Renewable and Sustainable Energy Reviews 67 (2017) 908–920

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Calculation of levelized costs of electricity for various electrical energy storage systems

Manasseh Obi [a,*], S.M. Jensen [b], Jennifer B. Ferris [c], Robert B. Bass [a]

[a] Department of Electrical & Computer Engineering, Portland State University, Portland, OR, USA
[b] Portland General Electric, Portland, OR, USA
[c] Bonneville Power Administration, Portland, OR, USA

ARTICLE INFO

Article history:
Received 16 July 2015
Received in revised form
26 May 2016
Accepted 9 September 2016
Available online 25 October 2016

Keywords:
LCOE
Energy Storage
Monte Carlo

ABSTRACT

Installed capacity of renewable energy resources has increased dramatically in recent years, particularly for wind and photovoltaic solar. Concurrently, the costs of utility-scale electrical energy storage options have been decreasing, making inevitable a crossing point at which it will become economically viable to couple renewable energy generation with utility-scale storage systems. This paper proposes a methodology for calculating Levelized Cost of Electricity (LCOE) for utility-scale storage systems, with the intent of providing engineers, financiers and policy makers the means by which to evaluate disparate storage systems using a common economic metric. We discuss the variables influencing LCOE in detail, particularly those pertinent to electrical energy storage systems. We present results of LCOE calculations for various storage systems, specifically pumped hydro, compressed air, and chemical batteries, which we then compare with a more traditional arbitrage option, the simple-cycle combustion turbine. Federal and State government electrical energy storage tax incentives are considered as well. We also analyze the sensitivities of LCOE to several key variables using Monte Carlo analysis. Considering the downward-sloping cost trends of storage systems and the increased penetration levels of stochastic and non-dispatchable renewable resources, large-scale storage is becoming a significant issue for utilities, thus justifying the development of a levelized costing algorithm.

Contents

* Corresponding author.
E-mail address: mobi@pdx.edu (M. Obi).

http://dx.doi.org/10.1016/j.rser.2016.09.043
1364-0321/

1. Introduction

In the United States and across the World, installed capacity of renewable energy resources has increased significantly over the past few years. In the U.S., wind power emerged as the top electricity generation investment during 2012, accounting for 42% of new generation capacity for the year [1]. In 2014, new installation of wind power was around 5 GW. At the beginning of 2015, the total nameplate[1] capacity of wind power in the U.S. was around 65 GW, an increase of over 8% from the year prior [2]. As of the fourth quarter of 2012, the total installed capacity of Photovoltaics (PV) in the U.S. was over 7 GW [3]. By 2014, 6.2 GW of new solar power capacity was brought online, a 30% year-on-year increase. This brought the total installed capacity of PV in the U.S. to 20 GW [4]. Globally, installed capacity of wind stood at 318 GW as of the end of 2013, a 12% year-on-year increase, while solar PV capacity rose to 139 GW over that same period, a 39% increase [5]. The increase in installed capacity of stochastic, non-dispatchable electrical energy resources has presented challenges to Balancing Authorities (BAs), dispatchers and marketers. The problems become particularly acute for participants operating within hourly or sub-hourly trading markets [6,7]. For instance, uncertainty regarding the forecast of wind ramping events, specifically the arrival timing and ramp rates, affect a dispatcher's options for maintaining balance between generation and consumption, and a marketer's ability to satisfy contractual energy delivery obligations. Consequently, more spinning reserves might be held in order to provide arbitrage opportunities [8,9]. Similar challenges arise with solar generation, for both PV and Concentrating Solar Thermal (CST), especially intermittencies and ramping events due to cloud coverage [10,11]. The inherent problems of these stochastic distributed generation resources may be mitigated by coupling them with electrical energy storage facilities, such as Pumped-hydro Energy Storage (PES), Compressed Air Energy Storage (CAES) and chemical Battery Energy Storage Systems (BESS) (uniquely, CST may be coupled with on-site thermal energy storage) [12–16]. PES comprises the overwhelming majority of installed storage systems, accounting for over 99% percent of all storage worldwide [17,18]. The example cases in this paper focus on three specific technologies: PES, CAES, and BESS. With regard to BESS, we consider lead acid, advanced lead acid, lithium ion and several varieties of flow batteries [19–21]. Rising popularity and burgeoning market parity of disparate energy storage technologies are the result of multiple concurrent drivers, including manufacturing advancements, smart-grid regulatory goals, government support measures for meeting renewable portfolio standards, and increased R&D funding. For instance, costs for lithium-ion batteries have been decreasing rapidly, largely spurred by market demands from the Electric Vehicle (EV) industry [17]. Nykvist and Nilsson analyzed over 80 academic and non-academic sources reporting between 2007–2014, from which they developed an understanding of recent cost trends for batteries [22]. Their review is specific to Li-ion BESS for EV's, rather than utility BESS. However, the EV market is a significant driver of battery costs. Nykvist and Nilsson noted that cost estimates for Li-ion BESS declined around 14% annually between 2007 and 2014 ($1000/kWh to $410/kWh). Their analysis lead them to predict that Li-ion capital costs will continue to decline, settling asymptotically within the $150–$300/kWh price range by 2025. The Electric Power Research Institute (EPRI) has indicated that in the near term, the cost of energy storage should continue to decrease, especially as the electric vehicle industry ramps up battery production [17]. Research efforts such as that of the U.S. Department of Energy's Advance Research Projects Agency (ARPA-E) aim to boost battery innovation by assessing design goals for new car batteries to include multipurpose abilities that provide grid support and other functions beyond vehicle needs. Considering renewables integration, storage systems need not be sized to cover the nameplate capacity of an entire plant for a multi-hour period. Rather, storage should be sized to reduce uncertainty regarding ramp rates and arrival times for wind, as well as cloud effects for solar, which require power levels much less than the plant nameplate and only sub-hourly durations [12,23,24]. Stochastic issues such as ramping can constrain the amount of renewable resource that may be integrated within a BA. Several regions are already experiencing challenges with high penetration levels of wind, particularly the Netherlands, Spain and Denmark in Europe, the Electric Reliability Council of Texas (ERCOT), the island systems of Hawai'i, and the Bonneville Power Administration in the Pacific Northwest of the U.S. [25–29]. Properly-sized storage systems can inject or absorb real power of appropriate level and duration to buffer ramping uncertainties, thereby increasing the penetration level of renewables within a BA. In addition to supporting renewables integration by smoothing

[1] “Nameplate power capacity,” or simply “nameplate,” is the colloquial term used in the power industry to refer to the power capacity of a facility.

ramping events and providing energy arbitrage, storage systems also offer services such as frequency regulation, transmission & distribution (T&D) system support, power quality improvement, volt-VAR support, spinning reserve, black-start assistance, and investment deferral [17]. Hence, there is tangible value in publishing LCOE algorithms that standardize the evaluation of electrical energy storage systems.

2. LCOE calculation for electrical energy storage systems

A LCOE calculation ascribes all future costs to the present value, resulting in a present price per unit energy value ($/MWh) [30,31]. For electrical energy storage systems, the LCOE provides a single levelized price that incorporates both the energy capacity costs ($/MWh) and the power costs ($/MW) over the life of the facility. In addition, the LCOE provides a useful metric for comparison between technologies that may have very different energy capacities, power capabilities, capacity factors, round-trip efficiencies, financing terms, incentives, or numerous other costs, provided the same LCOE methodology is applied to all cases.

There exists a need to compare the economic value of disparate energy storage technologies with each other. Often, these technologies are very different. For example, capacity factors, efficiencies, energy capital costs, and power capital costs vary significantly from one technology to another. As such, we developed an LCOE algorithm suited for comparing disparate storage technologies. Our motivation for writing this paper is to share this storage LCOE algorithm with other researchers who may also benefit from its utility.

Literature on LCOE pertaining to energy storage is usually case-specific, coupling storage with a particular generation technology. For example, Parrado, et al., propose LCOE improvements for Concentrating Solar Thermal (CST) plants with thermal storage, using molten salts to reduce the costs of storage [32]. Guerreiro, et al. showed that CST plants featuring high-performance Fresnel concentrators, combined with molten salt storage technology, have the potential to lower the LCOE for CST facilities [33]. Pawel applies LCOE analysis to energy storage, specifically coupled with renewable energy generation [34]. The analysis provides a method for calculating LCOE of energy storage technologies coupled with PV. Although discount rates, cost of equity and debt, and corporate tax provisions were considered, government incentives and rebates were not factored into the LCOE algorithm. In another paper by Parrado, et al., they calculate LCOE for a hybrid PV/CST plant coupled with thermal energy storage [35]. The analysis is specific to the Atacama desert of northern Chile. The authors conclude that given anticipated advances in PV technology, the LCOE for such hybrid systems will decrease over the coming decade. Their analysis presents a favorable future for such hybrid systems, particularly given the excellent solar resource of the Atacama region. The authors also conclude that coupling thermal storage with PV and CST serves to address the issue of energy intermittency, which is noted as a particular concern of the local mining industry.

