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# Blow wind blow: Capital deployment in variable energy systems

Adam R. Brandt<sup>1</sup>, Holger Teichgraeber<sup>1</sup>, Charles A. Kang<sup>2</sup>, Charles J. Barnhart<sup>3</sup>, Michael A. Carbajales-Dale<sup>4</sup>, and Sgouris Sgouridis<sup>5</sup>

<sup>1</sup>Department of Energy Resources Engineering, Stanford University

<sup>2</sup>ResFrac Corporation

<sup>3</sup>Department of Environmental Sciences, Western Washington University

<sup>4</sup>Department of Environmental Engineering and Science, Clemson University

<sup>5</sup>Dubai Energy & Water Authority

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## 1 Abstract

Future energy systems will inevitably rely much more on variable renewable energy. This transition has implications for capital equipment in the energy gathering, processing, and end-use sectors. We define a “flexible energy strategy” (FES) as an energy capital investment and associated operating strategy that can increase usage of variable renewable energy. The literature on FES options is vast and many options have been explored, such as electrochemical storage, demand management, or flexible manufacturing. However, FESs have been difficult to compare to date because of large variation in the details of technology characteristics and possible operating strategies. We develop a purposely simplified framework for consistent inter-comparison of FESs that uses the levelized cost of peak energy (LCPE) – energy provided at times of high electricity prices. We show that various FESs which differ in many details can be represented at a more abstract level with a small number of common terms (e.g., \$ per W). We develop analytical solutions for LCPE for four broad classes of FESs. We evaluate these equations for four template variability cycles with empirical FES data. Our simple framework recreates intuitive and oft-cited results from the literature (i.e., challenges of seasonal-scale variability) and points to concrete targets for energy storage technologies.

## 2 Introduction

Pre-industrial societies harnessed available energy from natural flows – wind, water, or sun – when available. A traditional European children’s rhyme illustrates this fact: “Blow wind blow, and go mill go / that the miller may grind his corn / and the baker may take it / and into bread make it / and bring us a loaf in the morn.” In such an economy, capital investment in machinery was predicated on partial usage, such that equipment could only be used when energy flows were available. The only effective large-scale storage of energy availability over seasons was biomass energy, either burned or consumed in human and animal-powered machinery. Despite this variability in energy supply, over time increasingly complex renewable-powered machinery was developed [1, 2]. For example, wind-powered milling, water-powered ore grinding, forging, and lumber sawing, and solar-powered food dehydration were developed. These technologies increased productivity and reduced requirements for menial human labor.

By shifting to fossil energy resources, energy supply became decoupled from natural flows [1, 2]. Energy was extracted as needed from stocks with exhaustion times of decades or centuries. Because energy could be delivered as needed, industries and other end users no longer needed to concern themselves with temporal variation in supply. This enabled energy transformation and use – and attendant large capital investment – with large power densities and high utilization factors. For example: 24-hour grain processing or ore crushing and milling – which would be impossible with wind-driven mills – becomes possible and capital efficient; with dispatchable energy the same investment in milling machinery can now produce more output.

Future energy systems will depend on larger fractions of renewable energy from variable, naturally-driven flows. Such systems will require more flexible use of capital for energy extraction, storage, conversion, and utilization, with lower capacity utilization factors. By definition, a lack of at-will extraction of energy from the environment requires some capital utilization flexibility to buffer the mismatch between demand and supply.

We will define broadly a flexible energy strategy (FES) as: (1) the combination of an energy technology and (2) its operating strategy that (3) increases the adaptability of the energy system to variable energy fluxes [3]. FESs can take innumerable forms and a vast number of papers have been written proposing FESs in energy supply, demand, and storage sectors. These FESs include investing in new energy technology, operating existing technology differently, or both. We will focus here on electrical energy system FESs. To the extent that non-electrical systems are involved, we will study them in their effect on electrical energy supply (e.g., thermal storage used to shift power-to-heat consumption).

Many different FESs are in use or have been proposed. First, dispatchable electricity generation is used to “fill in” gaps in variable power supply. When instantaneous demand exceeds supply, then dispatchable power generation systems (e.g., gas turbines) are called upon to provide additional power. These systems have become more important in regions with large penetration of variable renewable power. For example, in California, natural-gas-based power generators are called upon daily to increase production – by as much as 10-12 GW in a 40 GW system – as the sun sets and solar PV output stops [4].

Second, variable renewable power can be expanded, ideally in locations with

uncorrelated output so that generation at the new facilities can buffer variability at existing plants. When generating at times of high demand, these systems will reap high power prices, while excess power at times of low demand can be directed to another region via long-distance transmission or curtailed in worst-case scenarios [5]. For example, curtailment of excess wind power currently occurs in Texas at some times, when generation in remote West Texas exceeds local demand and the capacity of transmission lines to large East Texas demand centers [6].

Third, electrical energy can be stored at times of low value for use later. Electrical energy storage technologies include conventional batteries [7, 8], flow batteries [9], pumped hydroelectric storage [10, 11], compressed air energy storage [12], or rotational kinetic storage [13]. Electrical energy storage is currently challenged by high capital costs, although progress in lithium ion batteries is rapid.

Finally, demand may be managed with industrial, commercial, or residential demand response [14] or variable operation of energy-intensive capital equipment. Since 2014, numerous studies have examined variable operation of chemical facilities [15, 16, 17, 18], manufacturing [19], separations [20, 21], or primary metals processing [19]. In these papers, a common approach optimizes operating profiles given changing electricity prices.

Management of the grid under large penetration of variable renewable power is a subject of extensive research. [22, 23, 24]. Some of these studies overlap with the above literature on demand response in electricity intensive industries [25]. The key features of grid-specific optimization studies is that they can represent the spatial complexity (i.e., nodal structure of grid) as well as hourly operations management and dispatch [26, 27]. These features of the models add realism, but can obscure the fundamental features of the problem through their complexity.

Given the vast array of FES options, questions loom: Which type of FES technology should be used to address electricity over- or under-supply at various time scales? Are some technologies better suited to some kinds of fluctuations? When should we use storage technologies compared to simply shifting demand in time? What FES represents the most efficient deployment of capital? How will the profitability of an FES be affected by changes to future cycles in electricity prices?

The answers to these questions depend on numerous factors: a bewildering set of technical and economic details for each technology, which of many strategies might be used to operate the technology [3], and the existence of various interrelated economic and environmental goals motivating the use of a given FES.

We aim here to “cut through the clutter” by developing a simple framework to compare FESs. This approach is motivated by a goal of obtaining a simple set of relationships between these technologies with a minimum of terms. While we neglect many details about any given technology, the model we develop allows for analytical solutions that yield insights and intuitions not otherwise available. Our approach is purposely simplified and abstract as we feel that this allows for building of intuition that is lost when examining the details of any given FES. Our purpose here is to develop analytical models with a minimum of terms that would allow us to compare FESs that have widely varying characteristics.

We first derive a mathematical framework for comparing various FES options based on the common useful service they provide: providing energy at times of peak energy demand. To do this we propose a metric called leveled cost of peak energy (LCPE), which computes the cost in common units [\$/MWh] of supplying an ad-

ditional unit of energy or reducing a unit of demand at times of high power prices. Core to the concept is that FESs rely on utilization of capital in a flexible manner to deal with variable energy availability (and thus variable prices). Such FES deployments result in under-utilization of some form of capital, either supply or demand, at some time, as the system matches variable power supply with variable power demand. Tying these options together with capital intensity factors and utilization fractions allows a structurally similar set of equations despite the diversity of these FES options. We then take these derivations and apply them to simple “illustrative” temporal cycles in energy prices. We create four illustrative cycles that represent the kinds of fluctuations that will need to be mitigated by FESs. By examining the interaction of each FES strategy with cycles of different properties, we show that some FES classes excel at addressing some types of variability. Finally, we estimate LCPE using empirical data for 15 deployed or proposed FESs operated under our four illustrative cycles.

### 3 Flexible Energy Strategies (FESs): Model derivations

For simplicity we classify FESs into four categories:

- A “dispatchable generation” (DG) FES that provides energy on demand at times of high electricity prices;
- An “energy storage” (ES) FES takes in energy at one time period and supplies energy at times of high electricity prices (e.g., pumped hydro storage or lithium ion batteries);
- A “variable overbuild” (VO) FES overbuilds variable energy production technologies, from which energy is extracted for use at times of high prices and excess generation is sold for low price or curtailed at times of low demand;
- A “flexible production” (FP) FES varies the rate at which facilities use energy to create energy-intensive products or services, avoiding production at times of high prices by load shifting or load shedding.

