A Probabilistic Method for Reserve Sizing in Power Grids with High Renewable Penetration

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***Abstract*—Power systems employ reserves to ensure there is adequate generation and storage to meet demand. With the increased use of volatile and uncertain sources of electricity such as solar and wind, the need for reserves is becoming more critical to ensure reliable supply of electricity. Due to the high cost of reserves, methods are required to determine minimal reserves needed. This work proposes a probabilistic data-driven method to determine the minimum reserve size (both power and energy) to satisfy a specified reliability requirement for a bulk power grid. The proposed method is applied to data from two balancing authorities (BPA and CAISO), and the results are compared with those from an alternate deterministic method and to those from the current reserve sizing methods employed by BPA and CAISO. The reserve requirements do not seem to be predicted by simple indicators of volatility, such as installed capacity of wind and solar, which has implications for grid planning in a renewable rich future.**

I. Introduction

Volatile renewable energy sources (VRES) such as solar and wind are becoming a significant part of the power generation mix. Since VRESs are non-dispatchable and intermittent, the net-load, which is the difference between demand and generation from VRES, must be met by controllable resources. Traditionally, power systems have maintained reserves to cope with unforeseen changes in generation and demand. These reserves are provided by controllable generation or storage. With the increasing penetration of VRES, larger reserves are needed to maintain the same level of reliability. Since reserves are expensive irrespective of whether they are supplied by traditional generators or energy storage systems, there is a need for determining the minimal amount of reserves required to meet a certain level of reliability [1].

There is extensive literature on reserve sizing. The review [2] 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". Four years later, the authors in [3] conclude that "...thus far, contributions to the theoretical analysis of storage sizing had been limited". In a review of methods for energy storage system (ESS) siting and sizing from 2016 [4], results show that only two works, [5] and [6], utilize analytical methods without complex mathematical optimization tools to size energy storage with reliability constraints. Of these two references, the first presents a general methodology to determine the size of a backup storage unit for "a hospital, process plant, or a military base" [5]. The method in the second reference is demonstrated on a micro-grid [6]. Moreover, many other analytical sizing methods focus on specific use cases, such as on micro-grids [7, 8], on wind power and wind forecasting [9, 10], on photovoltaics [3, 11], or on small communities [12]. Methods for sizing reserves at this small scale usually do not consider reliability requirements.

In this work, we propose a method to determine the minimum reserve capacity requirement (power and energy) to satisfy a certain reliability measure. The loss of load probability (LOLP) is used as the reliability measure since "methods based on LOLP are...often applied to resource adequacy assessments" [13]. The method uses time series data of demand and renewable generation to fit a probabilistic model of the fast-varying component of the net-load that slowly ramping conventional generator may not be able to meet. The reserve needed to meet the specified LOLP requirement is then obtained from the probabilistic model.

While LOLP considers the probability of not meeting (power) demand, it does not consider the impact of unmet energy demand when a shortfall occurs. Severity of the unmet energy demand is quantified through the energy index of reliability (EIR). We quantify the EIR achieved when reserve sizing is performed for a target LOLP. Since both LOLP and EIR are existing bulk-system planning metrics, the proposed sizing methodology provides a helpful assessment of resource adequacy for bulk system reserve sizing.

Reserve needs in the context of bulk power systems are usually quantified in terms of power (Watt) alone, presumably since reserves are provided by traditional generators such as thermal and hydro. Thus, their energy (Watt-hour) capacity can be considered effectively infinite. In the future, if part of the reserve is supplied by batteries, energy will need to be part of reserve considerations. The proposed method computes both the power and energy capacity needed to meet a certain LOLP.

While many sizing methods – especially those for micro-grids – determine optimal sizing by minimizing an objective that incorporates the cost of reserves and the cost of not meeting demand due to inadequate reserves, we do not follow such an approach. The reason is to avoid sensitivity to parameters that such an optimization method suffers from. For instance, the cost of unmet demand is typically measured through the so-called value of lost load (VOLL), whose estimates vary by an order of magnitude [14, 15]. Similarly, the cost of reserve depends on highly time varying fuel prices (if thermal generators are used to provide reserves) or cost of rapidly evolving energy storage technologies.

Two case studies are presented for reserve sizing with the proposed method by applying it to data from Bonneville Power Administration (BPA) and California Independent System Operator (CAISO). The results are compared to those obtained

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by the deterministic method proposed in [16], and to that obtained by the methods currently used by these two balancing authorities. The requirements for power reserves and energy reserves do not have strong correlation, which may have an implication if an energy storage system is used to provide part of the reserves. It is also observed that the reserve requirements do not always have strong correlations with simple indicators of volatility, such as installed capacity of renewables. Had there been such a relation, it could have been used to easily predict reserve requirements for the future.

The rest of the paper is structured as follows: We first outline the contribution of the paper to the existing literature in Section I-A. Section II describes the proposed method, sometimes illustrating the various components of the method by using data from BPA. Section III provides two cases studies through application of the method to BPA and CAISO. Section IV discusses how to apply the method to estimate future reserve needs. Section V concludes the paper with a discussion.