It is not common to find details of LCOE algorithms that discuss how government incentives impact LCOE calculations related to electrical energy storage. Branker, et al., present a comprehensive review of LCOE-related research pertaining to PV [36]. They then present a LCOE methodology of their own, also specific to PV, which does allow for the inclusion of incentives as part of the cash inflow component of the LCOE calculation , though that inclusion is not elaborated to the degree that our LCOE algorithm addresses incentives. Hernández-Moro and Martínez-Duart present a very detailed study of an LCOE algorithm, including sensitivity analysis. The algorithm applies specifically to PV and CST, taking in to account twelve different parameters. However, none of these parameters pertain to incentive programs, nor does the algorithm accommodate storage. [37].

LCOE algorithms are sometimes presented in sources beyond the academic community. The research firm Lazard makes public its results from LCOE analysis for electrical energy storage systems, though not the details of its algorithm [38]. Lazard's analysis of energy storage LCOE is expansive, covering a wide variety of BESS chemistries, as well as PES and fly-wheel systems. The firm analyzes storage LCOE in context of eight different energy services, including peak plant replacement, frequency regulation and PV integration, among others. An excellent, freely-available resource for calculating LCOE is the spreadsheet developed by Agora Energiewende. Their algorithm provides a breadth of inputs for a user to manipulate, and it also includes sensitivity analysis. The capabilities available make the tool a very useful one. However, it is specific to generation plants, in contrast to our algorithm, which applies to energy storage [39].

For this work, we applied our storage LCOE algorithm to PES, CAES and BESS systems and then compared the results to two simple-cycle combustion turbine (SCCT) cases. We derive plant-specific data from numerous sources, including industry reports, white papers, government databases, and project summaries.

Because LCOE calculations depend on numerous assumptions, it is important to note that comparison of LCOE values should only be made in cases where the same LCOE methodology was applied.

3. Methodology

The values used in the terms of the LCOE calculator are explained for each type of storage technology. Predicting the behavior of an energy system over its lifetime is extremely challenging, so it is important to note that the LCOE assumptions are accompanied by uncertainty. In order to gain an understanding of this uncertainty, a sensitivity analysis was performed for each variable in the LCOE equation. This was done by increasing the value of a variable in the LCOE equation by a specified percentage point and observing the resulting percent change in LCOE. Variables that demonstrated significant sensitivity were then subjected to a Monte Carlo simulation. The sensitivity analysis and Monte Carlo simulations are further discussed in Sections 7 and 8 respectively.

Eqs. (1)–(10) describe the LCOE algorithm. We use Eq. (1) strictly for energy storage facilities. Eq. (2) applies to all types of generating facilities; in this paper we use it exclusively for analyzing the two SCCT base cases. Eqs (3)–(10) expand several of the key terms within Eqs. (1) and (2). Tables 1–3 describe all of the terms within Eqs. (1)–(10).

4. Assumptions

Assumptions governing LCOE pertain to installed costs, operations & maintenance (O&M), and performance of the facility during the span of its useful lifetime [36,40]. Per-unit annual costs for storage facilities range widely due to large technological variations between system types. Furthermore, systems of the same type sometimes have different methods of deployment. For example, the geological-dependent aspects of reservoir-based energy storage make uniformity among installed facilities nearly impossible [41]. This is further exacerbated by the placement of storage systems adjacent to other power plants, which creates distinctive siting needs for each system [20]. Comprehensive representation of storage systems was thus dependent on surveying several individual models, rather than the more common method of averaged statistical distributions for categorized plant expenses. Specific cases and relevant relational data are presented in Table 4.

Table 1
Nomenclature pertaining to LCOE Eqs. (1) and (2).

Nomenclature	
AOM_n	O&M costs, year *n* ($)
COG	Co-generation (displacement) (mmBTU/kWh)
DEP_n	Depreciation, year n ($)
EC	Equity cost, year 0 ($)
EC_{charge}	Electricity costs to charge ($/MWh)
$EC_{discharge}$	Electricity costs to discharge ($/MWh)
FC_n	Fuel costs, year *n* ($/mmBTU)
FNGT	Firm natural gas transport ($)
HR	Heat rate (mmBTU/kWh)
INT_n	Interest paid, year *n* ($)
IPC	Initial project costs, year 0 ($)
IT_n	Income tax, year n ($/year)
LP	Loan Payment ($)
M	System lifetime (years)
N	Loan period (years)
NRG_n	Annual energy production, year *n* (MWh)
PCC	Power Capital Costs ($/MW)
PTC	Production tax credit ($/MWh)
PT_n	Property tax, year n ($/year)
r	Discount rate (%/year)
RV_M	Residual value, year M ($)
TR	Tax rate (%)
η	Storage system round-trip efficiency (unitless)

Table 2
Nomenclature pertaining specifically to Eqs. (3)–(10).

Nomenclature	
BPC	Balance of Plant Costs, ($/MWh)
C_{annual}	Total cost of charging and discharging ($/year)
CF	Capacity factor (unitless)
ECC	Equity Capital Costs, ($/MWh)
ETO	Energy Trust of Oregon incentives ($)
FOM_n	Fixed annual O&M, year n ($/MW)
FTXC	Federal tax credit (%)
ITC	Investment tax credit (%)
PC	Project costs ($)
NGT	Natural gas transport ($/mmBTU)
NP	Nameplate Power Capacity (MW)
NPWh	Nameplate Energy Capacity (MWh)
STXC	State (OR) tax credit ($)
VOM	Variable O&M ($/MWh)

Table 3
Financial terms for all energy storage and SCCT cases.

Income Tax Rate	39.94 (%)
Property Tax	1.50 (%)
MACRS Depreciation	Yes
Debt Fraction	50 (%)
Equity Fraction	50 (%)
Debt rate	5.77 (%)
Equity valuation rate	10.75 (%)

Generalized and/or calculated values were assigned where information was not available.

4.1. Capital costs

Financial models of storage facilities must draw distinctions between capital costs relating to nameplate power capacity and those relating to energy capacity. Metrics for nameplate capacity refer specifically to the rated energy charge and discharge rate capabilities of a storage facility. Energy capacity refers to the size of the energy reservoir at the facility [17]. For generation assets, the nameplate power is a significant determinant of the plant capital costs. However, for storage systems, both the power capacity and energy capacity must be considered, and the capital costs for each of these are largely decoupled from each other. For example, a storage facility may have a large power capacity and a small energy capacity factor if its intended use is solar ramp mitigation, while another facility may have a larger energy capacity so that it may provide peak shaving.

LCOE varies considerably depending on the power and energy capital costs, as exemplified by the two compressed air case studies presented in this manuscript. Table 4 shows the assumptions and LCOE values for a small surface vessel with 50 MWh energy capacity (Sandia – Surface) and the 2900 MWh facility in Huntorf, Germany (NREL – Huntorf). The $/MW power capital costs are 36% higher for the man-made surface vessel than the naturally occurring cavern at Huntorf [42,43]. The surface vessel energy volume is much lower than Huntorf, but the comparative costs in using an above-ground holding vessel versus an underground cavern render the energy capital costs for the surface system more than 120 times greater than those of the underground Huntorf facility, on a $/MWh basis. The end effect of accounting for both power and energy capital costs in this comparison is a large deviation in LCOE between the two systems; the cost of energy of an above-ground CAES systems is far greater than that for a CAES that uses an underground cavern, $95/MWh compared to $16/MWh. Note that capacity factors and efficiencies also affect these LCOE. This example shows that large facilities are less expensive on a per-unit-energy basis, despite the fact that small plants have lower initial project costs. Had power capital cost been the only accounted metric, the difference between the LCOE values of the two systems would be marginal, giving an inaccurate portrayal of actual energy costs.

For our analysis, we grouped our case studies within two broad categories, reservoir-based storage and chemical batteries. In the following two subsections, we discuss some of the major influences on LCOE for each category.

4.1.1. Reservoir-based storage cost differentiators

CAES and PES project costs vary depending on geological siting, mainly in reference to the employed method and location of storage systems. Plant location affects the Initial Project Cost (IPC) through the type of technology employed, the required permitting processes, power capacity, and grid interconnection [15,41]. Within Table 4 we show a range of system types to demonstrate the diversity of cost parameters across a wide range of possible facilities. Significant variables affecting the LCOE for CAES and PES include:

- CAES: cost case, plant size, storage vessel type, hours of energy production[2] and capacity factor.
- PES: cost case, plant size, turbine speed characteristic, and reservoir geography.