In any FES, energy flows into and out of a *process* (a technology or inter-related set of technologies), at rates that vary depending on an operating strategy. Flow rates are denoted using dot notation (i.e.,  $\dot{e}$ ) and inflows and outflows are use subscripts  $i$  and  $o$ , respectively (e.g.,  $\dot{e}_i$ , energy flow into the process [MW]). The maximum flow or storage rates use double overbars, such as max inflow rate  $\ddot{e}_i$ . Energy can be stored in some processes denoted by  $E$ .

First law conversion efficiencies for energy transformations of both thermal and electrical energy are given by  $\eta$ ,  $[\frac{\text{MWh}_{\text{out}}}{\text{MWh}_{\text{in}}}]$ . For simplicity, we assume that a single efficiency can be used to represent a technology. In reality, processes may have efficiencies that differ by location installed or by operating strategy, but we neglect these complications.

To model operating strategies in analytical form without requiring numerical optimization, we assume time is decomposed into illustrative cycles with length  $\tau_{cy}$  [h or h/cycle]. Each cycle is comprised of a low price time with duration  $\tau_l$  [h] and a high price time with duration  $\tau_h$  [h], such that  $\tau_{cy} = \tau_l + \tau_h$ . The cycles

repeat with  $N$  cycles occurring in a year [cycles/y], so  $N\tau_{cy} = 8760$  [h/y]. Times of low prices  $\tau_l$  represent times of low local power demand relative to local variable generation, while  $\tau_h$  are times of high demand relative to local variable generation. The maximum number of times a system can be cycled over its lifetime is given by  $N^{max}$  [cycles].

Each process is paired with an operating strategy that acts to increase energy availability at times of high electricity prices  $\tau_h$  in a cycle. One could also model other operating strategies, and in real-world operations, optimization routines are used to determine optimal operating strategy for a given FES under any arbitrary price cycle. To facilitate analytical solutions here we: (1) assign a single indicative operating strategy to each FES; (2) consider only full-load operation of systems; (3) include no efficiency or cost penalties during transitions between different operating states; (4) ignore the time to transition between different operating modes (i.e., we ignore any transient effects); and (5) assume that the calculations hold for small scales of deployment such that we can ignore feedback between deployment of the technology and the resulting power price curves (i.e., investments are small enough to be price takers).

The values (prices) of each flow are denoted by  $p$  as follows:

- The price of electrical energy at times  $\tau_l$  is  $p_l \left[ \frac{\$}{\text{MWh}} \right]$
- The price of electrical energy at times  $\tau_h$  is  $p_h \left[ \frac{\$}{\text{MWh}} \right]$

The system has capital costs  $K$  associated with its maximum energy flow rates and maximum energy storage capacity (if applicable):

- Cost of energy inflow or outflow capacity,  $K_{\bar{e}_i}$  or  $K_{\bar{e}_o}$ ,  $\left[ \frac{\$}{\text{MW}} \right]$
- Cost of energy storage capacity:  $K_{\bar{E}}$ ,  $\left[ \frac{\$}{\text{MWh}} \right]$ ,

In some processes, the capital cost of the process is dominated by one of these factors. For example, in batteries, cost is driven mostly by  $\bar{E}$ , the total energy holding capacity, while in the case of a wind farm, the capital cost is proportional to the power output capacity  $\bar{e}_o$ . The equipment or process has a lifetime of  $y = (N_{max}/N)$  years. At an interest rate  $r$  the system will face a yearly capital recovery factor (CRF) of:

$$CRF = \left[ \frac{r(1+r)^y}{(1+r)^y - 1} \right], \quad \left[ \frac{1}{y} \right] \quad (1)$$

For our purposes, it will be useful to define an hourly capital recovery factor:

$$f = \frac{CRF}{N\tau_{cy}}, \quad \left[ \frac{1}{\text{h}} \right] \quad (2)$$

where  $N\tau_{cy} = 8760$  is the number of total hours per year.

## 4 Derivation of metrics for flexible energy strategies

In this work, each FES includes a single pre-defined operating strategy that responds at high price times  $\tau_h$  by either increasing energy supply or reducing energy demand. Some FESs have other effects as well: storage also consumes power at times of low prices, and production processes also produce material goods or services as they use energy.

For comparability, we will normalize benefits of each FES by the amount of energy availability provided at high price times. We compute the *levelized cost of peak energy* (LCPE). LCPE is defined analogously to the levelized cost of energy (LCOE): it is the annualized cost of operation divided by the annualized delivery of energy (in our case energy at times  $\tau_h$ ). LCPE is uniquely useful for comparing FES options because it measures electricity provision when it is most needed (during high price times), distinguishing it from LCOE, which measures electricity provision without special regard to timing. LCPE is defined as follows:

$$LCPE = \frac{C_{op} + CRF \times C_{cap}}{E_h} \left[ \frac{\$}{\text{MWh}} \right] \quad (3)$$

where  $C_{op}$  is the operating cost per year [\$/y],  $C_{cap}$  is the total capital cost of the FES [\$], and  $E_h$  is the total energy supply provided (or energy demand avoided) during high price cycle times  $\tau_h$  [MWh/y]. Note that for simplicity below, we generally do not include variable O&M costs in the  $C_{op}$  term, and neglect these evenly for all technologies. Operating costs are included for FESs that purchase energy such as dispatchable gas turbines buying natural gas or batteries buying power to store. Future work could include more operating cost terms.

By comparing LCPE instead of LCOE, we take into consideration that some energy is more useful than others to the system, and that capital is spent to provide that energy alone. In the case of LCPE, energy provided at times of high prices (i.e. at times of high net demand) is useful to the system, whereas energy provided at times of low prices (i.e. at times of low net demand) is not useful. The costs of the system are thus normalized by the useful fraction of energy  $E$ , which occurs at times of high prices  $\tau_h$ .

### 4.1 Dispatchable generation (DG)

The schematic operating profile for the DG FES is illustrated in Figure 1. At times of low prices the system does not generate power and at times of high prices  $\tau_h$  the system generates power. We make the simplifying assumption that the low power price  $p_l$  does not cover the marginal fuel cost of generating power, so the DG operator is not incentivized to generate during  $\tau_l$ . While generating there is no part-load operation, so  $\dot{e}_o = \dot{e}_{\bar{o}}$ .

Yearly variable fuel costs of power generation are:

$$N\tau_h\dot{e}_o\frac{1}{\eta_e}p_F \left[ \frac{\$}{\text{y}} \right] \quad (4)$$

where  $N$  is the number of cycles per year [cy/year],  $\tau_h$  is high price time per cycle [h/cy],  $\dot{e}_o$  is produced power [MW<sub>e</sub>],  $\eta_e$  is the efficiency of power generation



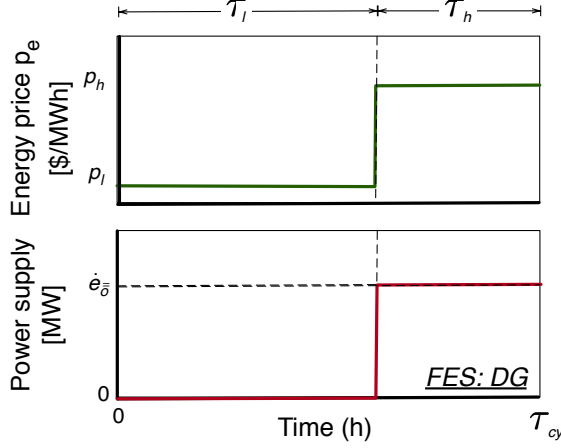


Figure 1: Schematic showing operating profiles for DG FES option with prices  $p_l$  and  $p_h$

