

A Dynamic Programming Model of Energy Storage

and generation capacity to serve charging loads with relatively high PE penetration. Thus, at least initially, the negative impacts of PE may be at the distribution level.

The distribution system is not able to accommodate the anticipated peak and this can be indicated by how far since the system may only achieve this peak during a handful of hours each year. An alternative is to sit storage on the constrained side of the distribution system. By charging storage when distribution is unconstrained and discharging when loads are high, the distribution system can be downsized. Moreover, such storage can provide additional value to the utility system operator (O) or customers beyond the distribution benefits. For instance, by operating storage in a dynamic islanding mode, it can provide backup energy to customers if there is a service outage. Similarly, storage can be used to provide ancillary services (A) or to arbitrage diurnal day-ahead or real-time energy price differences. A large excess generation capacity that a utility or O reserves to provide a buffer for real-time deviations between actual and forecasted energy demand or supply. [Nourai et al.](#) discuss a market-based distributed sodium-sulfur battery used by American Electric Power (AEP) to provide a distribution-level transformer in West Virginia using storage for utility applications presents operational

V^L penalty for unserved building load
hourly discount factor

Our model assumes that the storage has a minimum storage level R^{\min} . This accounts for technologies such as lithium-ion batteries which suffer from thermal degradation if the state of charge falls too low. The unitless ratios c and d represent efficiency losses from charging and discharging storage respectively.

P^{tr} is the transformer rated power capacity. The transformer can be operated above this capacity however which accelerates transformer aging and imposes a cost. This accelerated aging is typically studied using hot spot or top oil temperature models [24, 25] and [26, 27] respectively. Two examples of such models are [28] and [29]. Studying the effect of operating the transformer above its rated capacity on its overall lifetime. Combining this aging effect with an assumed transformer replacement cost gives a cost for operating the transformer above its rated capacity which would not be V^{tr}/v .

This function which we assume to be convex accrues on an hourly basis and represents the cost incurred in each hour during which the transformer is operated above its rated capacity. Allowing the transformer to be operated above its rated capacity is an added feature of our model compared to that developed by [24, 25]. V^L is the cost penalty for curtailing distribution level loads which are caused by system outages and distribution constraints. Therefore, we can be used however to reduce such curtailments.

2.2 Decision Variables

e_t^d energy discharged for sales in hour t
 e_t^c energy charged into storage in hour t
 e_t^l energy discharged from storage in hour t to serve distribution level load
 l_t distribution level load in hour t
 k_t regulation capacity sold in hour t
 v_t amount transformer is overloaded in hour t
 Also define $A_t = (e_t^d, e_t^c, e_t^l, l_t, k_t, v_t)$ as a vector of hour t decision variables.

2.3 State Variables

x_t total energy in storage at the beginning of hour t
 p_t^e market price of energy in hour t
 p_t^r market price of regulation in hour t
 D_t distribution level energy demand in hour t
 I_t binary variable indicating if there is a system outage (quasi) in hour t
 u_t dispatch to contract ratio of regulation up in hour t

and

$$\begin{array}{ccc} \mathbf{I}_{t+1} & \mathbf{I}_{t+1} & \mathbf{I}_t, \\ \mathbf{u}_{t+1} & \mathbf{u}_{t+1} & \mathbf{u}_t, \\ \mathbf{d}_{t+1} & \mathbf{d}_{t+1} & \mathbf{d}_t. \end{array}$$

Constraints f_1 and f_2 also demand that the amount that the transformer is operating above its rated capacity

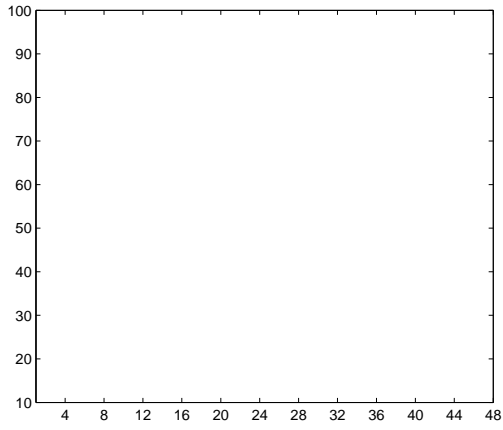
Algorithm 1: Phases of A DP Algorithm for Estimation of $\mathbf{F}_t^{\text{post}}$