We found significant variations between models in the capital costs for energy storage; the wide range of LCOE values calculated for reservoir-based systems is largely due to the diversity of reservoir styles and siting needs. For instance, the extremely low LCOE costs of the ‘BPA – John Keys’ PES case may be attributed to the absence of energy capital costs; the reservoir already exists and hence the facility LCOE is merely $15/MWh.

[2] The authors recognize that it is thermodynamically impossible to produce energy; the terms “produce” and “production” are colloquial terms commonly used within the power industry.

Table 4
List of assumptions and calculated LCOE for disparate electrical energy storage technologies. All costs were adjusted to 2012 dollars[72].

	Technology Case	Power Capital (Low∣High Cost) ($/MW)	Energy Capital (Low∣High Cost) ($/MWh)	Fixed O&M (Low∣High Cost) ($/MW)	Variable O&M (Low∣High Cost) (($/MWh)	Capacity Factor (%)	Efficiency (%)	LCOE 2012 (Low∣High Cost) ($/MWh)	Ref.
CAES									
	EPRI - 50 MW	2, 027, 000∣2, 235, 000	406, 000∣447, 000	4, 158∣6, 237	4.16∣5.20	26	70 – 85	115∣133	[17]
	EPRI - 135 MW	1, 040, 000∣1, 300, 000	130, 000∣63, 000	4, 158∣6, 237	4.16∣5.20	26	70 – 85	58∣78	[17]
	Texas Tech	749,710	3023	14,110	1.51∣(BoP = 50, 380)	33	73	29	[17,41]
	Sandia – Watkins	642,200	76,000	2106	Included in Fixed	29	70	36	[17,43]
	Sandia – Kern	523,550	3696	3080	(BoP=61,590)	29	73	29	[17,43]
	Sandia - Surface	667,500	148,000	12,320	(BoP=61,590)	14	79	95	[17,73]
	NREL - Huntorf	424,270	1210	7260	Included in Fixed	42	55	16	[42]
	NREL - McIntosh	424,270	36,360	7260	Included in Fixed	54	53	28	[42]
	NREL - 2700 MW	516,000	3632	3050	(BoP=61,000)	56	41	61	[74]
PES									
	EPRI	1, 560, 000∣1, 207, 098	260, 000∣281, 000	8, 316∣429, 306	Included in Fixed	24	80–82	95∣269	[17]
	Sandia	1,210,000	76,000	Included in Capital Cost Estimate		25–33	80	35∣44	[17,43,75–77]
	EIA	1,250,000	593,000	13,540	Included in Fixed	33	80	134	[17,61]
	NREL - Fixed Speed	1,232,000	12,319	3080	(BoP=4298)	33	78	28	[17,74]
	NREL - Variable Speed	1,294,000	12,319	3080	(BoP=4298)	33	78	30	[17,74]
	BPA - John Keys	779,611	0	18,180	Included in Fixed	38	79	15	[17,78]
	Swan Lake	228,226	162,703	28,181	Included in Fixed	30	80	42	[17,79]
Batteries									
	Vanadium Redox - T&D	3, 118, 440∣3, 541, 080	779, 610∣862, 770	15, 590∣51, 970	Included in Fixed	18	62–67	266∣312	[17,80]
	Vanadium Redox - RI	3, 222, 390∣3, 541, 080	644, 480∣686, 060	16, 632∣51, 970	Included in Fixed	18	65–70	274∣309	[17,80]
	Zinc Bromine	1, 793, 100∣2, 078, 960	358, 620∣415, 790	8, 320∣41, 580	Included in Fixed	21	63–68	131∣166	[17,80]
	Lead Acid - T&D	20,630	N/A	10, 320∣51, 580	Included in Fixed	14	85–90	103∣104	[17]
	Advanced Lead Acid - T&D	20, 630∣47, 450	N/A	5, 160∣51, 180	Included in Fixed	18	65–90	78∣198	[17]
	Advanced Lead Acid - FR	9, 800∣11, 860	N/A	15, 470∣92, 840	Included in Fixed	18	75–90	34∣47	[17]
	Lithium Ion - T&D	39, 710∣42, 290	N/A	9, 280∣72, 210	Included in Fixed	18	85–90	157∣169	[17]
	Lithium Ion - FR	11, 190∣44, 770	N/A	10, 320∣103, 160	Included in Fixed	18	85 – 90	39∣180	[17]
SCCT									
	Case 1 EIA - 215 MW	718,000	N/A	6910	10.18	10	37	125	[40,48,49,58]
	Case 2 EIA - 215 MW	718,000	N/A	6910	10.18	30	37	86	[40,48,49,58]

4.1.2. Chemical battery storage cost differentiators

Pricing portfolios for batteries vary depending on utilized technology and intended use. Most large power deployments of battery technologies focus on grid-supportive distributed systems in aggregate; intended for either bulk energy storage or frequency regulation [17]. These systems range from tens of kilowatts to tens of megawatts in capacity and are distinguished among our cost data models based on their use for T&D system support or renewable energy integration [17]. These systems are particularly useful as intermediaries in the landscape of large-scale storage developments with long lead times, similar to that of pumped hydro and compressed air systems [44]. A recent surge of interest in large utility-scale batteries has prompted technological exploration and wider system parameter variance. Variables affecting the LCOE of flow and conventional batteries include:

- Flow Batteries: cost case, battery size, technology distinction, grid stabilization and outside funding.
- Conventional Batteries (Lead Acid and Lithium Ion): cost case, system size, application and technology distinction.

The field of battery energy storage is in the midst of significant technological advancement and new demonstration, with rapid progress being made in new cathode, anode and electrolyte materials, as well as scalability [18,45].

4.2. Operations & maintenance

In Eq. (1), the Annual Operations and Maintenance cost term (AOM_n) is within the general operations summation, which also includes costs of charged and discharged energy. O&M is divided between Fixed (FOM_n) and Variable (VOM) costs. Fixed costs are associated with operational costs that do not change as a function of plant output. Variable costs address operational costs that change as a function of energy output. These relationships are shown in Eq. (6), with the dependence of total fixed cost on power capacity and total variable cost on energy production. Many of the data models provide statistically averaged operations and maintenance values, which incorporate variable costs into the fixed costs metric. This is the case for all surveyed battery systems. Balance of plant (BoP) statistics are provided for some reservoir-based storage models and are used as variable O&M costs in our calculations due to their correlation with energy output.

O&M costs for reservoir-based systems are highly dependent on reservoir siting and system capacity factor. Reservoir specifications influence the lifetime and robustness of operational components, which contribute to the FOM_n. The capacity factor influences system deterioration rate, increasing with higher frequency of use. This in turn impacts FOM_n, VOM and NRG_n. In CAES facilities, reservoirs sited above ground or using non-traditional geological resources will have higher O&M costs in comparison with traditional underground cavern-based storage facilities. Similar O&M implications in PES systems occur with closed-loop and man-made reservoirs. Per-unit annual O&M costs in reservoir-based storage ranged from $2106 to $429,306, due to the wide variance in system types.

Battery storage technologies vary in O&M costs mainly as a function of technology [17,46]. For instance, flow batteries differ from conventional batteries in the external storage of active materials, affording them an advantage in lifetime and comparative lack of self-discharge [47]. The advantage in terms of maintenance comes from partial replacement of parts and fuel for flow batteries, rather than replacement of the entire unit as seen with lead acid (LA) and lithium ion ($Li+$) systems. Carbon-enhanced LA technology is emerging as an effective means of lengthening cycle life for partial-state-of-charge operation. This functionally decreases O&M needs over time by extending the useful lifetime of the battery. The distinction between fixed and variable O&M costs becomes blurred with conventional batteries because their decay is contained within a sealed unit. Battery systems data for O&M were based on averaged AOM, which was not separated into variable and fixed subsets. AOM costs for battery systems ranged from $5160 to $103,160.

4.3. Capacity factor

Capacity Factor (CF) weighs the performance of a system as a ratio of operational hours to the capacity provided if the system was running at full capacity continuously. The ratio varies due to maintenance requirements, local weather patterns, load profile, and use of the unit in providing ancillary services such as ramping and regulation. Unique to energy storage, capacity factor also varies due to charge and discharge cycles. Eq. (7) illustrates the direct dependence of NRG_n on capacity factor. As shown in Table 4, system capacity factors ranged from 14% to 56% in our cases, and were mainly affected by the size and intended use of the facility. Depending on the purpose of the system, it may run on a steady and predictable basis, or function solely as support for grid services or variable generation smoothing. Capacity Factor metrics were calculated from discharge duration and frequency of usage.

4.4. Efficiency

Efficiency, η, accounts for losses incurred during both charging and discharging the storage resource. Efficiency determines the amount of energy that must be purchased $NRG_n\eta^{-1}$, in order to sell an amount of discharged energy, NRG_n. The total cost of charging and discharging the resource over a year is expressed using Eq. (9), which appears in Eq. (1) in the form shown in Equation (10).

