Determining Reserve Requirements for Energy Storage to Manage Demand-Supply Imbalance in Power Grids

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***Abstract*—Proper integration of energy storage systems (ESS) into existing or future grids will depend on the effectiveness of models which seek optimal placement and sizing at the transmission and distribution levels. Current literature reviews reveal sizing methodologies can be improved to ease infrastructure integration, and those works with models useful for planning focus solely on micro-grids, wind power and forecasting, photovoltaics, or small communities. It is of interest to create an efficient, reliable ESS sizing model for large scale grids that contains interpretable models, has less sensitivity due to low model uncertainty, yet still is dependable due to an imposed reliability criterion. This work determined the minimum feasible size ESS to satisfy reserve requirements for a power grid with a high penetration of renewable sources. Results showed imposing a reliability criterion through loss of load expectation (LOLE) and energy index of reliability (EIR) resulted in more conservative capacity needs.**

I. Introduction

As energy portfolios grow more diverse, a larger penetration of renewable sources, such as wind and solar power, can be found on the power grid. Integrating high levels of renewables presents challenges for system generation scheduling and ancillary services due to their intermittency [1]. The flexibility required by the future power grid can not be supported solely by existing infrastructure. Generation variability and uncertainty in production can impact reliability, power quality, efficiency, and many other aspects of both generation and transmission. Energy storage systems (ESS) have the potential to lessen the flexibility requirement by compensating when power generation and demand differ significantly [2].

Proper integration of ESS into existing or future grids will depend on the effectiveness of models which seek optimal placement and sizing at the transmission level. Existing models for sizing ESS lack the ability to translate results into a useful manner for utilities and planning [1]. In 2010, researchers at Pacific Northwest National Laboratory (PNNL) compiled a literature review of models and analytical tools which seek to optimize the siting, sizing, and economic value of energy storage in a smart grid infrastructure. Despite the breadth of models compared, the authors concluded that there was no tool "...that specifically [dealt] with sizing and locating energy storage under any optimality criterion that would be useful for infrastructure development" [1]. Ru, Klessi, and Martinez claimed in 2014 that, thus far, contributions to the theoretical analysis of storage sizing had been limited [3].

Moreover, many sizing models with analytical methods useful for planning focus solely on micro-grids, only wind power and wind forecasting, only photovoltaics, or small communities [3]–[11]. In a review of methods for ESS siting and sizing from 2016 [12], results show that only two works, [13] and [14], utilize analytical methods without mathematical optimization tools to size energy storage with reliability constraints. Of the two previously mentioned results from [12], the former presents a general methodology to determine the size of a backup storage unit for "a hospital, process plant, or a military base" [13]. The latter's method is demonstrated on a micro-grid [14]. Sizing ESS at this scale does not produce a need for reliability constraints because they only service single consumers. Thus, a universal methodology for determining reserve requirements for storage to manage demand and supply imbalance with ease of implementation and reliability guarantees for large scale power grids is necessary.

A. Reserve Sizing Methods

Various techniques have been explored to estimate energy storage requirements in the presence of a high penetration of renewables. A popular method, seen in [10], [15], [16], is to use stochastic optimization to find optimal ESS size while minimizing operation cost and considering transmission constraints. This is known as a system simulation approach [10], [17]. Results from Monte Carlo simulations or multiple scenarios provide the cost of a predefined level of reserves and an accurate computation of reliability [17], [18].

Deterministic and probabilistic techniques can be used to size reserves. Both approaches can be static or dynamic in reference to system conditions. An overview of both these methods can be found in [19]. Deterministic methods size reserves according to a specific event (e.g. largest credible contingency) and are advantageous because of their simplicity. No production cost models or comprehensive storage models are required for results. However, results may lead to an overestimate of reserves and costs for the system since there is no account for the probability of events. Seen in [20], the maximum feasible ESS size was determined by identifying different cycling components of the balancing power. Xiao, et. al. use a similar method to [20], but instead coordinate ESS sizing with a diesel generator for micro-grid applications [5]. Ru, et. al. size ESS as a finite horizon deterministic optimization problem, but results produce only lower and upper bounds of storage requirements [8]. In [6], methods from [20] are compared to a discrete wave transform (DWT) method for sizing hybrid ESS (NaS battery and compressed air), using wind power forecast error (WPFE) to size reserves. In addition, the authors utilize ESS properties to better size the reserve requirement.Dynamic probabilistic assessments are demonstrated in [21] to allocate the necessary storage requirement for hedging operational uncertainty induced by the wind power forecasts.