- 1: Initialize:
 - Discretize $\mathbf{a}_t, \tilde{\mathbf{t}}, \mathbf{x}_t^{\text{post}}$
 - Initialize $\tilde{\mathbf{m}}_t(\tilde{\mathbf{t}})$
 - Fix \mathbf{x}
- 2: **for** $j = 1$ to J **do**
- 3: Randomly generate a sample path, $\{\tilde{\mathbf{t}}_t^j\}_{t=1}^T$, from the continuous distribution
- 4: Round the continuous sample path to the nearest discretized sample path, $\{\tilde{\mathbf{t}}_t^j\}_{t=1}^T$
- 5: **for** $t = 1$ to $T - 1$ **do**
- 6: $(\tilde{\mathbf{a}}_t, \mathbf{y}_t) \in \arg \max \left\{ \hat{\mathbf{F}}_t^*(\mathbf{x}_t, \tilde{\mathbf{t}}_t, \tilde{\mathbf{m}}_t^{j-1}(\tilde{\mathbf{t}}_t)) \mid \tilde{\mathbf{a}}_t \in \mathcal{A}_{S_t}, (19), (20) \right\}$
- 7: Without loss of generality, suppose $\mathbf{f}_t^{\text{post}}(\mathbf{x}_t, \tilde{\mathbf{a}}_t)$ is the t th discretized value of $\tilde{\mathbf{x}}_t^{\text{post}}$ in rank ordering (*i.e.*, $\mathbf{f}_t^{\text{post}}(\mathbf{x}_t, \tilde{\mathbf{a}}_t) = \tilde{\mathbf{x}}_t^{\text{post}}$)
- 8: $\mathbf{n}_t^u \leftarrow \max\{0, \tilde{\mathbf{u}}_t^c \cdot \tilde{\mathbf{k}}_t - \tilde{\mathbf{d}}_t \cdot (\mathbf{x}_t - \tilde{\mathbf{R}}^{\min}) + \tilde{\mathbf{e}}_t^d + \tilde{\mathbf{e}}_t^l - \tilde{\mathbf{e}}_t^c\}$ and $\mathbf{n}_t^d \leftarrow \max\{0, \tilde{\mathbf{d}}_t \cdot \tilde{\mathbf{k}}_t - (\tilde{\mathbf{R}}^{\max} - \mathbf{x}_t) / \tilde{\mathbf{c}} - \tilde{\mathbf{e}}_t^d - \tilde{\mathbf{e}}_t^l + \tilde{\mathbf{e}}_t^c\}$ {compute unserved regulation}
- 9: $\tilde{\mathbf{x}}_t \leftarrow \tilde{\mathbf{c}} \cdot (\tilde{\mathbf{d}}_t \cdot \tilde{\mathbf{k}}_t - \mathbf{n}_t^d) - (\tilde{\mathbf{u}}_t^c \cdot \tilde{\mathbf{k}}_t - \mathbf{n}_t^u) / \tilde{\mathbf{d}}$ {compute change in storage level from regulation calls}
- 10: $\tilde{\mathbf{t}}_t, \tilde{\mathbf{t}}_t' \leftarrow \left[\hat{\mathbf{F}}_t^*(\tilde{\mathbf{x}}_t^{\text{post}} + \tilde{\mathbf{x}}_t, \tilde{\mathbf{t}}_t, \tilde{\mathbf{m}}_t^{j-1}(\tilde{\mathbf{t}}_t)) - \hat{\mathbf{F}}_t^*(\tilde{\mathbf{x}}_{t-1}^{\text{post}} + \tilde{\mathbf{x}}_{t-1}, \tilde{\mathbf{t}}_{t-1}, \tilde{\mathbf{m}}_{t-1}^{j-1}(\tilde{\mathbf{t}}_{t-1})) \right] / (\tilde{\mathbf{x}}_t^{\text{post}} - \tilde{\mathbf{x}}_{t-1}^{\text{post}})$ and $\tilde{\mathbf{t}}_t, \tilde{\mathbf{t}}_t' \leftarrow \left[\hat{\mathbf{F}}_t^*(\tilde{\mathbf{x}}_{t-1}^{\text{post}} + \tilde{\mathbf{x}}_{t-1}, \tilde{\mathbf{t}}_{t-1}, \tilde{\mathbf{m}}_{t-1}^{j-1}(\tilde{\mathbf{t}}_{t-1})) - \hat{\mathbf{F}}_t^*(\tilde{\mathbf{x}}_t^{\text{post}} + \tilde{\mathbf{x}}_t, \tilde{\mathbf{t}}_t, \tilde{\mathbf{m}}_t^{j-1}(\tilde{\mathbf{t}}_t)) \right] / (\tilde{\mathbf{x}}_t^{\text{post}} - \tilde{\mathbf{x}}_{t-1}^{\text{post}})$
- 11: **for** $i = 1, \dots, M_t$ and $\mathbf{z} \in \tilde{\mathbf{t}}_t$ **do**
- 12:
$$t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}) \leftarrow \begin{cases} (1 - j) \cdot \tilde{\mathbf{m}}_t^{j-1}(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}) + j \cdot \tilde{\mathbf{t}}_t, & \text{if } \mathbf{z} = \tilde{\mathbf{t}}_t, i, \\ & \text{and } i \in \{1, \dots, +1\}; \\ \tilde{\mathbf{m}}_t^{j-1}(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}), & \text{otherwise} \end{cases}$$
- 13: **end for**
- 14: **for** $i = 1, \dots, M_t$ and $\mathbf{z} \in \tilde{\mathbf{t}}_t$ **do**
- 15:
$$\tilde{\mathbf{m}}_t^j(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}) \leftarrow \begin{cases} t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \tilde{\mathbf{t}}_t), & \text{if } \mathbf{z} = \tilde{\mathbf{t}}_t, \tilde{\mathbf{x}}_{t,i}^{\text{post}} < \tilde{\mathbf{x}}_{t,i}^{\text{post}} \\ & \text{and } t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}) \leq t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \tilde{\mathbf{t}}_t) \\ t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \tilde{\mathbf{t}}_t), & \text{if } \mathbf{z} = \tilde{\mathbf{t}}_t, \tilde{\mathbf{x}}_{t,i}^{\text{post}} > \tilde{\mathbf{x}}_{t,i}^{\text{post}} \\ & \text{and } t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \mathbf{z}) \geq t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \tilde{\mathbf{t}}_t) \\ t(\tilde{\mathbf{x}}_{t,i}^{\text{post}}, \tilde{\mathbf{t}}_t), & \text{otherwise} \end{cases}$$
- 16: **end for**
- 17: $\mathbf{x}_t \leftarrow \mathbf{f}_t^{\text{post}}(\mathbf{x}_t, \tilde{\mathbf{a}}_t)$