[MWh<sub>e</sub>/MWh<sub>th</sub>], and  $p_F$  is the cost of fuel [e.g., natural gas, \$/MWh<sub>th</sub>]. Capital costs are:

$$C_{cap} = K_{\bar{e}_o} \bar{e}_o \quad \left[ \frac{\$}{y} \right] \quad (5)$$

where  $K_{\bar{e}_o}$  is the cost of power output capacity [\$/MW],  $\bar{e}_o$  is the size of the system in output energy [MW]. Annualized costs  $C$  are thus:

$$C = N\tau_h \bar{e}_o \frac{1}{\eta_e} p_F + CRF \times K_{\bar{e}_o} \bar{e}_o \quad \left[ \frac{\$}{y} \right] \quad (6)$$

Applying the simplifying assumption that the system operates at nameplate capacity ( $\dot{e}_o \rightarrow \bar{e}_o$ ) we can compute the cost per unit of peak energy provided (energy supply high price times  $\tau_h$ ):

$$LCPE \equiv \frac{C}{N\tau_h \bar{e}_o} = \frac{1}{\eta_e} p_F + \frac{CRF}{N\tau_h} K_{\bar{e}_o} \quad \left[ \frac{\$}{J} \right] \quad (7)$$

Some quantities here will appear throughout the derivations below. We can define a *utilization factor*  $u$  as the fraction of time per year spent providing useful service, so:

$$u = \frac{\tau_h}{\tau_{cy}}, \quad \therefore \quad \tau_h = u\tau_{cy} \quad \tau_l = (1-u)\tau_{cy}. \quad (8)$$

In the case of dispatchable power this is when the facility is active, i.e. flexible energy supply at times of high prices. Also recall the capital recovery factor per hour defined above as  $f = CRF/\tau_y = CRF/N\tau_{cy}$  [1/h]. So, in more concise form:

$$LCPE_{DG} = \frac{1}{\eta_e} p_F + \frac{1}{u} f K_{\bar{e}_o} \quad \left[ \frac{\$}{MWh} \right] \quad (9)$$

It is also useful to re-frame our capital cost in consistent units for simplicity of exposition. If  $K$  is the cost per MW [\$/MW], then we can combine it with the

hourly capital recovery factor  $f$  [1/h] to obtain a levelized cost of capital per MWh, which we denote as  $\kappa$  [\$/MWh]:

$$LCPE_{DG} = \frac{1}{\eta_e} p_F + \frac{1}{u} \kappa_{\bar{e}\bar{o}} \quad \left[ \frac{\$}{\text{MWh}} \right] \quad (10)$$

Other ways to derive this result are possible. Using similar definitions as above, and accounting for the fact that the power generated during peak times will be sold for  $p_h$ , we compute a yearly profit function for the operator of a plant. We can subtract operating costs and annualized capital costs from revenues:

$$P = R - C = N\tau_h \dot{e}_{\bar{o}} \left( p_h - \frac{1}{\eta_e} p_F \right) - CRF \times K_{\bar{e}\bar{o}} \dot{e}_{\bar{o}} \quad \left[ \frac{\$}{\text{y}} \right]. \quad (11)$$

Through similar manipulations as above, we compute an effective breakeven price at high times,  $p_{h,0}$  that makes the yearly profit equal to 0. At  $p_h$  higher than this value  $p_{h,0}$ , yearly operating profits will be positive and NPV will be positive. We see that:

$$p_{h,0} = \frac{1}{\eta_e} p_F + \frac{1}{u} \kappa_{\bar{e}\bar{o}} \quad \left[ \frac{\$}{\text{MWh}} \right] \quad (12)$$

Therefore:  $LCPE$  is identical to the high price  $p_h$  required to cause the system to have positive NPV when only operating at times  $\tau_h$ . We will structure the other schematic FESs similarly below to render all comparable, focusing on the LCPE (though noting that breakeven prices could be used as well).

## 4.2 Energy storage (ES)

We treat energy storage simply, ignoring factors such as degradation and labor costs. Using a similar derivation as above, the yearly variable costs of storage are the costs of buying power to charge the battery:

$$N \dot{e}_o \frac{1}{\eta_{rt}} \tau_h p_l \quad \left[ \frac{\$}{\text{y}} \right] \quad (13)$$

where we note that the total power into the battery at low price times of a cycle is multiplied by the duration and the round trip storage efficiency to account for storage losses, or  $\frac{1}{\eta_{rt}} \dot{e}_o \tau_h$ . To provide service under a given cycle, a storage system needs sufficient storage capacity measured in service time as an energy-to-power ratio with units time (i.e., [h]). This ratio is defined as  $\bar{\bar{E}}/\dot{e}_{\bar{o}}$  [h]. For example, for 1 MW power delivery on a daily cycle with 6 MWh of storage, the energy-to-power ratio would be 6 h. We only consider utilization factors  $u \leq 0.5$ , and because we assume charge and discharge at full battery capacity (equal on input and output side), charging the battery is then not limited by  $u$ . If the number of cycles per year is small and the delivery time is long, e.g., in seasonal storage with one charge-discharge cycle per year,  $\bar{\bar{E}}$  is much larger than  $\dot{e}_{\bar{o}}$  to obtain the useful service. That is, the characteristic discharge time for small  $N$  is very large.

We follow the model of Safaei and Keith [7] and describe storage capital costs as the sum of energy-specific and power-specific capital costs:

$$K_{ES} = K_{\bar{e}\bar{o}} \dot{e}_{\bar{o}} + K_{\bar{\bar{E}}} \bar{\bar{E}} \quad [\$]. \quad (14)$$

Yearly capital costs are therefore:

$$CRF \left( K_{\bar{e}_o} \dot{e}_{\bar{o}} + K_{\bar{E}} \bar{E} \right) \quad \left[ \frac{\$}{y} \right] \quad (15)$$

Assuming that the battery will return to its original state at the end of the cycle ( $\eta_{rt} \dot{e}_i \tau_l = \dot{e}_o \tau_h$ ), the yearly operating cost for the facility then becomes:

$$C = N \dot{e}_o \frac{1}{\eta_{rt}} \tau_h p_l + CRF \left( K_{\bar{e}_o} \dot{e}_{\bar{o}} + K_{\bar{E}} \bar{E} \right) \quad \left[ \frac{\$}{y} \right]. \quad (16)$$

As above we assume operation at full capacity and that the peak energy provided is yearly supply at high price times as  $E_h = N \tau_h \dot{e}_o$ . We then simplify to the same terms as in Eq. 10:

$$LCPE_{ES} = \frac{1}{\eta_{rt}} p_l + \frac{1}{u} (\kappa_{\bar{e}_o} + \tau_h \kappa_{\bar{E}}) \quad \left[ \frac{\$}{\text{MWh}} \right]. \quad (17)$$

### 4.3 Variable energy overbuild (VO)

The variable energy overbuild (VO) FES strategy overbuilds variable generation that generates, when available, at times of high demand ( $\tau_h$ ). For example, a remote wind farm may be connected to an urban region to provide power at peak times. At times of low demand  $t_l$ , two alternatives are possible: (1) the power is sold for the low price  $p_l$ , whatever this happens to be, as the marginal cost of generation of VO is negligible, or (2) the power is curtailed. We focus on case (1) but case (2) is simple to derive.

The cost of VO is dependent on how correlated production from the VO is with other variable local generation that is driving the power price curve. If VO is positively correlated with other local variable generation, little of it may be available at times of peak prices  $\tau_h$ , as times of peak prices are times of high demand relative to local generation. If the invested VO is anti-correlated with local variable generation then it should often provide its power at times  $\tau_h$ . We represent this synchronicity with power prices with a term  $S$  [h/h], that represents the dimensionless fraction of VO generation occurring at times of high prices  $\tau_h$ .

Figure 2 shows three cases of  $S$ , where power generation is: anti-correlated with local generation and therefore correlated with price (top), uncorrelated with local generation and therefore occurring randomly with respect to price (middle); or correlated with local generation and therefore occurring at times of low prices (bottom).