This simple model assumes fixed prices for charging and discharging. A more sophisticated model would accommodate time-varying prices, such as locational marginal pricing, to better assess the resource's revenues in a dynamic market. When charging, $NRG_h\eta_h^{-1}$ is the amount of energy purchased for storage during hour "h" and EC_h is the cost of energy during that hour; and likewise with discharging. In recognizing that efficiency depends on the rate of charging and discharging, an efficiency that is a function of the charge/discharge rate used during a particular hour may also be included.

LCOE values are very sensitive to efficiency values, as we discuss in Section 7. Factors governing the efficiency of a system vary with siting and technology. For reservoir-based systems, efficiency is dependent upon the quality of reservoir and conduit sealing, as well as turbine speed control. Battery efficiencies vary with utilized anode, cathode, chemical substrate and sealing technologies. Efficiencies ranged from 41% to 90%, depending on the system and were based on reported figures [40,48,49].

Efficiencies for storage systems have been improving due to numerous technological advancements. Advances in reservoir-based systems include improved methods and materials for sealing, and sophisticated algorithms for turbine control. Battery advancements are more varied than those of reservoir systems because of their diversity of application, scalability and relatively lower level of technological maturity. Many subsets exist within the range of battery systems. For instance, flow batteries differ from conventional batteries in the external storage of active materials [47]. This affords a different set of options and criteria for technological advancements to improve efficiency. Their method of storage gives flow batteries the advantages of lower rates of self-discharge and higher efficiencies [47]. Lead acid batteries have seen efficiency improvements through carbon enhancement, which effectively combats self-discharge. Lithium ion batteries boast the highest efficiency ratings and are improving with demands from the electric vehicle industry in rapid charge-discharge cycles, and ancillary PEV storage for distributed generation capabilities. Efficiency ratings on battery systems vary as a result of highly diverse technology, fabrication materials, and industrial drivers.

5. Financing & regional government tax incentives

5.1. Financing

The LCOE equations are applicable to a wide variety of financial scenarios. Financing terms used in our analyses derive from utility cases and are shown in Table 3. Financial terms include corporate income tax rate, property tax rate, debt to equity ratio, debt cost, and equity costs. Financing also assumes MACRS (Modified Accelerated Cost Recovery System) depreciation, which is the tax depreciation method used in the United States. The terms in Table 3 reflect generic Cost of Service modeling used by utilities. A loan duration of 20 years was assumed for all cases.

Financing terms influence the LCOE algorithms through the scalar variables initial project cost (PC), equity cost (EC) and loan payment (LP), as well as two vectors, interest payment (INT_n) and depreciation (DEP_n). These vectors derive from a cost flow analysis spreadsheet that incorporates the financing terms of Table 3 and calculates the elements of each vector for each year of the loan term, N. The Income tax (IT_n) and property tax (PT_n) vectors apply within each year of the System lifetime, M.

5.2. Global government incentives

At the recently completed Paris Climate Agreement of 2015, government representatives from over 180 countries overwhelmingly agreed to curtail the impact of greenhouse emissions and invest in alternative energy generation and electrical energy storage. Although the amount of funds and tax incentives that will be allocated to energy storage technologies is unknown, experts believe that the Paris Agreement will provide many opportunities for energy storage [50]. In Europe for example, with the help of the EU's Research and Innovation Program Horizon 2020, energy storage projects may receive funding from almost 6 billion Euros allocated to the energy sector [51]. In Asia, the Chinese government has embarked on an aggressive measure to reduce air pollution by increasing its electrical energy storage capacity. In 2015, Lux Research projected that the Chinese storage market (electricity and vehicle battery storage systems) will grow by $9 billion and 31 GWh by 2025 [52]. Between 2015 and 2016, the governments of Japan and South Korea are expected to finance new electrical energy storage systems of approximately 510 MW and 280 MW respectively [53]. Since 2007, the U.S. Energy Independence and Security Act of Congress identified energy storage as a threat to the country's energy independence and initiated the Electricity Advisory Committee. In 2009, the American Recovery and Reinvestment Act provided $185 million in federal matching funds to support energy storage projects with a total value of $772 million [54].

5.3. U.S.-specific incentives

We discuss U.S. Federal and State incentives applied to the U.S state of Oregon in Sections 5.3.1–5.3.4. Since every energy market is different, our approach does not delimit the application of LCOE derivations to the U.S. alone.

The LCOE Eqs. (1) and (2) contain a range of incentive options, including investment tax credits, production tax credits, accelerated depreciation, and those applied on a per peak Watt or per MWh basis. The energy storage and SCCT cases noted in Table 4 do not depend on incentives, but we include this discussion to demonstrate how incentives operate within the LCOE equations.

In Eqs. (1) and (2), the IPC (calculated in Eq. (5)) has the potential to substantially affect LCOE values. The IPC is a significant component of the LCOE equations for both generation and storage and the effect of incentives can be significant. The following incentives detail the variables listed in Eq. (5).

5.3.1. Federal incentives

The Federal Tax Credit (FTXC) is a personal tax credit available to residential renewable energy systems while the Investment Tax Credit (ITC) is a corporate federal tax credit which offers 30% credit for solar (no maximum capacity), fuel cells (0.5 kW minimum) and small wind (100 kW maximum); 10% for geothermal, microturbines (2 MW maximum) and Combined Heat and Power (CHP) cogeneration (50 MW maximum).

There are currently no U.S. federal incentives available for energy storage systems. It is reasonable to infer from the effect of the FTXC and ITC for solar systems that, if similar incentives were applied to energy storage systems, the effect on storage LCOE would be significant.

5.3.2. State incentives

U.S. state incentives come in a wide variety of forms. We use the U.S. state of Oregon for demonstration purposes. The Oregon Renewable Energy Tax Credit (STXC) is a personal tax credit program, known as the Residential Energy Tax Credits (RETC), which has been extended through 2018. The program provides tax credits in equal sums to system owners over a four year time period, and hence the $n = 1$–4 span of the summation in Eq. (5). The commercial/utility scale system incentive represented in the STXC was the Oregon Business Energy Tax Credit (BETC) [55].

Currently there are no state incentives in Oregon for energy storage systems. It is reasonable to conclude from the generation incentive amounts that if energy storage had a state incentive similar to that of PV systems, their LCOE figures would have a more competitive value.

5.3.3. Energy Trust of Oregon

We included a term within the LCOE equations for rebate-based incentives, labeled ETO. The Energy Trust of Oregon (ETO) provides a cash-based incentive for some types of energy generation systems that is separate from federal and state incentives [56,57]. Note this incentive does not affect the IPC for the LCOE storage Eq. (1). We include this variable to demonstrate how incentives like ETO's could affect energy storage LCOE if such mechanisms became available.

5.3.4. Electrical energy storage tax credits

In the near future, LCOE for energy storage systems could be significantly affected by incentives. For instance, U.S. Senate Bill 1845 (the STORAGE Act) was proposed in 2011. It included two aspects: one, a 20% tax credit for investments of storage systems that tie directly to the electric grid, with a $40 M cap; and two, a 30% non-business energy tax credit for installation of equipment in a principle residence [58]. As tax credits, these would be accounted with FTXC or ITC.

6. Data sources

6.1. Electrical energy storage market prices

LCOE calculations for energy storage systems depend on the price of electricity while charging and discharging. For wholesale calculations, 2011 Mid-Columbia (Mid-C) wholesale spot prices were used. Prices while charging (buying) were assumed to be \$19.98/MWh, the 2011 annual average off-peak spot price. For discharging (selling), the price was assumed to be \$29.10/MWh, the 2011 annual average on-peak spot price [48,59]. Electricity prices exhibit a degree of volatility over time, which adds uncertainty to the selection of buy and sell values. Our sensitivity analysis, presented in Section 7, shows that LCOE are particularly sensitive to variations in both the buy and sell prices. Alternatively, a vector of prices could be used as we do for IT_n and PT_n in Section 5.1, and for FC_n and $FNGT_n$ below.

Utility-scale natural gas combustion turbines and simple-cycle combustion turbines (SCCT) are used in our analysis to contrast traditional support for ramping and peak power demand with electrical energy storage systems. The LCOE values derived for energy storage cases can then be baselined against the current grid-supportive technology, the SCCT. Specifically, two cases were developed for a 215 MW SCCT peaking facility, with one case assuming a 10% Capacity Factor (CF) and the other a 30% CF [40,48,49].

