP plant in an energy-only market is adapted to include a capacity payment. The same approach can be used for our dynamic program.

Alternatively, real-time (as opposed to day-ahead) energy prices may have greater coincidence with LOLPs. This is because real-time prices are generated closer to market settlement, and reflect the most up-to-date load and capacity availability data. Day-ahead prices may not signal capacity shortages efficiently, since forced generator outages often manifest when units are started up and operated in real-time. One could also augment the dynamic program model to have storage operations optimized against day-ahead prices, but allow for interim schedule adjustments based on new capacity availability information that becomes available between day-ahead and real-time. Either of these steps could improve capacity values without the need for supplemental payments. An issue with optimizing against real-time prices is that one may have to model price uncertainty, since real-time prices can be more difficult to predict *ex ante* than day-ahead prices [26].

These results also demonstrate that storage's capacity value is dependent on the broader optimization criteria used. Capacity value estimations done to date assume energy-based profit-maximization or cost-minimization [11], [12], [22]. We use the same approach here, since there are no other obvious optimization criteria for which required data are available from all of the systems examined. Nevertheless, storage can be put to many different uses (*e.g.*, frequency regulation, voltage control) [23], resulting in very different operating patterns and capacity values.

B. Maximum Potential Generation Method

We compare our proposed method to the maximum generation approximation. We approximate the capacity values by considering the 10, 100, and 1000 hours of each year with the highest loads, since capacity factor approximations can be sensitive to this parameter [15], [20]. Table II summarizes the capacity value estimates given by our proposed method and the approximation. The numbers in the table are average annual capacity values over all of the utility systems and years studied. The capacity values are given as percentages of the assumed 80 MW net storage discharging capacity.

TABLE II
AVERAGE ANNUAL CAPACITY VALUE ESTIMATES [%]

Hours of	DP Method		Maximum	Generation	Approximation
Storage	ECP	ELCC	Top-10	Top-100	Top-1000
1	40.74	36.26	57.83	53.75	52.24
2	55.53	49.76	73.16	68.54	66.53
4	74.63	66.75	86.46	84.38	80.60
8	93.74	84.74	96.83	95.26	92.59
10	97.92	89.48	99.00	97.28	95.09

Our results show that the approximation overestimates capacity values relative to our method. The overestimation is due to the limitation of the approximation discussed before—it does not account for the effect of a time-t shortage on the subsequent storage level at time $t' > t$. Figs. 3 and 4 show that power systems can have multiple consecutive high-LOLP hours. Even if the storage operator plans to store energy during a high-LOLP period, the expected storage level at the end of a consecutive block of high-LOLP hours may be lower than the d_t^μ values suggest. For instance, $d_{16}^\mu = 100$ MW on the day shown in Fig. 3. Thus, the maximum generation approximation assumes that the storage plant provides a full 80 MW of capacity (net of efficiency losses) during this hour. Our dynamic program recursion shows that when accounting for the likelihood of outages earlier in the day, the storage plant only has about a 94% probability of having energy available during this hour. These differences result in the maximum generation approximation overestimating the capacity value.

The approximation method provides better ECP estimates for relatively energy-unconstrained storage (*i.e.*, eight and 10 hours of storage). This is because such storage devices have a relatively low probability of being depleted at the end of a block of high-LOLP hours. This result is, of course, dependent on the load and generation outage patterns in the historical data used in our analysis. Future power systems may have different LOLP patterns, that may be governed to a large extent by the availability of variable renewable resources.

The approximation is also rather sensitive to the number of hours considered. Using the 1000 highest-load hours of the year provides the closest approximation for an eight-hour storage device whereas considering the 100 highest-load hours provides the best approximation for a 10-hour device. This suggests that if these methods are to be applied to storage, one must be judicious in selecting the number of hours to consider.

VII. CONCLUSIONS

This paper presents a dynamic program-based method to estimate the capacity value of storage. This method properly accounts for system shortages on subsequent storage levels and the amount of energy that storage can provide to mitigate shortages. Using a numerical case study, we demonstrate its use and provide baseline capacity value estimates. We show that the capacity values of storage devices with between one and 10 hours of discharging capacity range between 40% and 100% of nameplate capacity. The capacity values are shown to be sensitive to the coincidence of energy prices and LOLPs. This gives rise to considerable interannual capacity value variability of up to 40%, since LOLP and diurnal price peaks may not be perfectly coincident. We also demonstrate that the only existing approximation method overestimates capacity values for energy-limited storage by up to 22%. While approximations are better for less energy-constrained storage, they are not robust insomuch as the capacity value estimate is sensitive to the number of periods included in the calculation.

The method we outline and our numerical examples only consider the effect of storage's state of charge on its availability. Thus, we implicitly assume that the device does not suffer mechanical failures. Recursive equations (23) and (24) can be easily adapted to account for unplanned storage failures that are unrelated to state of charge. Doing so captures the effect of such failures on the capacity value. Our case study also neglects the effects of transmission constraints and assumes that the system has sufficient capacity to deliver stored energy wherever it is needed. If transmission constraints or outages prevent this, actual capacity values could be lower than our estimates suggest [19].

Although our case study examines a single storage device, our method could be applied to multiple devices. If the devices are operated independently, the dynamic program model can be applied to each device individually. In this case, there is no curse of dimensionality due to having multiple devices. If, on the other hand, there is some interaction between the devices (*e.g.*, they are owned and operated by a single entity that seeks to maximize portfolio profits), one would instead have to solve a larger integrated dynamic program. In this case, there may be scaling issues.

Our model and case study assume that storage is naïvely operated to maximize energy profits only, without accounting for the possibility of shortages and their effect on subsequent storage dispatch. We make this assumption so our underlying behavioral model mimics that used in the maximum generation approximation, providing a meaningful comparison. Our model is, however, agnostic to the specific objective. Tuohy and O'Malley [11], [12] examine PHS that is operated by the system operator to minimize system operation costs. This optimization criterion may result in more stored energy being available during high-LOLP periods, resulting in higher capacity values than our results suggest. Using the maximum generation approximation would nevertheless overestimate the capacity value, due to the inherent limitations discussed before.

Other criteria, such as capacity payments, could be incorporated into the model. Based on our findings, a capacity payment may increase the capacity value of limited-energy storage devices and reduce interannual variability. One could also model non-convex storage startup costs, which may be applicable to certain technologies. Our dynamic program could also be extended to explicitly model shortage probabilities and include future price uncertainty in optimizing storage dispatch. Indeed, if one models a high energy price (*e.g.*, equal to an assumed VOLL) during outage events, this may provide the same incentive to limited-energy storage devices to have energy stored during high-LOLP periods. This could avert the need for a capacity payment mechanism.

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