Algorithm 2 of A DP Algorithm Obtain a Near Optimal Policy

- 1: Fix \mathbf{x}
- 2: **for** $t = 1$ to T **do**
- 3: Observe \mathbf{x}_t from continuous distribution and round it to the nearest discrete $\tilde{\mathbf{x}}_t$
- 4: **if** $t > 1$ **then**
- 5: $\mathbf{n}_t^u \leftarrow \max\{0, \mathbf{u} \cdot \mathbf{k}_{t-1} - d \cdot (\mathbf{x}_{t-1} - \tilde{\mathbf{x}}_{t-1})\}$

R^{nom} and α are the minimum and maximum capacity for each week (as a percentage of R^{nom}). Figure 1 further indicates that the batteries charging and discharging efficiencies are temperature dependent.



its rated capacity is given by the following convex piecewise linear function

$$V^{\text{tr}}(v_t) = \begin{cases} v_t, & \text{if } v_t \in [0, P^{\text{tr}}], \\ P^{\text{tr}} - \frac{v_t - P^{\text{tr}}}{2}, & \text{if } v_t \in [P^{\text{tr}}, 2P^{\text{tr}}], \\ P^{\text{tr}} - \frac{v_t - 2P^{\text{tr}}}{2}, & \text{if } v_t \in [2P^{\text{tr}}, 3P^{\text{tr}}], \\ P^{\text{tr}} - \frac{v_t - 3P^{\text{tr}}}{2}, & \text{if } v_t \in [3P^{\text{tr}}, 4P^{\text{tr}}], \\ P^{\text{tr}} - \frac{v_t - 4P^{\text{tr}}}{2}, & \text{if } v_t \in [4P^{\text{tr}}, 5P^{\text{tr}}], \\ P^{\text{tr}} - \frac{v_t - 5P^{\text{tr}}}{2}, & \text{if } v_t \in [5P^{\text{tr}}, 6P^{\text{tr}}], \\ \dots & \dots \end{cases}$$

Exogenous Random Variables

Although our model and solution algorithm do not require any specific correlation among the exogenous random variables (other than the Markovian property we assume in our case study) that p_t^e , p_t^r , D_t , I_t , u_t and d_t are actually independent. Further assume that p_t^e , p_t^r , D_t , u_t and d_t are serially independent over time.

Historical energy and regulation capacity prices show very little correlation. In particular, these prices had a correlation of about -0.1 . This is because high energy prices signal less generation capacity being available and higher cost generation having to be used to serve the load. High regulation prices signal access of fast responding generation. Indeed, energy prices tend to pair with capacity

gross regulation up and down energy deployment ratio. The data do not show any diurnal or seasonal patterns in the ratios. Thus we assume that the distributions are time-invariant. Hypothesis testing suggests that a Gaussian distribution best fits the historical data, which we assume. Maximum likelihood estimators of the mean and standard deviation are used.

and \mathcal{P}^t discretize the \mathbf{v}_t variables using the breakpoints shown in equation (2.1). The distributions of the \mathbf{p}_t^e , \mathbf{D}_t and \mathbf{d}_t^d random variables are discretized into k_v possible outcomes and the distributions of the \mathbf{p}_t^f random variables into four possible values using brackets. The distribution of \mathbf{I}_t needs no discretization as it can only take on two values.