6.2. Natural gas fuel models for the SCCT cases

Natural gas cost projections are from two sources. Data from the U.S. Energy Information Agency (EIA) provide projections through 2035 for various markets and data from the Northwest Power and Conservation Council (NWPCC) provide wholesale price projections through 2030 for various wholesale trading locations [40,49,60]. Both the EIA and NWPCC data sets include projections for the Henry Hub spot price, thereby allowing for comparison between the two sets of projections. The projections differed and neither correlated well to an exponential best-fit curve. Because exponential models cannot be used to produce reasonable fits to these price projections, the LCOE equations are not designed to use annual percent price increases. Rather, we use a cash-flow style of analysis, imbedding a vector of fuel costs, FC_n, within the second summation term of Eq. (2). A vector for annual Firm Natural Gas Transport costs ($FNGT_n$) is also included in order to account for pipeline costs that may vary by year. The NWPCC provided upper and lower ranges to its U.S. Wellhead projections, demonstrating a large amount of uncertainty with these forecasts.

The EIA distinguishes natural gas pricing tiers according to residential, commercial, industrial and electric power charges. For the SCCT LCOE calculations, we used the EIA electric power price projections. According to the EIA, the term 'electric power' plants are those that sell electricity only to the public [49].

6.3. Simple-cycle combustion turbine baseline

Two baseline cases were developed to serve as reference against the three storage technologies (CAES, PES & BESS). These are a 215 MW SCCT used as a peaking facility and considered at capacity factors of both 10% and 30%. Key assumptions for each and LCOE results are noted in the bottom rows of Table 4.

Capital, fixed O&M and variable O&M costs were derived from the 2010 report from the U.S EIA [61]. Capital costs were specific to EIA models developed for Portland, Oregon. The EIA's Advanced Combustion Turbine (CT) model was used to derive values for the SCCT. The Advanced CT SCCT model represents a 210 MW F-Class turbine, with an adjusted capacity of 215 MW to accommodate regional ambient temperatures in Portland, OR. O&M costs and capital costs were assumed to increase by 2.5% per year.

7. Sensitivity analysis

For this study, we performed sensitivity analysis similar to that done by Ren, et. al. [62]. All the variables of the storage LCOE equation, Eq. (1), were subjected to a $\pm 5\%$ variation. This enabled us to identify the influential parameters in the LCOE equation. While the LCOE is relatively insensitive to some variables (i.e., O&M, BoP costs and residual value), it is very sensitive to numerous others. Although some researchers have shown significant sensitivity to financial parameters, particularly discount rate, loan structure, tax credits, and depreciation, our discussion does not focus on these aspects of sensitivity analysis [63,64,36]. Instead, this paper focuses on sensitivities unique to energy storage. The 2012 NREL-McIntosh CAES case was chosen to demonstrate sensitivities because of its mid-range LCOE. To highlight these sensitivities, the percentage change in LCOE as a function of several variables are plotted in Fig. 1.

Four of these parameters show non-linear dependence on the LCOE, notably the round-trip storage efficiency, capacity factor, system lifetime and loan period. The other eight parameters are functionally linear around the unperturbed LCOE. As shown in Fig. 1, LCOE is particularly sensitive to the round-trip storage efficiency, capacity factor, electricity buy and sell price, impacting the system LCOE by more than 5% for every 5% change from the baseline of these variables.

Next, for each technology case within the CAES system (the NREL-McIntosh, EPRI 50 MW and Sandia-Kern 300 MW cases were considered for this paper), the LCOE equation variables were extracted from the respective sensitivity plots. We have termed the occurrence of two or three parameters appearing within the same technology case as the 'Most Sensitive' parameters. These 'Most Sensitive' parameters were then ranked by order of sensitivity, from top to bottom. Capacity factor, project cost and loan period appear in each system type and for each technology case, across the board (Table 5).

To better understand the level of risks and uncertainty associated with utility-scale storage/generation systems LCOE as

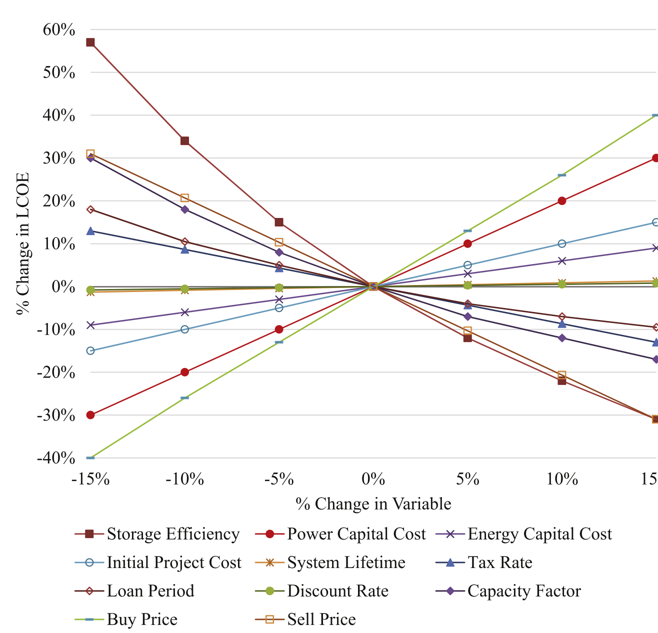

Fig. 1. LCOE Sensitivity for NREL McIntosh CAES system.

Table 5
Sensitivity Analysis comparison of select three CAES technology cases. (Variables ranked in order, from the most sensitive to the least sensitive).

EPRI 50 MW CASE	SANDIA KERN 300 MW CASE	NREL McIntosh CASE	Most Sensitive (% points for Monte Carlo)
Capacity Factor	Capacity Factor	Storage Efficiency	Storage Efficiency (10%)
Project Cost	Sell Price	Buy Price	Buy Price (20%)
Loan Period	Storage Efficiency	Capacity Factor	Sell Price (20%)
Tax Rate	Buy Price	Sell Price	Capacity Factor (5%)
Energy Capital	Project Cost	Project Cost	Project Cost (10%)
Power Capital	Loan Period	Loan Period	Loan Period (ignored)

certain input variables fluctuate, we turn our attention to Monte Carlo simulations, applied to the NREL-McIntosh CAES case.

8. Uncertainty determination and monte carlo simulations

The benefit of Monte Carlo analysis is that it helps assess the risk to the LCOE presented by the probabilistic uncertainties of the 'Most Sensitive' parameters highlighted in Table 5. Monte Carlo analysis provides a means for quantifying the level of uncertainty present in an assumption, either by varying one parameter at a time while keeping the rest constant or by varying multiple parameters concurrently.

A normal distribution was applied to each variable and 10,000 trials were performed. Although we only analyze the NREL-McIntosh CAES case, this approach can be readily applied to any storage system type. Acceptable levels of variation for each of the LCOE variables must be justified. Fig. 2 summarizes the tolerances (by percent variations) applied to the LCOE parameters for the Monte Carlo Simulations. In the following subsections, we examine each of the 'Most Sensitive' parameters and describe how we arrived at an acceptable percentage tolerance range used for the Monte Carlo simulation.

8.1. Storage efficiency

In a Sandia National Lab study, round trip storage efficiencies were calculated based on three criteria, namely, system

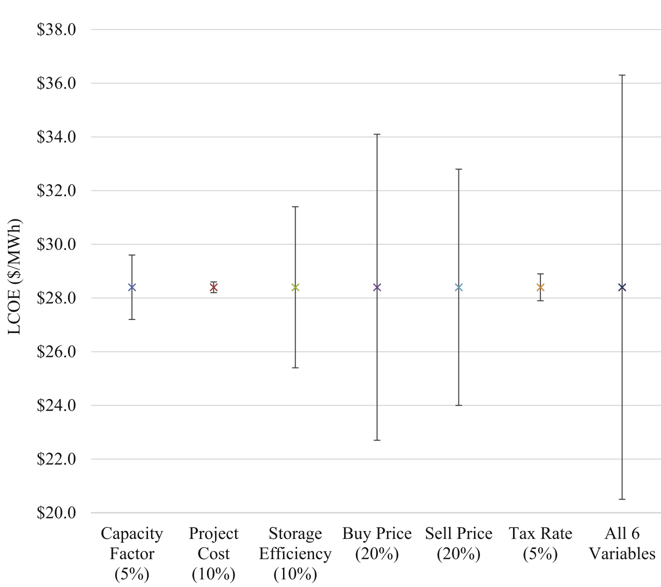

Fig. 2. Monte Carlo distribution of LCOE key variables for the 2012 NREL/McIntosh CAES showing 95% Confidence Interval. Note that the % represents the maximum amount of variation applied to the LCOE Monte Carlo simulation.

performance assumptions, standards for the respective storage technologies and expert opinion [43]. In a U.S. Department of Energy report on grid energy storage, a 20% variation for major storage systems while at partial operational capacity was reported [65]. For our Monte Carlo analysis, the round trip storage efficiencies for each system was compared them with similar systems reported [43,65]. Storage efficiency can also be considered in terms of the operating capacity of the respective system [43]. Since the storage efficiency is system specific and likely to vary depending on the loading conditions and the capacity factor, we use $\pm 10\%$ variance for the LCOE Monte Carlo simulations.