Though more complex and computationally intensive, probabilistic methods allow for reserve sizing based on an imposed reliability criterion. Using a probability density function (PDF), desired reliability can be used as a cutoff to determine the amount of reserves. In [9], a probabilistic approach is used to determine requirements for a hybrid energy storage system composed of a lead-acid battery and super capacitor for a single wind farm. A similar approach in [17] is used to estimate reserve requirements and further categorize the reserves based on imbalance drivers for North Sea Country. However, reserves are only sized to suit uncertainty in WPFE, similar to [6].

B. Need for Simpler ESS Sizing Models

It is of interest to create an efficient, reliable ESS sizing model that does not use optimization, but utilizes a probabilistic approach. The benefits of such a model are that it has a more physically interpretable model, has less sensitivity due to low model uncertainty, yet still is dependable due to an imposed reliability criterion. At the time this paper was completed, there was no existing work which sought to satisfy all of the above requirements for a large scale grid except for [17]. This work differs from the aforementioned paper in the use of reserves sized. Our work assumes that both highly-variable and unpredictable generation will contribute to the amount of reserves instead. This means that concurrent ESS used to satisfy reserve requirements will cater to a portion of predictable generation, in addition to the unpredictable generation. This will be further specified in II.

The objective of this research is to determine the minimum feasible size of ESS to satisfy reserve requirements for a power grid with a high penetration of renewable sources. The methodology used in [20] will be followed to identify the reserve requirements from imbalance power. Subsequently, a loss of load probability (LOLP) will be specified and the required power and energy capacities will be chosen. Results with and without the imposed LOLP will be compared. Lastly, the selected LOLP will be equated to an additional reliability index for thoroughness and to enhance interpretability.

II. METHODOLOGY

The required capacity of ESS depends on both load and the controllable generation that supplies part of the net load, the latter being load minus the renewable generation. We start with definitions of these quanities.

A. Decomposition of Balancing Power

The ability of a generator to dynamically vary output can be quantified by ramp rate and ramp duration. When unexpected events occur, such as a large step change in generation set-point, generators may be required to modify their output to meet demand. If this adjustment requires faster ramp rates with shorter ramp durations, existing generators may have difficulty adapting. Varying generation set-points often require these ramp characteristics. As the power grid sees higher penetrations of renewable sources, varying generation set-points become more common. With this, the difference between demand and generation will be large, resulting in frequency deviations and possible generator shut down as a contingency measure. ESS can assist in managing this mismatch or imbalance by acting as *regulating* or *ramping* reserves as defined in Table I by Holttinen [19].

In an ideal setting, total demand, $D(t)$, equals total generation $G(t)$ plus the power delivered by the ESS, $S(t)$:

$$D(t) = G(t) + S(t), \tag{1}$$

where all three quantities have the unit of power (Watt). The quantity $S(t)$ can be positive or negative; $S(t) > 0$ means the ESS is discharging (acting as a generator) and $S(t) < 0$ means it is charging (acting as a load) at time t. Power generation can be separated into two components, $G_c(t)$ and $G_r(t)$:

$$G(t) = G_c(t) + G_r(t). \tag{2}$$

Controllable generation; nuclear, hydro, fossil, and biomass, is represented by $G_c(t)$. The symbol $G_r(t)$ refers to the uncontrollable renewable generation from solar and wind sources.

Because $D(t)$ and $G_r(t)$ are known, they can be rewritten as $\tilde{D}(t)$, the net-load signal in (3), and must be supplied by controllable generation and ESS.

$$\tilde{D}(t) \triangleq D(t) - G_r(t) \tag{3}$$

Net-load will also be referred to as net-demand or imbalance power. Decomposing $\tilde{D}(t)$ into low and high frequency components using an appropriately designed filter allows a balancing authority to identify portions of the net-load to be supplied by controllable sources and energy storage devices. In particular, the slowly-varing "low-pass" component of the net-demand can be supplied by controllable generators, while the remaining high-pass component is assumed to be supplied by ESS. We denote the low-pass component of the net-load as $\tilde{D}_{LP}(t)$. Thus,

$$\tilde{D}(t) = \tilde{D}_{LP}(t) + \tilde{D}_{HP}(t) \tag{4}$$

where $\tilde{D}_{HP}(t)$ is the high pass component. The cutoff frequency of the low-pass filter, which we denote by ω, is the highest frequency sinusoid that can be tracked by the controllable generators. This frequency is determined by the ramp rate constraints of all the controllable generators.