These assumptions yield a discrete dynamic program given by (2.1) which can be solved using the dynamic programming algorithm. Moreover, we can exploit the structure of our problem to further reduce the feasible action space over which we must search for an optimal solution at step t of Algorithm 2. First, note that due to roundtrip efficiency loss, it is suboptimal to simultaneously charge and discharge energy; thus for all t , \mathbf{e}_t^c cannot be nonzero if at least one of \mathbf{e}_t^d and \mathbf{e}_t^l is and *vice versa*. Hence, the total number of combinations that \mathbf{e}_t^c , \mathbf{e}_t^d and \mathbf{e}_t^l can take in a given hour is M^2 where

$$M = |\{\mathbf{R}^{\min}, \mathbf{R}^{\min} + \mathbf{p}, \mathbf{R}^{\min} + \mathbf{p}^{\text{tr}}, \dots, \mathbf{R}^{\max}\}|.$$

Furthermore, due to the high probability on unserved building loads, the value of \mathbf{l}_t can be determined by (2.1) through (2.3) and the values of \mathbf{I}_t , \mathbf{e}_t^c , \mathbf{e}_t^d , \mathbf{e}_t^l , \mathbf{k}_t and \mathbf{v}_t are completely determined by $\mathbf{l}_t \in \{\mathbf{D}_t, \mathbf{e}_t^l\}$. Otherwise, if \mathbf{I}_t then $\mathbf{l}_t \in \{\mathbf{D}_t, \mathbf{P}^{\text{tr}} + \mathbf{v}_t, \mathbf{e}_t^l\}$. This structural property is that a maximum of $M^2 \cdot |\mathbf{v}_t| \cdot \mathbf{P}^{\text{tr}}$ combinations of action variables are feasible and could be optimal in (2.1).

4. A DP Algorithm Implementation

Nascento and Powell (2017) prove that the piecewise linear approximations of the $\mathbf{F}_t^{\text{post}}$ functions which are stated in Algorithm 2 converge to the

battery costs from regulation and that it provides much more regulation than arbitrage. This is because regulation is primarily a capacity service resulting in relatively little energy charging or discharging. This means that this service tends to incur little cost and compareably high revenues. Although the dispatch to contract ratio in a particular hour can be high (e.g. wind cases of up to 100%), in the historical PJM data the regulation up and down signals tend to cancel out in the long run. Our situation has high ratios of up to 100% but the average ratio over the year is much lower at 20% which is consistent with the historical PJM data. Thus on average providing regulation results

Table 1: Upper and lower bounds on optimal DP objective function value

Bound	Value [\$]	Standard Error [\$]
B_L	2172.7	18.74
B_U	2215.4	22.39

Long-Term Distribution Infrastructure Design

Optimizing distribution infrastructure design involves an economic trade-off between the upfront transformer upgrade and battery installation capital costs and the associated straddle of revenues and avoided costs. These are combined with an assumed annual discount rate to compute the net present value (NPV) of different infrastructure designs and to determine an NPV-maximizing deployment. We compute this NPV over a 20-year period, which is a standard design life of a distribution transformer. Below we present the results of this analysis with the cost and revenue assumptions underlying it.

5.2. Cost Assumptions

Our cost assumptions are based on typical values reported to us by AEP. The transformer is assumed to cost \$120,000 per MVA, with a 20-year life. The battery is assumed to cost \$1,000 per kWh, with a 10-year life.

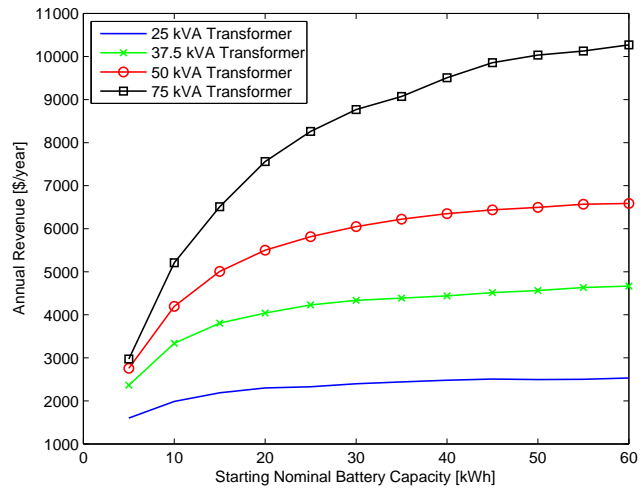


Fig Expected annual battery operating revenue

larger battery or transformer gives greater revenue since

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