8.2. Buy price and sell price

The electricity buy and sell prices are some of the most important variables when calculating the LCOE for electrical energy storage systems [66]. Referred to as Energy arbitrage, the act of buying electricity during off-peak periods and selling during on-peak periods is a means for generating revenue from energy storage systems [17]. Buy and sell price vary between markets, and they fluctuate based on weather, time of day, season and other variables that influence supply and demand. Wholesale electricity prices vary quite considerably; in 2014, the Mid-Columbia wholesale price daily spot price ranged from a minimum of $12/MWh to $315/MWh, though the annual weighted average daily spot price was around $39/MWh. Owing to such wide variations, we have applied a $\pm 20\%$ variance to the electricity buy and sell prices to represent the uncertainty of these prices within an electricity market.

8.3. Capacity factor

Electrical energy storage systems tend to have low capacity factors because they spend a significant portion of their operational time operating at below rated capacity. Storage systems coupled with renewables will have lower capacity factors since they would only operating in reaction to the availability of the renewable resource [67,68]. In an EPRI whitepaper, the capacity factor was simply assumed and the need to compare dispatch prices against hourly system load performances was ignored [17]. For the three technology cases under consideration, the capacity factor varied significantly between 14% and 56%, 24%, 33% and 18–21% for the CAES, PES and BESS respectively. Due to the wide variations between the systems under consideration, we expect the capacity factor to be within $\pm 5\%$ increments for both the CAES and PES systems and $\pm 3\%$ for BESS.

8.4. Project cost

Depending on the type of energy storage system, we expect the project costs to have one of the highest uncertainties. A number of factors like late delivery of items to the construction site, personnel change in project team, loss of a major supplier or vendor, change in project scope and the technology learning curve to mention can impact the project costs. This fluctuation varies between each system and as such, for some cases, conceptual estimates have been used to accommodate contingencies in the project and other unknowns in the technology application [17]. An EPRI team used a 10% project contingency for CAES system, 5–15% was used for BESS but concluded that for PES system, the project costs will vary significantly by site [17]. A $\pm 10\%$ variation in project cost is used for our NREL-McIntosh Monte Carlo simulation.

8.5. Loan period

The time between the investment start date and maturity date is typically a mutually agreed upon period between the lender and the borrower. Any deviation from the pre-determined loan period could adversely affect the project cost resulting into additional interests which will negatively further affect the project. We have chosen to ignore compensating for any variation of the loan period in our Monte Carlo analysis because in practice, it is unlikely that the loan period will change. In addition, extending the loan period is usually a costly undertaking because the loan period is usually decided upon at the onset of the project.

8.6. Tax rate

The tax rate of most electric utilities, businesses and public companies tend to either remain flat or vary only slightly over time. More recently, the global financial crisis of 2008 have forced some governments to either reduce or keep their tax rates flat so as to encourage businesses and bolster economic growth. There exists a strong correlation between taxation and financial leverage because fluctuations in corporate tax rates tends to affect the amount of debt that a utility is willing to take on [69]. Unless there is a major change in the classification of an organization, the tax rate should not swing by wide margins. For this purpose, a $\pm 5\%$ tax rate variation was applied to our Monte Carlo simulation.

8.7. Energy capital and power capital

We established in Eq. (3) that the project cost is a function of the energy capital and power capital costs. However, for the Monte Carlo simulation, the energy capital and power capital percentage fluctuations are largely fixed due to their dependency on the project cost. Once the project cost has been established for a particular project, the energy and power capital costs are less likely to fluctuate widely. Because the Monte Carlo results obtained by varying the project cost provided adequate insight into how both the energy and power capital would respond to the LCOE equation, the energy and power capital costs were not included in our Monte Carlo analysis.

8.8. Summary of Monte Carlo Simulations

The Monte Carlo simulations highlight the risks and the uncertainty present in the LCOE for the systems under consideration. 10,000 random trials were used for the Monte Carlo analysis. In Fig. 2, we show the results obtained by applying the percentage variations described above to each of the 'Most Sensitive' LCOE variables, first independently and then, all at once. As expected, the later had the widest price variations. For example, with all 6 variables from the 'Most Sensitive' column of Table 5 applied, the LCOE range for the NREL-McINTOSH case was $15.80/MWh between two standard deviations from the mean on both sides of the normal distribution curve (minimum value of $20.60/MWh and maximum value of $36.40/MWh). Compare this to a $5.90/MWh range between two standard deviations from the mean on both sides of the normal distribution curve for the 10% storage efficiency simulation (minimum value of $25.60/MWh and maximum value of $31.50/MWh). The Monte Carlo analysis suggests the former as the less certain factor. The percentage point variation applied to each simulation (i.e, 5% Capacity Factor or 10% Capacity Factor) as well as the sample size observed affected the results. When multiple parameters are varied simultaneously, the uncertainty range was observed to widen.

The sensitivity analysis and Monte Carlo simulation results presented in this report were all conducted using the NREL-McIntosh CAES case and are intended for illustrative purposes. The same approach and methodology can be applied to any technology case or storage system under consideration.

9. Discussion

LCOE is an effective means for standardizing metrics when comparing costs of disparate energy systems. Our study focused specifically on comparing costs for utility-scale energy storage against traditional gas turbine peaking facilities.

As discussed in Section 5.3, although U.S. Federal and Oregon state specific tax credits were applied in arriving at the LCOE obtained in this study, our approach is, by design, generalized. The algorithm can accommodate a variety of incentive programs, and as such it may be used by researchers, policy makers and marketers in jurisdictions beyond our location of focus.

We use Simple-Cycle Combustion Turbines (SCCT) as the baseline technology against which we compare our LCOE results, because SCCT is the technology with which utility-scale storage systems must compete. Both feature the ramping and frequency regulation requirements required for mitigating the stochastic nature of wind and solar PV generation. SCCTs with 10% and 30% capacity factors served as our baseline cases, returning LCOE values of $125 and $86 (Table 4), respectively. Such capacity factors are typical for SCCTs dedicated to ramping and regulation duties. As well, these capacity factors are used by other researchers, with whom we compare our analysis below [40,70,71].

We observed that pumped hydro, compressed-air, and lead-acid energy storage systems tend to have the most competitive LCOE, base-lined against SCCT facilities. LCOE values for storage systems range quite considerably, largely due to reservoir-related factors. Excluding extreme cases (outside $\mu_{\text{all}} + / - \sigma_{\text{all}}$), we found the mean LCOE to be $46 ($\sigma_{\text{PESsubset}}$=$23) for PES, $55 ($\sigma_{\text{CAESsubset}}$=$24) for CAES, and $64 ($\sigma_{\text{LAsubset}}$=$25) for LA batteries.

Our calculations of LCOE for SCCTs, using Eq. (1), are similar to LCOE values calculated by others. As we have stated earlier, one must be weary of comparing LCOE values derived from different methodologies, as data sources, financing terms, and other variable assumption can be very different from study to study. None the less, LCOE for specific technologies under similar circumstances should be close. Stodard, et al., found LCOE for a model SCCT to be $215/MWh. Their model assumes a 10% capacity factor, a 9700 BTU/kWh heat rate, capital cost of $576/kW; financial terms are not specified. They also assume a gas price of $8.8/MBTU and assumes a 2.5% annual rate of growth. These values are quite different from those used in our calculations, which likely contribute to the difference in LCOE. [70] The U.S. EIA calculated LCOE for a gas-fired conventional combustion turbine with a 30% capacity factor to be $150/MWh. The EIA also calculated an LCOE of $121/MWh for a gas-fired advanced combustion turbine, also with a 30% capacity factor. For both cases financial terms, heat rate and fuel assumptions were not stated [71]. As a fourth example of similar LCOE for SCCTs, the Northwest Power & Conservation Council calculate LCOE for an SCCT in their 6th Power Plan, finding an LCOE of $132 for an SCCT with a 25% capacity factor, 9370 BTU/kWh heat rate and $1050/kW capital costs. [40] Limited financing terms were provided.

The sensitivity analysis provides insight into technology-specific impacts on LCOE such as power and energy capacities as well as reservoir sighting. The sensitivity analysis, with results presented in Fig. 1, shows that LCOE has strong sensitivity to three variables in particular, these being the storage efficiency, electricity buy price and electricity sell price. LCOE values are moderately sensitivity to three other parameters; capacity factor, project cost and loan period.