Substituting (2) and (4) into (1), produces (5) below.

$$\tilde{D}_{LP}(t) + \tilde{D}_{HP}(t) - G_c(t) - S(t) = 0 \tag{5}$$

For an ideal, isolated system, the low-frequency component of the net-load signal should be nearly equal to controllable generation.

$$\tilde{D}_{LP}(t) = G_c(t) \tag{6}$$

This reduces (5) to a simple equality where the high-pass component of the net-load signal should be equal to the amount of required storage.

$$\tilde{D}_{HP}(t) = S(t) \tag{7}$$

Therefore, the required power capacity for an energy storage device up to time k in an interval $[0, K]$ is given by (8). It follows, the required energy capacity is the sum of power capacity up to time k multiplied by time increment, Δt.

$$P_k \triangleq \tilde{D}_{HP}(t) \qquad E_k \triangleq \sum_{j=1}^{k} P_j \Delta t \tag{8}$$

To explain further , consider an alternate form of (6) and (7). Substituting (3) into (6) and (7), results in (9) and (10). This result illustrates that the high-frequency component of the demand signal and renewable energy generation will be serviced by ESS. Energy storage ramping capabilities are better suited for fast regulation and load following, which are synonymous with the intermittent nature of renewable sources. Also, a portion of $D(t)$ and $G_r(t)$ can be serviced by $G_c(t)$. Renewable generation is much less predictable than demand, so $G_r(t)$ can be considered random while $D(t)$ can be modeled as deterministic, making $S(t)$ a stochastic variable. Further, the net load is modeled as a stochastic process.

The remaining, low pass component will be well serviced by generator set-points arising out of the real-time planning process by the grid operator, which are based on the predictable portion of the demand and renewable generation. What is more, it is useful to mention $G_c(t)$ is not random, and considered to be known since their power consumption can be varied slowly.

$$(D(t) - G_r(t))_{LP} = G_c(t) \tag{9}$$

$$(D(t) - G_r(t))_{HP} = S(t) \tag{10}$$

For a bulk power system, ω can be identified by an assessment of the Fourier Transform of $G_c(t)$. Aside, the reference method [20], divides $\tilde{D}(t)$ into four ranges: slow-cycling, intra-day, intra-hour, and real-time. However, theit partial balance results state that slow-cycling and intra-day are assumed to be handled by existing generators and ESS will compensate for the intra-hour and real-time frequency components of the net-load. Thus, the reference method divides the imbalance signal in a similar, almost identical, fashion to this work.

B. Capacity Formula

The proposed method seeks to determine the storage capacity $C_{P,E}$ such that the probability of failing to deliver the charging/discharging requirement $S(t)$ is smaller than α for some small $\alpha > 0$. The number α is called the Loss of Load Probability (LOLP)[22]. A smaller choice of α will necessitate a larger and thus more expensive ESS, but the probability of failing to meet the demand will be reduced. A larger α will have the opposite effect.

For computing the relevant quanitities, we need a probabilistic model of the storage requirement. To facilitate this development, we introduce two intermediate stochastic processes. The first one, called daily required power, $P_i^{req,d}$ is defined as

$$P_i^{req,d} \triangleq \max_{k \in \mathcal{K}^{(i)}} |P_k| \qquad E_i^{req,d} \triangleq \max_{k \in \mathcal{K}^{(i)}} |E_k| \tag{11}$$

where $\mathcal{K}^{(i)}$ is the set of time indices corresponding to the i-th day. In short, $(P_i^{req,d}, E_i^{req,d})$ is the minimum capacity of a battery that can fulfill the requirements on the i-th day.

We assume that the $P_i^{req,d}, E_i^{req,d}$ are stationary stochastic processes. In the sequel we denote by $P^{req,d}, E^{req,d}$ two random variables whose pdfs describe the marginal pdfs of the any of the $P_i^{req,d}, E_i^{req,d}$'s. The minimum capacity P_{store}, E_{store} for a given LOLP α is now defined as

$$P_{store} \triangleq \min_{C_P} \{C_P | Pr(P_{req,d} \leq C_P) \geq 1 - \alpha\} \tag{12}$$

$$E_{store} \triangleq \min_{C_E} \{C_E | Pr(E_{req,d} \leq C_E) \geq 1 - \alpha\} \tag{13}$$

The rationale for introducing these is the stationarity assumption. A stationary model is much more convenient to deal with than a non-stationary model. A fast sampling period is necessary to capture all the large spikes in net demand that have a strong impact on grid balancing. With a fast sampling, the stochastic processes P_k, S_k will exhibit highly non stationary behavior due to the intra-hour or intra-day variations in the statistics of renewable generation. These strong daily variations get aggregated in the daily requirements. Even though seasonal variations remain, a stationary assumption on the daily requirements is much more defensible than on the minute-by-minute requirements.