It is simpler to derive VO using the formulation of the LCPE defined as the breakeven  $p_h$  which results in \$0 NPV. VO is assumed to have no variable costs of operation. The yearly total cost is then:

$$C_{VO} = CRF \times K_{\bar{e}_o} \dot{e}_{\bar{o}} \quad \left[ \frac{\$}{y} \right] \quad (18)$$

and the revenues are:

$$R_{VO} = f_c \dot{e}_{\bar{o}} N \tau_{cy} (S p_h + (1 - S) p_l) \quad \left[ \frac{\$}{y} \right] \quad (19)$$

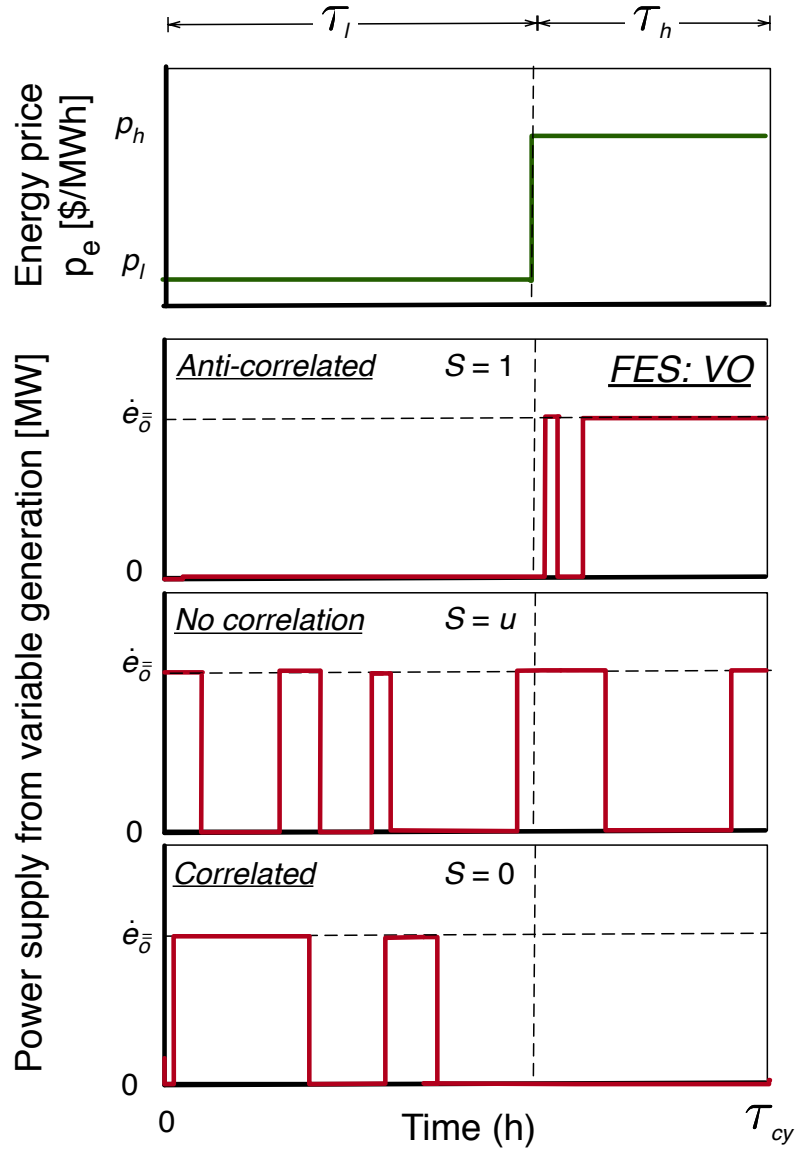


Figure 2: Schematic chart showing a system where remote variable power is built and utilized at times of high demand while curtailed at times of low demand. Three charts show different levels of synchronicity  $S$  corresponding to various levels of alignment between the curtail-able generation and local prices.

The amount of energy provided during  $\tau_h$  depends on the correlation of the available variable generation and the power demand. The amount of electricity supplied at times  $\tau_h$  is:

$$E_p = N\tau_{cy}\dot{e}_{\bar{o}}Sf_c \quad \left[ \frac{\text{MWh}}{y} \right] \quad (20)$$

where  $f_c$  is the capacity factor of the variable resource. The levelized cost of peak energy is the price  $p_h$  at which revenues equal costs:

$$LCPE_{VO} = - \left( \frac{1-S}{S} \right) p_l + \frac{1}{S} \frac{1}{f_c} \kappa_{\bar{e}\bar{o}} \quad \left[ \frac{\$}{\text{MWh}} \right] \quad (21)$$

Some indicative values of  $S$  are worth exploring. In the case of perfect correlation between local and curtail-able generation,  $S = 0$  and all generation occurs at times  $\tau_l$  (see Figure 2 bottom) and LCPE goes to  $\infty$  because no power is generated at times  $\tau_h$ . With perfect anti-correlation between local and VO generation,  $S = 1$  and all VO generation occurs at times  $\tau_h$ . With random synchronicity between the two series, the probability that power will be generated at times of high prices is equal to  $u$ , the fraction of cycle hours in  $\tau_h$ .

In reality, placing VO generation near the point of consumption is likely, in a high renewables future, to result in poor (low) effective  $S$  if the local market is saturated with variable renewable energy. In this case, one may want to include the capital cost of transmitting power over a distance which the curtail-able generation becomes uncorrelated, with an additional loss factor and a second term  $\kappa_{t,\bar{e}\bar{o}}$  representing the capital cost of transmission per MWh (see below).

## 4.4 Flexible production (FP)

A production process that consumes electrical energy to produce a product or a service can be operated flexibly to manage electricity demand. In our case, we assume an energy-intensive manufacturing process producing units of product output (e.g., computation cycles or tonnes of steel). In real-world operations, a rationally-operated facility would only use energy prices to dictate production decisions if the marginal value of producing the next unit was rendered negative by the energy price increase. In our case, we imagine that production is curtailed and compute the cost associated with that curtailment.

We consider a flexible production FES with two operating modes: non-operating and operating. Our simple operating strategy dictates that the production process is non-operating during time  $\tau_h$ , and all material and service flows are zero during this time (Figure 3). For simplicity we assume the production process is not constrained by storage limits like warehouse space. It is useful to define for the production process an energy intensity of production  $\epsilon_{pr} = \dot{e}_i / \dot{r}_o$  [MWh/unit], where  $r_o$  is the product output rate [units/h] and  $\dot{e}_i$  [MW] is the energy input rate to the facility.

We examine two different FP operating strategies. In these cases (see Figure 3), we assume that before FES deployment the facility is operated continuously, and current utilization rates are high ( $\geq \tau_l$ ). The facility in this base operating case consumes energy at some pre-FES rate of  $\dot{e}_i^*$ . The first case, “load shifting”, FP-LS, shifts energy demand from high price times  $\tau_h$  to low price times  $\tau_l$  – while still maintaining product output – by adding capacity and operating this expanded capacity at times of low energy prices  $\tau_l$ . If such capacity is added, the same amount of material or service production can occur in a smaller number of hours and energy consumption can be shifted to times of low prices. In contrast, our second case, called “demand destruction”, or FP-DD, foregoes production during times  $\tau_h$ , incurring lost product or service output but requiring no additional capital cost.

Note we assume as above binary operating conditions. If for engineering reasons (physical or chemical) the modulation of production does not permit complete on/off conditions over shorter cycle times (e.g. aluminum smelting), the approach could be modified to apply for the part of the production that can modulate (for example, linearly scaling capital efficiency factors by the degree of load reduction possible). We avoid such cases for simplicity here.

### 4.4.1 Load-shifting in flexible production

We address load shifting (Figure 3 middle) first.