The confidence interval is useful for analyzing the upper and lower limits within which the LCOE is expected to fall. Furthermore, the confidence interval can help decision makers and stakeholders understand if a storage project will fall within a predicted cost range with a certain degree of confidence. Fig. 2 shows the 95% confidence interval for the 2012 NREL/McIntosh CAES case; i.e, we can say with 95% confidence that the LCOE will be between \$22.81/MWh and \$34.11/MWh, should the electricity buy price fluctuate by 20% or less of the 2012 purchase price.

The LCOE storage algorithm was designed to provide versatility. We have showed its application to several data models, thereby providing a level comparison between disparate technologies. When comparing cases though, analysts should take note of the LCOE parameters, especially for the six highly sensitive parameters noted previously.

$$LCOE_{storage} = \frac{IPC + \sum_{n=1}^{N}\left[\frac{LP - (DEP_n + INT_n)TR}{(1+r)^n}\right] + \sum_{n=1}^{M}\left[\frac{AOM_n + IT_n + PT_n + NRG_n\left(\frac{EC_{charge}}{\eta} - EC_{discharge}\right)}{(1+r)^n}\right] - \frac{RV_M}{(1+r)^M}}{\sum_{n=1}^{M}\frac{NRG_n}{(1+r)^n}} \quad (1)$$

$$LCOE_{generation} = \frac{IPC + \sum_{n=1}^{N}\left[\frac{LP - (DEP_n + INT_n)TR}{(1+r)^n}\right] + \sum_{n=1}^{M}\left[\frac{AOM_n + IT_n + PT_n + NRG_n[FC_n(HR - COG) - PTC] + FNGT_n}{(1+r)^n}\right] - \frac{RV_M}{(1+r)^M}}{\sum_{n=1}^{M}\frac{NRG_n}{(1+r)^n}} \quad (2)$$

$$PC = (ECC + BPC)NPWh + (PCC)NP \quad (3)$$

$$EC = (EquityFraction)PC \quad (4)$$

$$IPC = EC - ETO - PC(FTXC + ITC) - \sum_{n=1}^{4}\frac{STXC}{(1+r)^n} \quad (5)$$

$$AOM_n = FOM_n(NP) + VOM(NRG_n) \quad (6)$$

$$NRG_n = NP(8760\ hr/yr)CF \quad (7)$$

$$FNGT = (NGT)(NP)(8760\ hr/yr)(HR - COG) \quad (8)$$

$$C_{annual} = (NRG_n\eta^{-1})EC_{charge} - (NRG_n)EC_{discharge} \quad (9)$$

$$C_{annual} = NRG_n(EC_{charge}\eta^{-1} - EC_{discharge}) \quad (10)$$

10. Conclusion

Our motivation for publishing this work is to provide the research community with an LCOE algorithm suitable for electricity-specific energy storage systems. In particular, we found existing LCOE algorithms within literature were not suitable for PES, BESS and CAES storage technologies and did not provide the wide range of inputs needed for a thorough assessment of these storage systems.

Using the U.S. Federal and Oregon State tax incentives, we have developed an LCOE storage algorithm that can be used to evaluate the impact incentives have on a wide range of energy storage technologies, allowing for analysis of disparate storage technologies on a level playing field. The algorithm lends itself to easy adaptation and implementation regardless of the finance-, technology-, fuel-, incentive-, plant- and regional tax-specific variables and therefore it is easily adaptable to a wide range of energy storage applications.

We demonstrated the value of the storage LCOE algorithm by applying it to two classifications of storage technologies; reservoir-based technologies and chemical batteries. Regarding reservoir technologies, our analysis revealed that both CAES and PES cases have wide variations in LCOE, and most of these cases fall below the threshold set by the benchmark SCCT cases. The LCOE of reservoir-based technologies varied largely due to the wide discrepancies in cost associated with the reservoirs.

Regarding chemical batteries, battery systems designed to provide bulk storage require more energy capacity than systems designed to provide frequency regulation support. Hence, the former tend to have higher LCOE than the latter (compensation for providing ancillary services such as regulation was not considered). In contrast to the SCCT baseline, very few of the battery technologies are currently price-competitive.

We have used the storage algorithm to evaluate a variety of storage technologies and baseline those technologies against the price points of traditional systems that provide ramping support, load shifting, and price arbitrage. Storage projects require a lot of initial capital investment and are expected to be in service for many years. We have demonstrated that sensitivity analysis using Monte Carlo simulation can be used for predicting what the LCOE will be if the unit price of key variables can be forecast, thereby strengthening or weakening the case for embarking on an electrical energy storage project with a certain degree of confidence.

Funding

Funding for this research was provided by Portland General Electric (PGE). PGE played no role in the design and analysis of the study, nor the interpretation of findings. Nor did PGE participate in the writing of this report or the decision to submit this article for publication.

References

[1] American Wind Energy Association (AWEA). U.S. wind industry first quarter 2013 market report. Technical Report, AWEA Data Services; 2013.
[2] American Wind Energy Association (AWEA). U.S. wind industry first quarter 2014 market report. Technical Report, AWEA Data Services; 2014.
[3] Solar Energy Industries Association. U.S. Solar Market Insight Report 2012 Year-in-Review; 2013.
[4] Solar Energy Industries Association. U.S. Solar Market Insight Report 2014 Year-in-Review; 2014.