III. Application to BPA data

To illustrate how the proposed method in Section II can be applied to an existing power system, we apply the method to a year of 5-minute sampled data available from Bonneville Power Administration [23]. This time interval was chosen to correspond with the common expression of LOLP in units of days per year [22].

Since ramp rate constraints of all the generators in BPA's jurisdiction were not available, we estimate the frequency ω described in Section II-A from a Fast Fourier Transform (FFT) of the conventional generation data. FFT analysis showed that the highest frequency serviced by conventional generators was roughly $\frac{1}{30 minutes}$; the amplitude of generation FFT reduces significantly at frequencies higher than this point. A second

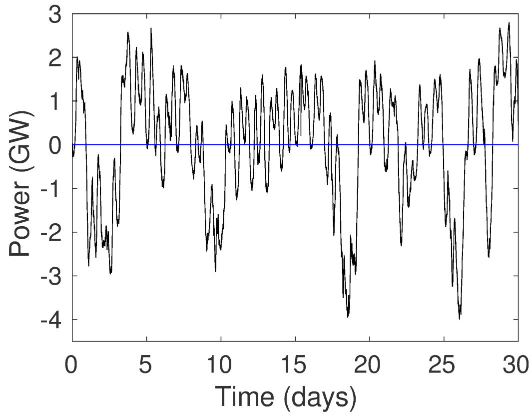

Fig. 1: Power Profile for One Week in 2016.

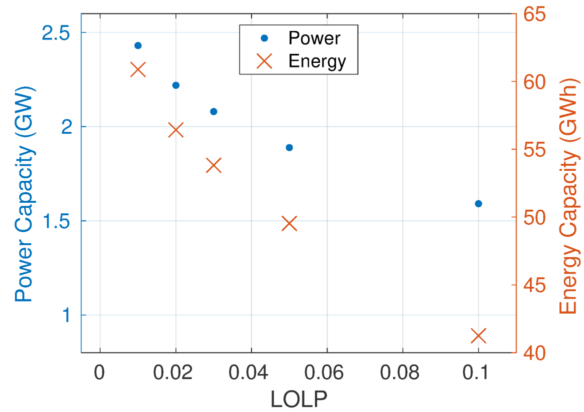

Fig. 2: Resulting capacity from varied α values (2016).

TABLE I: Comparison of the ESS Capacities for 2016

	Makarov's Method [20]	**Proposed Method**	**Percent Reduction**
Power Capacity	4.2 GW	2.4 GW	53.2%
Energy Capacity	70.5 GWh	60.9 GWh	14.7%

order high-pass Butterworth filter with $\omega = \frac{1}{30minutes}$ was used to find P_k. Energy capacity E_k is computed as the cumulative trapezoidal integral of P_K, with spacing Δt. The samples of P_k for one are shown in Fig. 1 for reference.

Once samples of P_k and E_k were obtained for a particular time interval, the daily requirements were computed over the same interval. We first used the data for 2016, which yielded 365 samples of the random variable's $P^{(req,d)}$ and $E^{(req,d)}$. PDFs of $P^{(req,d)}$ and $E^{(req,d)}$ are first estimated using a Kernel Density Estimator (KDE) in Matlab© using these 365 samples. A Gaussian kernel with optimal bandwidth is used in the KDE estimation. Then, the PDFs are summed and smoothed to create a single PDF for time period $[0, K]$. Using ideal bandwidth from MATLAB's *fitdist* function, PDF results showed multi-modal, non-symmetric distributions with heavy-tails. Finally, the probabilities in (12) and (13) are computed from the estimated pdfs. The ESS capacities can be simply determined from the cumulative distribution functions (CDF) as the capacity values corresponding to $1 - \alpha$. Table I shows the resulting capacities for 2016, with $\alpha = 0.01$. For comparison, results obtained by using the deterministic sizing method of [20] are also shown. As expected, the proposed probabilistic method leads to a smaller capacity requirement than the deterministic method of Makarov. It is noticeable that relaxing the reliability to 99% from 100% (i.e., deterministic) reduces the power capacity by nearly half which is anticipated to have a large impact on cost. However, a cost discussion is beyond the scope of this work.