Examining Figure 3, the operating expenditures on energy for the load shifting case is:

$$\Delta C_{op} = N\tau_l \dot{e}_i p_l \left[ \frac{\$}{y} \right] \quad (22)$$

How much larger is  $\dot{e}_i$  than our previously defined pre-FES facility energy consumption rate  $\dot{e}_i^*$ ? If production from the facility is to remain constant and per unit energy consumption remains the same, then:

$$N\tau_{cy} \dot{e}_i^* = N\tau_l \dot{e}_i \quad (23)$$

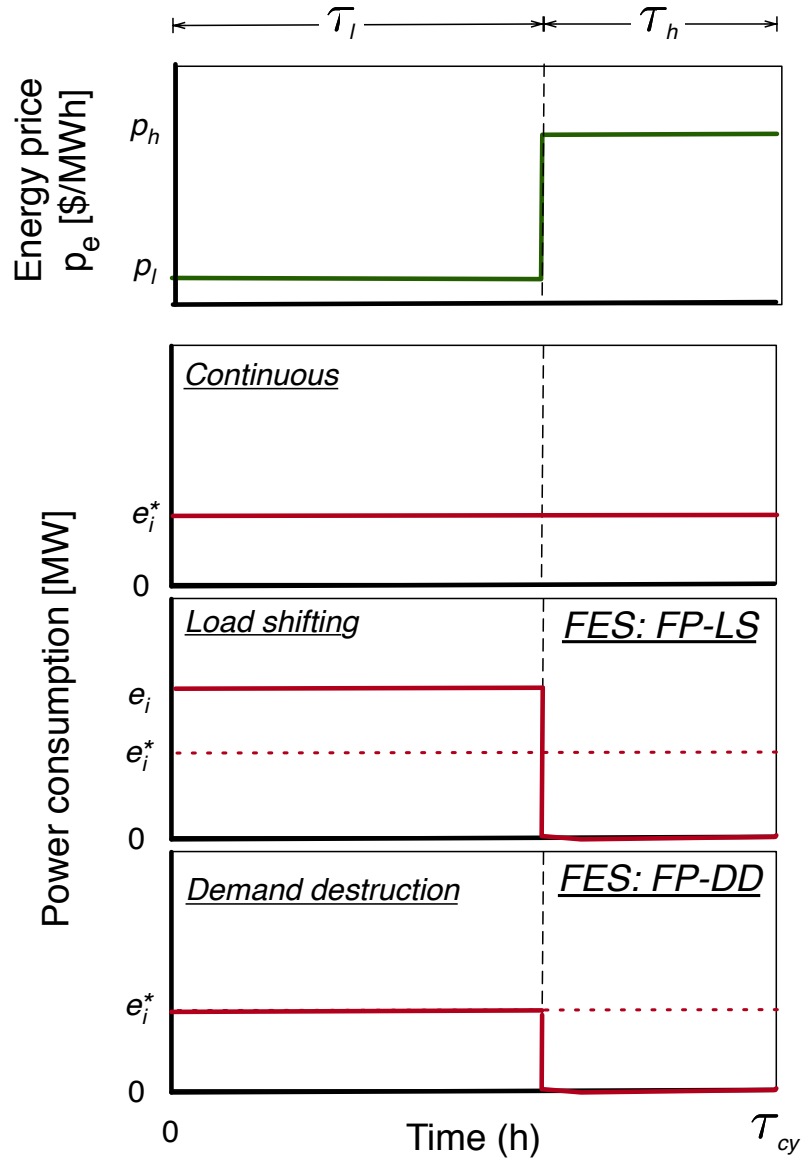


Figure 3: Schematic chart showing energy-consuming production processes that are currently operated continuously are re-organized to avoid consumption during times of high demand and high prices ( $\tau_h$ ). The two approaches maintain overall production (load shifting) or do not maintain overall production (load-shedding).

so  $\dot{e}_i = \dot{e}_i^* (\tau_{cy}/\tau_l)$ . Substituting this in our equation for energy costs:

$$C_{op} = N\tau_{cy}\dot{e}_i^* p_l \quad \left[ \frac{\$}{y} \right] \quad (24)$$

We assume the only change in capital cost to provide the FES is associated with the increased production capacity:

$$C_{cap} = CRF \times K_{ei} \left( \dot{e}_i - \dot{e}_i^* \right) \quad \left[ \frac{\$}{y} \right] \quad (25)$$

Substituting in  $e_i = \frac{\tau_{cy}}{\tau_l} e_i^*$ , we then write capital expenditure as follows:

$$C_{cap} = CRF \times K_{ei} \dot{e}_i^* \left( \frac{\tau_{cy}}{\tau_l} - 1 \right) \quad \left[ \frac{\$}{y} \right] \quad (26)$$

Dividing our increase in capital expenditure by the amount of energy shifted  $N\tau_h \dot{e}_i^*$ , and using the above derived relations for  $\tau_l$  and  $\tau_h$  ( $CRF$  in terms of  $u$  and  $\kappa$ ),  $N\tau_{cy}$ , and  $K$ :

$$LCPE_{FP-LS} = p_l + \frac{1}{(1-u)} \kappa_{ei} \quad \left[ \frac{\$}{MWh} \right] \quad (27)$$

Thus the following qualitative conclusions can be drawn about conditions that favor variable operation in the FP-LS case:

- High differentials in energy costs between operating and non-operating times, i.e.,  $p_h - p_l$ ;
- Low capital recovery factors  $f$  caused by long capital lifetime or low interest rates leading to lower annualized capital costs;
- Low capital cost of the facility per unit power consumed  $\kappa_{ei}$ , resulting in less foregone capital per unit of energy saved;
- High FES utilization fractions  $u$  (more time non-producing) increase the size of the second term (capital inefficiency cost). This is opposite in effect to the other FESs where increases in utilization factor  $u$  reduce the cost of the FES.

#### 4.4.2 Load shedding in flexible production

The cost of lost sales due to curtailed production via load shedding (calling demand destruction, DD, here to avoid confusion with load shifting LS) is:

$$\Delta R_{pr} = N\tau_h r_o^* p_r \quad (28)$$

Given our definition for the energy intensity of product output ( $\epsilon_{pr} = \dot{e}_i^*/\dot{r}_o$  [MWh/tonne]) and noting that the energy we save by curtailing production during high price times is equal to  $N\dot{e}_i^*\tau_h$ , we see that:

$$LCPE_{FP-DD} = \frac{1}{\epsilon_{pr}} p_r \quad \left[ \frac{\$}{MWh} \right] \quad (29)$$



## 5 Comparison

We now compare these FESs in equivalent units of LCPE [\$/MWh]. For easier comparison we assume neutral synchronicity  $S = u$  for VO generation.

$$\begin{aligned}
 \underline{LCPE} &= \text{Var. Inputs} + \text{Power Cap.} + \text{Energy Cap.} \\
 LCPE_{DG} &= \frac{1}{\eta_e} p_F + \frac{1}{u} \kappa_e \\
 LCPE_{ES} &= \frac{1}{\eta_{rt}} p_l + \frac{1}{u} \kappa_e + \frac{1}{u} \tau_h \kappa_E \\
 LCPE_{VO} &= -\left(\frac{1-u}{u}\right) p_l + \frac{1}{u} \frac{1}{f_c} \kappa_e \\
 LCPE_{FP-LS} &= p_l + \frac{1}{(1-u)} \kappa_e \\
 LCPE_{FP-DD} &= \frac{1}{\epsilon_{pr}} p_r
 \end{aligned} \tag{30}$$

We give the terms descriptive names as follows. ‘‘Var. Inputs’’ are the required variable inputs or purchases needed to enable the FES. In the case of DG, this is chemical energy in fuels with cost  $p_F$ , while in the case of energy storage and flexible production variable inputs are power consumed at times of low price with cost  $p_l$ . The case of load shedding variable inputs as lost revenue from non-produced product.

The ‘‘Power Cap.’’ costs are the costs of capital proportional to power output, modulated in all cases by the usage factor  $u$ . Lastly, ES faces a cost of ‘‘Energy Cap.’’, or capital investment proportional to the storage capacity.

These models support three intuitive conclusions regarding (1) capital cost, (2) spreads in electricity prices, and (3) importance of synchronicity for LCPE of variable FESs.

First, capital that is less expensive per unit energy generated or used at full load (smaller  $\kappa_e$  measured in [\$/MWh]) should be used for FESs. For each  $\kappa$  we can re-cast the capital cost per unit of energy supplied by noting dimensionally that,  $\kappa_{\bar{e}}$  has units of \$ per unit of energy and represents the capital cost per unit of service at full load (i.e., \$/MWh in practical terms for energy systems). Because the capital intensity of energy  $K$  is multiplied by  $f$ , the hourly capital recovery factor, lower interest rates result in improved economics for FESs. Capital cost is modulated in all cases fundamentally by  $u$ . Note that  $u$  is analogously defined with the same definition in each equation ( $u = \tau_h/\tau_{cy}$ ), but its interpretation in the operating profile is slightly different in each case. For example: the flexible production option reduces energy use at times  $\tau_h$ , while the battery discharges power and increases supply at times  $\tau_h$ .