[5] REN21 Secretariat. Renewables 2013 global status report; 2014.
[6] Bitar E, Rajagopal R, Khargonekar P, Poolla K, Varaiya P. Bringing wind energy to market. IEEE Trans Power Syst 2012;27:1225–35.
[7] Ela E, Edelson D. Participation of wind power in LMP-based energy markets. IEEE Trans Sustain Energy 2012;3:777–83.
[8] Liu G, Tomsovic K. Quantifying spinning reserve in systems with significant wind power penetration. IEEE Trans Power Syst 2012;27:2385–9.
[9] Ummels B, Gibescu M, Pelgrum E, Kling W, Brand A. Impacts of wind power on thermal generation unit commitment and dispatch. IEEE Trans Energy Convers 2007;22:44–51.
[10] Jewell W, Ramakumar R. The effects of moving clouds on electric utilities with dispersed photovoltaic generation. IEEE Trans Energy Convers EC 1987;2:570–6.
[11] Omran W, Kazerani M, Salama M. Investigation of methods for reduction of power fluctuations generated from large grid-connected photovoltaic systems. IEEE Trans Energy Convers 2011;26:318–27.
[12] Brekken T, Yokochi A, von Jouanne A, Yen Z, Hapke H, Halamay D. Optimal energy storage sizing and control for wind power applications. IEEE Trans Sustain Energy 2011;2:69–77.
[13] Mills D, Morgan R. Solar thermal power as the plausible basis of grid supply. In: Proceedings of ISES world congress 1–5; 2007. p. 191–7.
[14] Daneshi H, Srivastava A. Security-constrained unit commitment with wind generation and compressed air energy storage. IET Gener Transm Distrib 2012;6:167–75.
[15] Denholm P, Sioshani R. The value of compressed air energy storage with wind in transmission-constrained electric power systems. Energy Policy 2009;37:3149–58.
[16] Yang B, Makarov Y, Desteese J, Viswanathan V, Nyeng P, McManus B, et al. On the use of energy storage technologies for regulation services in electric power systems with significant penetration of wind energy. In: 5th international conference on European electricity market; 2008. p. 1–6.
[17] Rastler D. Electricity energy storage technology options: a white paper primer on applications, costs, and benefits. Technical Report, Electric Power Research Institute, Palo Alto, CA; 2010.
[18] Evans A, Strezov V, Evans T. Assessment of utility energy storage options for increased renewable energy penetration. Renew Sustain Energy Rev 2012;16:4141–7.
[19] Diaz-Gonzalez F, Sumper A, Gomis-Bellmunt O, Villafafila-Robles R. A review of energy storage technologies for wind power applications. Renew Sustain Energy Rev 2012;16:2154–71.
[20] Beaudin M, Zareipour H, Schellenberglabe A, Rosehart W. Energy storage for mitigating the variability of renewable electricity sources: an updated review. Energy Sustain Dev 2010;14:302–14.
[21] Ibrahim H, Ilinca A, Perron J. Energy storage systems – characteristics and comparisons. Renew Sustain Energy Rev 2008;12:1221–50.
[22] Nykvist B, Nilsson M. Rapidly falling costs of battery packs for electric vehicles. Nat Clim Change 2015;5:329–32.
[23] Bludszuweit H, Dominguez-Navarro J. A probabilistic method for energy storage sizing based on wind power forecast uncertainty. IEEE Trans Power Syst 2011;26:1651–8.
[24] Bloemink J, Green T. Increasing Photovoltaic Penetration with local energy storage and soft normally-open points. In: Power and energy society general meeting. IEEE; 2011. p. 1–8.
[25] Ackermann T, Ancell G, Borup L, Eriksen P, Ernst B, Groome F, et al. Where the wind blows. IEEE Power Energy Mag 2009;7:65–75.
[26] Ummels B, Gibescu M, Pelgrum E, Kling W. System integration of large-scale wind power in the Netherlands. In: Power engineering society general meeting. IEEE; 2006.
[27] Durrwachter HL, Looney SK. Integration of wind generation into the ERCOT market. IEEE Trans Sustain Energy 2012;3:862–7.
[28] Miller N, Manz D, Johal H, Achilles S, Roose L, Griffin J. Integrating high levels of wind in island systems: lessons from Hawaii. Technical Report, IEEE Sustainable Energy Technologies (ICSET), Kandy, Sri Lanka; 2010.
[29] Louie H. Characterizing and modeling aggregate wind plant power output in large systems. IEEE power and engineering society general meeting; 2010. p. 1 – 8.
[30] National Renewable Energy Laboratory. Simple Levelized Cost of Energy (LCOE) Calculator Documentation, Online; 2010. ⟨http://www.nrel.gov⟩.
[31] IEA. Projected Costs of Generating Electricity. International Energy Agency; 2015.
[32] Parrado C, Marzo A, Fuentealba E, Fernández A. 2050 LCOE improvement using new molten salts for thermal energy storage in CSP plants. Renew Sustain Energy Rev 2016;57:505–14.
[33] Guerreiro L, Canavarro D, Pereira MC. Efficiency improvement and potential LCOE reduction with an LFR-XX SMS plant with storage. Energy Procedia 2015;69:868–78.
[34] Pawel I. The cost of storage – how to calculate the levelized cost of stored energy and applications to renewable energy generation. Energy Procedia 2014;46:68–77.
[35] Parrado C, Girard A, Simon F, Fuentealba E. 2050 LCOE (levelized cost of energy) projection for a hybrid PV (photovoltaic)-CSP (concentrated solar power) Plant in the Atacama Desert, Chile. Energy 2016;94:422–30.
[36] Branker K, Pathak M, Pearce J. A review of solar photovoltaic levelized cost of electricity. Renew Sustain Energy Rev 2011;15:4470–82.
[37] Hernández-Moro J, Martínez-Duart J. Analytical model for solar PV and CSP electricity costs: present LCOE values and their future evolution. Renew Sustain Energy Rev 2013;20:119–32.
[38] Lazard. Lazars's levelized cost of storage analysis version 1.0, Online; 2015. ⟨https://www.lazard.com/⟩.
[39] Agora Energiewende. Calculator of levelized cost of electricity for power generation technologies, Online; 2014. ⟨https://www.agora-energiewende.de/en/⟩.
[40] Northwest Power and Conservation Council. Sixth northwest conservation and electric power plan; 2010.
[41] Pate K, Li Z, Watson L. Primer project – energy storage. Technical Report, Texas Tech University, Texas; 2012.
[42] der Linden SV. The commercial world of energy storage: a review of operating facilities. Technical Report, Brulin Associates, Energy Storage Council; 2003.
[43] Schoenung S. Energy Storage Systems Cost Update: A study for the DOE energy storage systems program. Sandia National Laboratories; Sponsoring Organization: USDOE; 2011.
[44] Gilbert K, Lee H, Manwaring M. What's so hard about licensing a pumped hydro project? HydroWorld 2010.
[45] Boyles J. R & D Activities, Technology and cost considerations. Technical Report, National Energy Technology Laboratory; 2012.
[46] Eyer J, Corey G. Energy storage for the electricity grid: benefits and market potential assessment guide. Technical Report, Sandia National Laboratories, Albuquerque, NM and Livermore, CA; 2010.
[47] Nguyen T, Savinell R. Flow Batteries. Electrochem Soc Interface 2010;19:54–6.
[48] Federal Energy Regulatory Commission. Electric market overview. Regional spot prices: 2009–2011, Online; 2012. ⟨www.ferc.gov⟩.
[49] U.S. Energy Information Administration. Analysis projections: annual projections to 2035, Online; 2011. ⟨www.eia.gov/analysis/projection-data.cfm⟩.
[50] Deign J. Green Tech Media. Paris climate deal expands opportunities for energy storage, Online; 2015. ⟨www.greentechmedia.com⟩.
[51] EU Directorate-General for Energy Working Paper. The future role and challenges of energy storage, Online; 2016. ⟨www.ec.europa.eu⟩.
[52] Lilia Xie, Laslau C. Clearing the haze: demystifying energy storage opportunities in China. Online; 2015. ⟨www.luxresearchinc.com⟩.
[53] Becky Beetz. US, Japan and South Korea to Install 14 GW of energy storage between 2015–16, Online; 2015. ⟨www.pw-magazine.com⟩.
[54] Electricity Advisory Committee. 2012 Storage report: progress and prospects: recommendations for the U.S. Department of Energy, Online; 2012. ⟨www.pw-magazine.com⟩.
[55] Oregon Department of Energy. Office of innovative partnerships and alternative funding innovative partnerships program. Online; 2012. ⟨www.oregon.gov⟩.
[56] Energy Trust of Oregon. Solar electric for homes: energy trust incentives, Online; 2012.
[57] Energy Trust of Oregon. Solar electric for business: energy trust cash incentives, Online; 2012. ⟨www.energytrust.org⟩.
[58] Sen. Ron Wyden (sponsor). S 1845: Storage act, 112th U.S. Congress; 2011–12.
[59] U.S. Energy Information Administration. Office of Energy Analysis, Wholesale Electricity and Natural Gas Market Data, Online; 2016. ⟨http://www.eia.gov/electricity/wholesale/⟩.
[60] Northwest Power and Conservation Council. Update to the Council's Forecast of Fuel Prices; 2011.
[61] Hahn V, Fix J, Schmalz J, Wennen M, Couppis E, Ratafia-Brown J. Updated capital cost estimates for electricity. U.S. Energy Information Administration, U.S. Department of Energy; 2010.
[62] Ren H, Gao W, Ruan Y. Economic optimization and sensitivity analysis of a photovoltaic system in residential buildings. Renew Energy 2009;34:883–9.
[63] Darling S, You F, Veselkad T, Velosa A. Assumptions and the levelized cost of energy for photovoltaics. Energy Environ Sci 2011;4:3133–9.
[64] Boonnasa S, Namprakai P. Sensitivity analysis of the capacity improvement of a combined cycle power plant (100–600 MW). Appl Therm Eng 2008;28:1865–74.
[65] United States Department of Energy. Grid energy storage, Online; 2013. ⟨www.Energy.gov⟩.
[66] Nourai A. Installation of the first distributed energy storage system at American electric power. Sandia National Laboratories; Sponsoring Organization: USDOE; 2007.
[67] Musial W, Butterfield S. Future for offshore wind energy in the United States. Prepared for EnergyOcean by the National Renewable Energy Laboratory; 2004.
[68] Li P, Loth E, Simon T, de Ven JV, Crane S. Compressed air energy storage for offshore wind turbines. 2011 International Fluid Power Exhibition (IFPE); 2011.
[69] Graham J. Debt and the marginal tax rate. J Financ Econ 1996;41:41–73.
[70] Stodard L, Abiecunas J, O'Connel R. Economic, energy, and environmental benefits of concentrating solar power in California. Technical Report; 2006.
[71] U.S. Energy Information Administration. Levelized cost of new generation resources in the annual energy outlook, Online; 2013.
[72] U.S. Bureau of Labor Statistics. Inflation Calculator 2012.
[73] Schoenung S, Hassenzahl W. Long- vs. short-term energy storage technologies analysis. A life-cycle cost study, Sandia National Laboratories, U.S. Department of Energy; 2003.

[74] Steward D, Saur G, Penev M, Ramsden T. Lifecycle cost analysis of hydrogen versus other technologies for electrical energy storage. U.S. Department of Energy, National Renewable Energy Laboratory; 2009.
[75] Western Electric Coordinating Council (WECC). 2011 Economic study requests to TEPCC. Northern Tier Transmission Group; 2011.
[76] Federal Energy Regulatory Commission (FERC). Copy of pre-issued preliminary permits, FERC ELibrary; 2011.
[77] Bose K. Federal Register Vol. 76, No. 83 Notices, Federal Energy Regulatory Commission (FERC); 2011.
[78] Todd W. Hydroelectric pumped storage for enabling variable energy resources within the federal columbia river power system. Bonneville Power Adm 2010.
[79] Symbiotics, Swan lake north pumped storage hydroelectric project, FERC No. 13318, Riverbank Power, Symbiotics, LLC; 2011.
[80] Hanley C, Peek G, Boyes J, Klise G, Stein J, Ton D, Duong T. Technology development needs for integrated grid-connected PV systems and electric energy storage. In: 34th IEEE Photovoltaic Specialists Conference (PVSC); 2009. p. 1832–37.