For $\alpha = 0.01$, with an ESS of this capacity the balancing authority is expected to meet the demand at least 99% of time, or 361.35 days per year. Increasing the chosen α results in smaller capacities, as expected, but the amount of days demand is met would decrease. Fig. 2 shows how the capacities vary with α.

Although LOLP defines the probability of shortage, it does not describe the severity. An alternate metric that does capture the severity of shortage is Expected Energy Not Served (EENS) [10]:

$$EENS \triangleq \frac{1}{N}\sum_{i=1}^{365}(E_{req}^{(i)} - E_{store})\mathbb{1}_{(E_{req}^{(i)} > E_{store})} \tag{14}$$

EENS is a measure of lost electricity demand when demand exceeds available generation. As seen in (14), EENS is the sum of probabilities on the days when required energy is greater than ESS energy capacity.

Expected energy demand (EE) is the total energy demanded by the grid, which would be the sum of all E_k at each time index i.

$$EE \triangleq \frac{1}{N}\sum_{i=1}^{365} E_{req}(i) \tag{15}$$

Normalizing EENS by EE produces the energy index of reliability (EIR), an additional metric normally used by transmission system operators (TSO) to assess adequacy of generation and transmission systems. It ensures that both large and small systems can be compared on an equal basis and that the evolution of load in a system can be tracked [24]. Use of EIR is becoming more popular because it reflects the true risk of not meeting demand and has more physical significance than LOLP [25]. Eq. (16) was used to compute EIR values [10].

$$EIR = 1 - \frac{EENS}{EE} \tag{16}$$

In this context, EIR quantifies the risk of ESS being too small, or the effect of ignoring the amount of load lost if the ESS is sized based on P_{store} and E_{store} but the true need exceeds these values. Fig. 3 shows a how varying α correlates to EIR. The relationship between $1 - \alpha$ and EIR is almost directly proportional as expected, indicating that when load can be met for more days per year the severity of deficiencies is

TABLE II: Comparing α using the Proposed Method

	LOLP		
	1 day/year	**3.65 days/year**	**Percent Reduction**
α	0.00216	0.01	N/A
Power Capacity	3.2 GW	2.4 GW	28.7%
Energy Capacity	70.5 GWh	60.9 GWh	14.7%
EIR	1.000	0.9998	0.02%

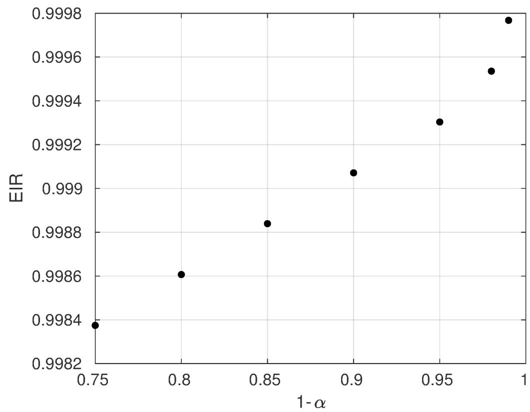

Fig. 3: EIR vs. $1-\alpha$ (2016).

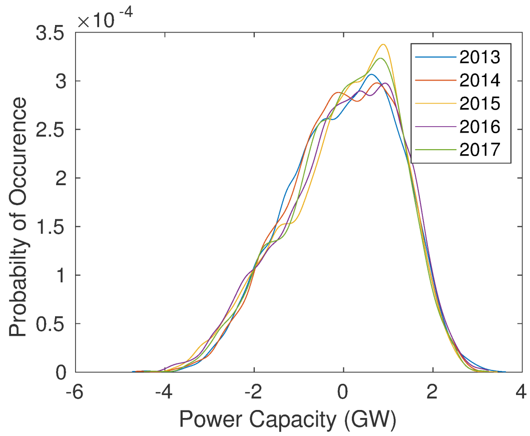

Fig. 4: PDFs for BPA Data 2013-2017

smaller (close to 1). However, when load cannot be met as often (higher α, lower $1-\alpha$), EIR reduces significantly leading to more consumer impact. With our method, it is possible to provide ESS capacity estimates up to a LOLP of 0.79 days per year, or $\alpha = 0.00216$. Table II shows a comparison of the aforementioned LOLP and capacities.