Notably, flexible production faces capital cost penalties with changing  $u$  that are opposite to the other FESs: the smaller the utilization fraction  $u$ , the more expensive the other FESs become and the less expensive flexible production becomes. As the peak energy times become a smaller and smaller fraction of the hours per year, the less expensive it is to satisfy it with load shifting (i.e.,  $LCPE_{FP-LS} \propto 1/(1-u)$ ), and the more expensive it is to satisfy it with buildout of dispatchable or variable generation (i.e.,  $LCPE_{DG} \propto 1/u$ )

Also, note that the units of capital cost terms are identical across these broad classes of technologies. That is,  $K_e$  has the same units of \$/W whether the technology is a factory, wind turbine, a battery or a dispatchable power source. This \$/W framework makes it possible to to evaluate, in a consistent and unified manner,

divergent classes of energy-using, energy-storing, and energy-supplying capital. For example: a factory has a capital cost in \$ per W just like a wind turbine does (albeit the power is flowing into the facility rather than out of it).

Second, larger spreads in the cost of energy over a cycle (i.e., lower  $p_l$  for a given  $p_h$ ) improve the value of FESs. In energy storage, larger spreads lead to lower cost for energy to charge up. In flexible production, larger spreads increase the value that can be captured by temporal load shifting.

Note that in reality the price differential ( $p_h - p_l$ ) is a function of  $u$ : if the utilization factor is increased – for example, a battery spends more time discharging – the price differential between producing and non-producing times must drop due to the shift in cutoff positions on the cumulative power price curves [28].

Third, it is useful to note that  $LCPE_{VO}$  contains a term  $f_c$ , – the co-occurrence factor or synchronicity factor – that does not appear in any other FES Type. This is due to a fundamental difference between variable and dispatchable FESs. There are two different types of capital cost challenges for FESs: the capacity factor challenge, given by  $u$  in the above equations, and the synchronicity challenge. The capacity factor challenge reflects that additional capacity must be built to accommodate demand during peak times. The synchronicity challenge reflects that the additional capacity expansion must be synced up with high price times. Dispatchable FESs are subject only to the capacity challenge as they can be synced at will, while variable FESs are subject to both capacity and synchronicity challenges (e.g.  $LCPE_{VO} \propto \frac{1}{f_c} \frac{1}{u}$  while in other FES options  $LCPE \propto \frac{1}{u}$ ).

For variable FESs, synchronicity strongly affects the cost associated with meeting peak demand. Consequently, estimates for variable FESs have a wide range of effective capital costs depending upon the synchronicity value. The two capital cost challenges are multiplicative: the synchronicity challenge ( $1/S$ ) and the capacity factor challenge ( $1/f_c$ ). In a case with neutral synchronicity,  $1/S = 1/u$  and the capital cost is simply modulated by an additional factor of  $1/f_c$ . But synchronicity can vary between 0 and 1, resulting in a wide range of effective capital costs.

We will explore these equations further below using four indicative cycle scenarios and indicative data for real FES technologies.

## 6 Data

In order to analyze the different FESs, we gathered empirical data for the above models for energy technologies as installed in 2018. These data are summarized in Table 1. We assume a common yearly capital recovery factor of  $CRF = 0.1$  (approximately  $y=30$ ,  $r = 10\%$ ).

### 6.1 Dispatchable power generation

Natural Gas Combustion Turbines (NGCT) and Combined Cycle Gas Turbines (CCGT) are widely deployed and operated technologies for flexible and rapidly dispatchable power generation. Investment costs for new build CCGTs are approximately 1 \$/W. For example, the Panda Power Funds “Patriot” generating station in Pennsylvania USA was commissioned in November 2016 at a cost of 830 M\$ for a plant with two 460 MW net power output combined cycle systems (cost of  $\approx 0.9$

\$/W) [29]. The LHV CCGT efficiency for the Patriot station is reported at 60-61% at full load output [29], or a HHV efficiency of 55%. Because a mix of less efficient plants also exist, we assume a range of HHV efficiencies of 40-45%. Cost of gas for power generation in North America ranged from  $\approx$  3-5 \$/mcf over 2013 to 2018 [30], or 11.5 - 19.0 \$/MWh<sub>th</sub> at HHV = 1030 BTU/scf. We assume a central price of 15 \$/MWh<sub>th</sub> (4 \$/mcf).

We use the following ranges for the DPG case:

- $\kappa_{\bar{e}o} = 0.8-1.2$  \$/W
- $p_F = 15$  \$/MWh
- $\eta_e = 0.40-0.45$

For better comparison with other no-carbon FESs, we also include a case with carbon capture and storage, assuming that this doubles the capital intensity of the power plant and reduces the efficiency by a nominal 7.5% to 32.5 - 37.5%.

## 6.2 Energy storage

We take energy storage costs largely from Safaei and Keith [7, Table 1]. Safaei and Keith include capital investment costs per unit of power (\$/kW) and per unit of energy (\$/kWh), as well as round-trip efficiencies, with ranges from literature summarized and listed for a variety of sources. We use their data for pumped hydroelectric storage, or PHS, which stores energy in gravitational potential of raised water; compressed air energy storage, or CAES, which stores energy in pressurized air; classical lead-acid batteries (Pb-A) as found in vehicles and older grid storage applications; and sodium-sulfur (Na-S) batteries. Safaei and Keith list their “best estimates” in bold text in Table 1 of that paper and we use these bold ranges directly. For round trip efficiencies, we use the same bold range from the table. For round-trip efficiencies, Safaei and Keith Safaei2015 find that pumped hydro storage and CAES have lower efficiencies of 0.7-0.8, while batteries can be more efficient with Pb-A reaching 0.9. Capital costs range from low for CAES and PHS, at 10s of \$/kWh, while those of batteries are higher at 100s of \$/kWh.

For lithium-ion batteries and H<sub>2</sub> storage, we use cost data from Zakeri and Syri [8]. For Li-Ion, we use their power control systems cost range (25th to 75th percentile range of 398 to 530 EUR/kW, or  $\approx$  0.4 to 0.5 EUR/W). Their estimates of cost per kWh are quite high, given the older nature of the paper. More recent Li-Ion cost estimates are in the range of 150-250 \$/kWh, so we use this range [31]. For H<sub>2</sub> storage, values for 25th to 75th percentile range from Zakeri and Syri are used directly for power delivery systems and storage system costs. Conversion from EUR to dollars is at 1.15 \$/EUR (Q3 2018).

## 6.3 Variable overbuilt

Our VO case examines wind power. Recent wind costs, at the project level (not turbine level) range from 1-2 \$/W of capacity, with a 2020 average in the United States of 1.44 \$/W [32]. Capacity factors in modern plants can often exceed 40%, with a 2020 average performance of 41% for projects installed between 2015-2018.

We therefore assume a capital cost range of 1 to 2 \$/W and a range of capacity factors between 0.35 and 0.45.

We also create a case where we assume the wind farm is developed in a remote location. Wind energy becomes decorrelated at reasonable distances. Empirical functions exist for correlation as a function of distance for wind resources [33, 34, 35], with many different functional forms proposed. Empirically, distances of 1000-2500 km are sufficient to achieve nearly complete decorrelation between local wind generation and remote wind generation.

In this case,  $\kappa_{e\bar{o}}$  is augmented to include transmission costs as well, modeled here as  $\approx$  \$1/W per 1000 km [36]. Such decorrelation would allow the synchronicity factor  $S$  to approach  $u$ , the simple fraction of high price times.

We assume therefore the following properties for VO with wind power:

- $\kappa_{e\bar{o}} = 1 - 2$  \$/W, or  $2 - 3$  \$/W for cases with required long-distance transmission.
- $f_c = 0.35-0.45$

## 6.4 Flexible production processes

No single source exists for cost of capital investment in energy-intensive industrial processes. We therefore gather data from a variety of sources on five electricity-intensive processes: aluminum smelting, chlor-alkali process, steel electric arc furnace (EAF), air separation units (ASU), and reverse osmosis desalination (RO). For simplicity we assume for all of these processes that they can flexibly respond to the cycles above, while in reality engineering challenges may arise if load shifting or load shedding becomes too intensive or long-lasting (e.g., damage to equipment or product quality degradation).

For aluminum smelting, CRU Strategies found capital cost of 4500 \$/(ton-year) capacity [37, p. 3-6] and specific power consumption of 0.00169-0.00176 MW/(ton-year) of capacity. This results in effective energy-specific capital costs of 2.5-2.6 \$/W. Akhmedov et al. assume 5000 \$/(ton-year) and 12.1-13.3 MWh per ton of aluminum, or 3.3-3.6 \$/W energy-specific capital cost [38].

For the chlor-alkali process, data on recent investment in a Dow-Mitsui plant suggest costs of  $\approx$ 500 \$/ton-year of chlorine [39]. Sridhar et al. [40] give a wide range of capital costs, ranging from 550-2700 \$/tonne-y. Energy costs are estimated at 2.4 - 2.9 MWh per tonne of Cl<sub>2</sub>. These results combine to give energy-specific capital costs of 1.8 - 8.2 \$/W, with the low end anchored at 500 \$/tonne Cl<sub>2</sub> and 2.4 MWh/tonne Cl<sub>2</sub>.

For steel EAF, investment costs range from 150-300 \$/ton-year [41], while energy costs are approximately 0.55 MWh/ton [42]. This corresponds to a energy-specific capital cost range of 2.3-4.7 \$/MW.

For air separation, a reference conventional ASU plant from an NETL study of air separation for oxyfuel combustion was used [43]. This plant produces 539.8 tonne O<sub>2</sub> per hour ( $\approx$ 95% purity O<sub>2</sub>). Total power cost of main compressors and auxiliaries for the ASU are 126.7 MW. Cost is 254.2 M\$, including equipment cost, material cost, direct and indirect labor cost, engineering contingency, process contingency, and project contingency. This leads to an energy-specific capital cost of 2.0 \$/W.

For RO desalination, reported energy costs of desalination for modern systems ranges between 2.5-4 kWh/m<sup>3</sup> [44]. Capital costs are reported to range between 2

Table 1: Capital cost characteristics ( $\kappa$ ) per unit energy and per unit power, as well as efficiencies of various FES technologies. Various data sources and notes, see text above.

Class	Type	$\kappa_{\bar{e}_0}$ [\$/W]		$\kappa_{\bar{E}}$ [\$/kWh]		Eff. [W/W]		Sources
		Low	High	Low	High	Low	High	
DPG	CCGT	0.8	1.2	-	-	0.45	0.55	[29, 30]
	CCGT + CCS	1.6	2.4	-	-	0.35	0.45	Assump
RVG	Wind	1	2	-	-	-	-	[32]
	Wind - remote	2	3	-	-	-	-	[33, 34, 35, 36, 47]
ES	PHS	1.5	2	10	100	0.75	0.8	[7]
	CAES	0.85	2	5	25	0.7	0.8	[7]
	Pb-A	0.45	0.55	300	450	0.75	0.9	[7]
	NaS	0.35	0.8	250	400	0.75	0.85	[7]
	Li-Ion	0.46	0.61	150	250	0.85	0.90	[8, 31]
	H <sub>2</sub>	1.50	3	29	40	0.33	0.42	[8]
FPP	Al. smelter	2.5	3.5	-	-	-	-	[37, 38]
	Chlor-alkali	1.8	8.2	-	-	-	-	[39, 40]
	Steel EAF	2.3	4.7	-	-	-	-	[42]
	Air separation	1.5	2.5	-	-	-	-	[43]
	RO desalination	5	25	-	-	-	-	[48, 45, 46, 44]

and 7  $\$/\text{m}^3\text{-y}$  [45, 46]. This implies energy-specific capital costs of 5-25  $\$/\text{W}$ .

These costs are summarized in Table 1. Note that the exact values from the text are not included in all cases, but are used to create round ranges in many cases.

## 7 Four illustrative cycles

We now define four illustrative cycles, as shown in Figure 4. We see in real-world (California) power price curves (left) some patterns that we can abstract to create simple cycles (right). Any real power system price profile will exhibit a complex mixture of these kinds of cycles (and many more as well at different frequencies). Great complexity exists in methods to create illustrative time series of power prices or renewable power output [49, 50, 51], and we recognize those challenges. The motivation for creating these four indicative cycles is that they are simple enough to provide insights and intuition.

Two of the cycles are daily cycles, with high prices for 6 hours ( $\tau_h$ ) and low prices for 18 hours ( $\tau_l$ ). The *Daily - Current* variant ranges from  $p_l = 30$   $\$/\text{MWh}$  to  $p_h = 70$   $\$/\text{MWh}$  in low and high price times, respectively. The *Daily - High renewables* variant represents a world where large investment in – for example – solar PV installations drives down prices during most hours of the day, but peak demand and less firm generating capacity results in increased electricity prices at peak times. Thus, the *Daily - High renewables* cycle ranges from  $p_l = 15$   $\$/\text{MWh}$

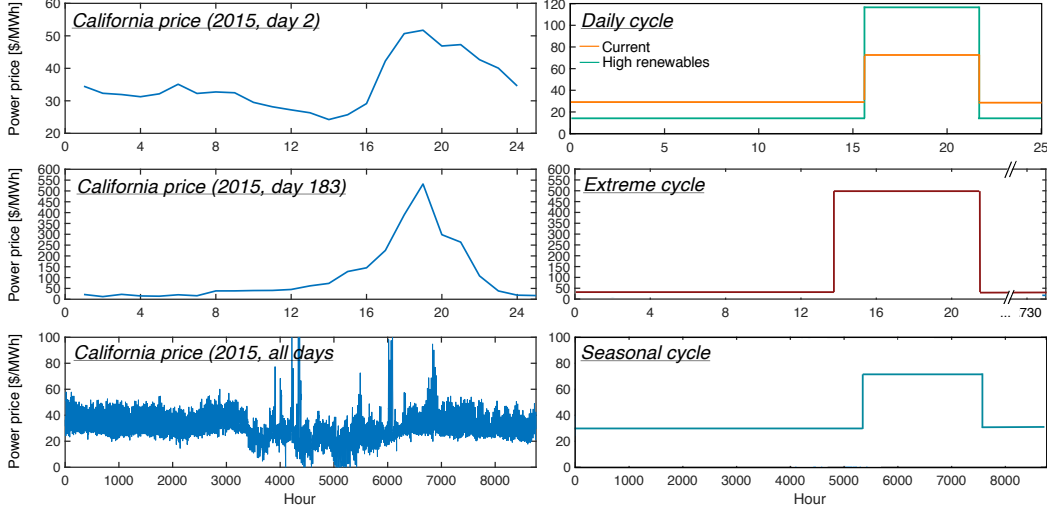


Figure 4: Schematic showing 2015 California electricity prices (STANDFD2\_1\_N011 node) on the left and indicative cycles on the right.

Table 2: Four indicative cycles

Cycle	Cycles	Duration	Duration	Low price	High
	per year	low price	high price	price	price
	$N$	$\tau_l$	$\tau_h$	$p_l$	$p_h$
	[cycle/y]	[h]	[h]	[\$/MWh]	[\$/MWh]
Daily - Current	365	18	6	30	70
Daily - High renewable	365	18	6	15	115
Seasonal	1	6570	2190	30	70
Extreme	12	722	8	35	500

to  $p_h = 115$  \$/MWh. The third cycle is the *Extreme* cycle, which has low prices for most time periods, but has extremely high prices of  $p_h = 500$  \$/MWh for 8 hours at a time, 12 times per year, i.e. the cycle lasts 730 hours. Lastly, the *Seasonal* cycle has the same prices as the *Daily - Current* cycle, but has 9 months of low prices and 3 months of high prices.

Table 2 outlines the characteristics of the cycles. Using these indicative cycles, we can examine the FESs described above with empirical data. The results are summarized in Figure 5 and Table 3.