A. Future Work

Follow-up to this investigation will be the development of a parametric model to generate time series PDFs used in the prediction of future ESS needs. No clear trends were found in the comparison of yearly PDFs, seen in Fig. 4. Moreover, there was poor correlation between installed BPA wind capacity and our ESS capacity results, shown in Fig. 5, indicating that

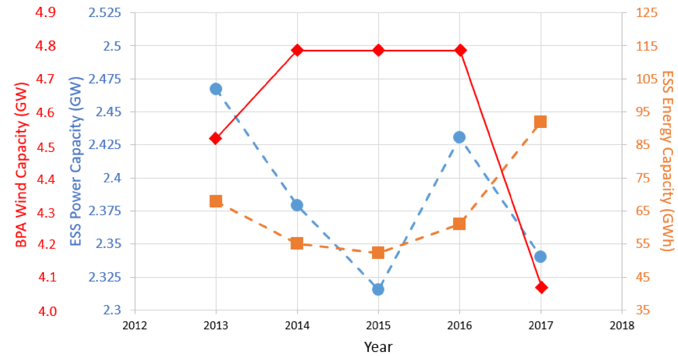

Fig. 5: Comparison of yearly capacity requirements for BPA Data 2013-2017

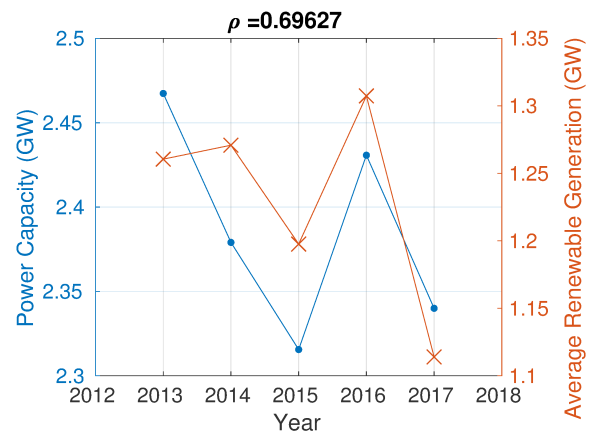

Fig. 6: ESS Power Capacity and Average Renewable Generation Trends for BPA 2013-2017

installed renewable energy capacity is not a good predictor of ESS needs for large scale power grids. Alternative metrics must be used to assist in this more difficult planning problem.

Average demand and renewable generation proved to be more useful metrics which followed similar trends to the sizing requirements produced by our method. As shown in Fig. 6, there was a correlation coefficient of roughly 0.7 between average renewable energy generation per year and required ESS power capacity. Plus, average demand and energy capacity revealed a correlation of about 0.85, seen in Fig. 7. These strong correlations give us confidence in our capacity estimates, and hence, our method. Furthermore, these dominant relationships will assist in providing a more interpretable model for future use in predicting ESS capacity needs. Compiling Fig. 5 with correlating trends in Fig. 6 and Fig. 7, a model which takes the year as an input index and outputs the required capacities can be created.

IV. Conclusion

Load and renewable generation data from Bonneville Power Administration (BPA) were used to identify regulating reserve requirements from imbalance power for yearly intervals. Results showed imposing a reliability criterion through loss of

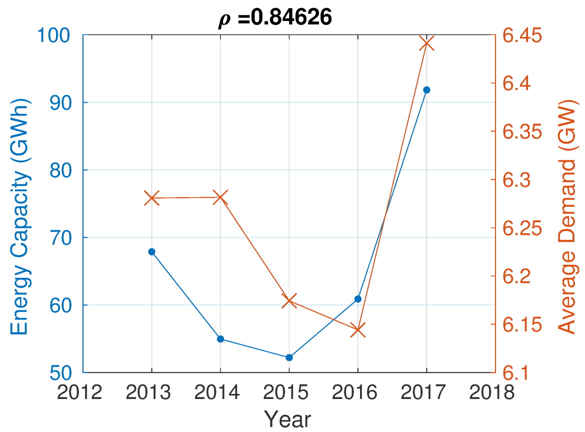

Fig. 7: ESS Energy Capacity and Average Demand Trends for BPA 2013-2017

load probability (LOLP) resulted in more conservative capacity needs for an energy storage system (ESS). Additionally, the interchangeability of LOLP with energy index of reliability (EIR) was shown to illustrate this method's ease of implementation for balancing authorities. The outcome of this work can be used to answer a key decision problem resource adequacy planning: How much regulating and ramping reserves are necessary in a specified time frame? And, how can ESS satisfy those reserves? Future work will explore a predictive model generated by similar methodology for ESS in future grid development.

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