The insights that emerge illustrate the implications of the technologies examined. First, DG has identical LCPE for all indicative cycles except ‘Extreme’. If the utilization factor  $u$  and cost of input energy remain the same, the cost of DG is not affected by the type of cycle: 25% utilization in a seasonal cycle is as affordable as 25% in a daily cycle. In contrast, for the same value of  $u$  and the same low-high price differential, ES can have wildly different costs. For example compare ‘Daily - Current’ and ‘Seasonal’ cycles. Both have the same low and high prices, and both have  $u = 0.25$ . However, because of the small number of discharge cycles in

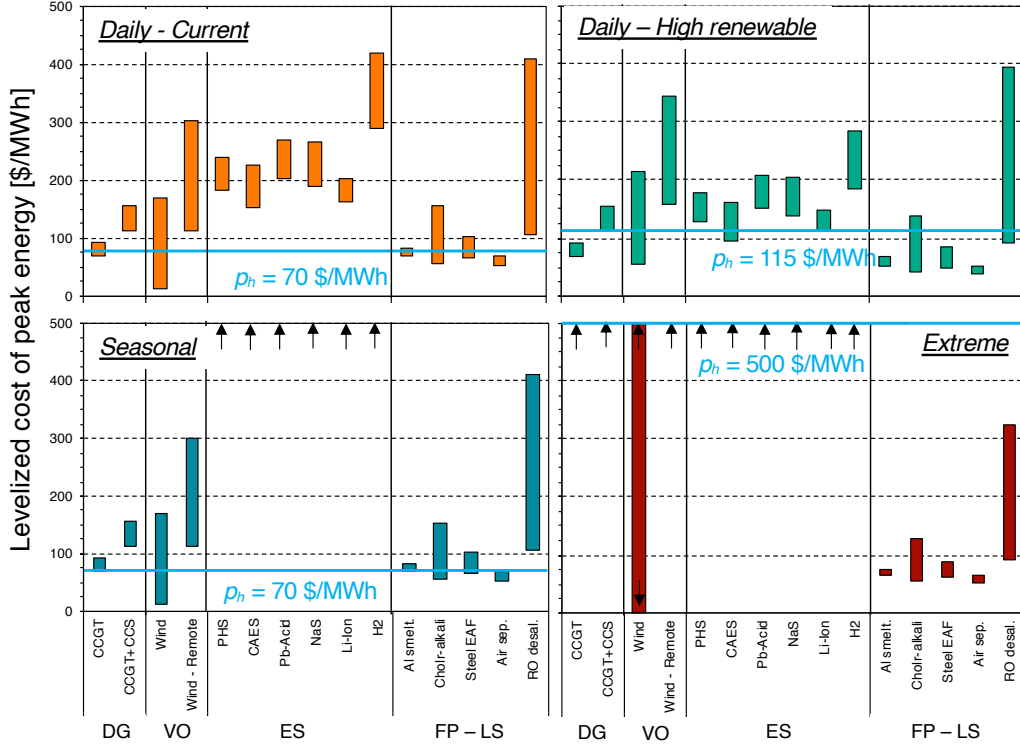


Figure 5: Levelized cost of peak energy (LCPE) for technology options under the four indicative cycles. Arrows represent LCPE higher than the maximum value plotted on  $y$ -axis. For each indicative cycle the high price  $p_h$  is plotted, allowing comparison with LCPE.

‘Seasonal’ (seen in the equation as the long  $\tau_h$  or the long characteristic discharge time, ES is wildly expensive for ‘Seasonal’. This will apply to any storage technology only cycled a small number of times per year.

Despite similar capital costs per W, DG and VO have somewhat different LCPEs. This is because of the combined effect of the utilization  $u$  and the capacity factor  $f_c$  which requires large capital expenditure. These results have been seen in capacity expansion planning models where very large investments (“overbuild”) is needed to provide the last amount of renewable energy in a 100% renewable system.

In general, mitigating ‘Extreme’ cycles is very expensive with LCPEs exceeding 1000 \$/MWh. In general, building capital solely to mitigate infrequent events (in this case 12 times per year) results in incredibly large costs per unit of peak energy provided. This shows the advantage of FP methods: the capital cost is only foregone or disused during peak times, instead of being disused in non-peak times. Thus, LCPEs in the extreme cycles are less than 100 \$/MWh in many cases for FP-LS cases.

## 8 Synthesizing results and discussion

Again, our purpose here was to develop analytical models with a minimum of terms that would allow us to compare FESs that have widely varying characteristics. The

Table 3: Breakeven high prices  $p_h^*$  [\$/MWh] for indicative cycles and technologies above.  $p_l$  in each indicative cycle is equal to that in Table 2

		Daily - Current		Daily - High ren.		Seasonal		Extreme	
		Low	High	Low	High	Low	High	Low	High
DG	CCGT	70	92	70	92	70	92	867	1288
	CCGT+CCS	113	156	113	156	113	156	1707	2546
VO	Wind	11	171	56	216	11	171	-844	2794
	Wind - Remote	113	301	158	346	113	301	1471	5770
ES	PHS	184	239	127	179	1181	10211	5594	7128
	CAES	153	227	96	162	651	2720	4876	6804
	Pb-Acid	203	268	153	208	30121	45145	6478	8535
	NaS	190	266	137	206	25122	40157	6164	8378
	Li-Ion	162	202	112	149	15121	25134	5239	6435
	H2	291	421	184	284	3183	4410	9325	13030
FP	Al smelt	68	83	53	68	68	83	64	75
	Cholr-alkali	57	155	42	140	57	155	56	130
	Steel EAF	65	102	50	87	65	102	62	89
	Air sep.	53	68	38	53	53	68	52	64
	RO desal.	213	654	198	639	213	654	174	508

models are applicable in the basic form for understanding the strategies for investment in FESs for mitigating different types of variability cycles. With additional details and terms for the different FES types, more detailed analysis could be performed. And obviously, more detailed analysis would require applying the models to more detailed time series datasets.

The capital cost penalties associated with disuse of capital during times of a cycle either grows with  $1/u$  or  $1/(1-u)$ , depending on the FES. These two effects occur in the cases of capital providing energy (DG, RVG,  $ES \propto 1/u$ ) and the FES in which disuse of capital increases energy availability ( $FP \propto 1/(1-u)$ ). These two multipliers are equal at  $u = 0.5$ . All else equal, above this level of utilization ( $u > 0.5$ ), it is better to actively invest in capacity such as DG or ES, while at  $u$  less than 0.5 it is more favorable to curtail use of industrial capital via strategies FP. This is a fundamental result that will scale to dealing with cycles of all kinds of frequency of occurrence: the more rare the cycle the more beneficial it is, from a capital usage perspective, to address it by curtailing demand rather than actively supplying energy.

A key challenge with the simplifying framework used here is the artificial separation between deployment of FES technologies and the price cycles. Clearly, over large deployment investments and long time frames, the FESs deployed will strongly affect the price cycles that arise (i.e., installing more storage to deal with a daily cycle will reduce the magnitude of the daily cycle). At the margin, explored here, we believe that this does not invalidate the basic intuition gained. In future work,



longer-term effects could be explored with capacity expansion planning or systems dynamics models.

Another clear area for future work is the superposition of various cycles. Clearly real power price time series are complex mixtures of many different cycle lengths and magnitudes, as well as significant random variability. A given FES may, in reality, be deployed to address multiple kinds of cycles at once, each operating at a given frequency. This suggests that the degree of value harvesting from an FES applied to one of our indicative cycles may be a lower bound.

It is of great interest how we can place all energy generating and producing technologies on the same capital scale of \$ per W of production or consumption. Notably, industrial production processes tend to have higher capital costs  $K$  [\$/W] than DPG or OV. A prime example is RO desalination, which although energy intensive and therefore a potential target for load shifting, is particularly expensive in terms of capital cost. This factor, as illustrated in the above derivations, makes it a less advantageous target for load shifting or shedding. Put more plainly: It does not make sense to solve a capacity shortfall where additional generation capital costs are  $\approx$ \$1 per W by shuttering energy-using capital with capital costs of 10-40 \$/W.

Seasonal storage is likely to be extremely expensive due to low numbers of cycles and high costs of energy storage media inherent in bulk storage of large amounts of energy. Even given the very low cost per kWh stored of CAES, the cost of seasonal storage is prohibitive. Unless this fundamental barrier is overcome, it is much more likely that production of energy intensive products will become seasonal as in earlier economies where primary production was much more seasonal in nature. In these applications, the energy is effectively ‘stored’ in warehoused/storable products waiting for demand.

Further, the framework shows very clearly dedicating capital to mitigate infrequent extreme cycle behavior is likely to be extraordinarily expensive. These cycles occur infrequently enough that the capital costs required to mitigate them with supply are prohibitive. The opposite is true of foregoing production energy demand via the FP strategy. Over a small fraction of hours, energy demand can be shuttered or shifted, resulting in negligible additional capital investment and large monetary savings. This is in line with intuition that a number of responses to variable output of energy are required and that a single FES class – like energy storage – cannot serve as a “silver bullet”.

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