A. Comparison With Prior Work

There are few existing works which seek to determine reserve requirements using existing power system metrics and reliability guarantees useful for bulk system planning. In [1], the additional reserves needed when wind generation is added to the balancing area are sized based on a Gaussian assumption. We do not make a Gaussian assumption, and size reserves for the entire balancing area with no additional assumptions on existing operating reserve adequacy. In [17], authors subdivide reserve sizing results into slow and fast response reserves with a note that fast reserves may be under-sized using their method. The methodology in [18] employs a cost function with constraints for LOLP and focuses solely on energy storage, whereas our method can be adapted to many types of reserve options. Other similar works include [19] and [20] which are hybrid unit commitment solutions to the reserve sizing problem. Their pitfalls are the multiple sources of uncertainty which impact problem constraints. The method described in [21] uses a Dynamic Bayesian Belief Network with added probabilistic criterion to size reserve needs. However, this artificial intelligence-based technique is computationally intensive and needs adequate time for model training.

Our method also has certain similarities with the deterministic method proposed by Makarov *et al.* [16] since we use frequency domain analysis to separate the components of the net-load based on time scale. The method of [16] does not provide a reliability measure and is limited to the worst-case extreme event observed in the data. In contrast, our method uses a parametric model to predict low probability events that have not been observed in the data, and thus is useful in planning for a high level of reliability.

This paper makes two main contributions over the existing literature on reliability-based reserve sizing methods. The first and the most significant is that it enables reserve sizing (for both power and energy) for LOLP values far smaller than what is directly observed in the data, which is made possible by fitting a probabilistic power-law model to data. The second contribution is an outcome of the case studies on future reserves needs for two balancing authorities (Section III). This study shows that simple measures such as installed renewable generation capacity are poor predictors for future reserve needs.

A preliminary version of this work was published in [22]. The contributions of this paper over prior art (listed in the previous paragraph) also hold over the preliminary version. In addition, this paper examines the effect of generator ramping capability in the reserve requirement (Section III), which was not in [22].

II. Methodology

A. Method Overview

The reserves needed for a certain level of reliability depend on the fast-varying part of the net-load, the latter being load minus VRESs. The slow-varying part of the net-load is supplied by controllable generators such as thermal power plants. We start with definitions of these quantities.

Time is assumed discrete: $k = 0, 1, \dots,$ with a sampling period Δt between time ticks. The *net-load* $\tilde{D}_k$ is

$$\tilde{D}_k := D_k - G_k^r \tag{1}$$

where D_k, G_k^r are the demand and renewable generation at time k, respectively. All three quantities have the unit of power (Watt). We decompose the net-load into two components, $\tilde{D}_k^{\mathrm{LP}}$ and $\tilde{D}_k^{\mathrm{HP}}$, such that

$$\tilde{D}_k = \tilde{D}_k^{\mathrm{LP}} + \tilde{D}_k^{\mathrm{HP}}. \tag{2}$$

The low-pass, or slow-varying, component $\tilde{D}_k^{\mathrm{LP}}$ is assumed to perfectly track controllable power generation G_k^c, hence,

$$G_k^c = \tilde{D}_k^{\mathrm{LP}}. \tag{3}$$

This slowly varying component of the net-load is subject to an appropriate choice of generator cutoff frequency. The cutoff frequency, which we denote by ω_c, is the highest frequency of a sinusoid that can be tracked by controllable generators. This frequency is determined by the ramp rate constraints of all the controllable generators. The remainder of the net-load, the fast-varying component $\tilde{D}_k^{\mathrm{HP}}$, must be provided by the reserves. In this work, $\tilde{D}_k^{\mathrm{HP}}$ is extracted using a high-pass filter with cutoff frequency ω_c.

As an aside, the deterministic method in [16] initially divides $\tilde{D}_k$ into four ranges: slow-cycling, intra-day, intra-hour, and real-time using a Fourier analysis of the net-load. However, their results state that slow-cycling and intra-day components are assumed to be handled by existing generators, and reserves will compensate for the intra-hour and real-time frequency components of the net-load. Our approach is similar to their conclusion in that we use two frequency bins instead of four.

Let P_k^{req} be the power that the reserve is required to deliver at k. The quantity P_k^{req} can be positive or negative; positive means the reserve is discharging (delivering power) and negative means it is charging (consuming power) at time k. In an ideal scenario with adequate reserve, we will have

$$P_k^{\mathrm{req}} = \tilde{D}_k^{\mathrm{HP}}, \quad \forall k, \tag{4}$$

in which case the isolated power system will achieve demand supply balance at all times, since the total power supply, which is the sum of controllable generation, renewable generation, and power delivered/consumed by the reserve is equal to the total power demand:

$$\begin{aligned} G_k &= G_k^r + G_k^c + P_k^{\mathrm{req}} \\ &= (D_k - \tilde{D}_k) + \tilde{D}_k^{\mathrm{LP}} + \tilde{D}_k^{\mathrm{HP}}, \text{ from (1), (3), (4)} \\ &= (D_k - \tilde{D}_k) + \tilde{D}_k = D_k, \text{ from (2).} \end{aligned}$$

Similarly, the required energy reserve at time k, denoted by E_k^{req} is the integral of the required power delivery by the reserve:

$$E_k^{\mathrm{req}} = \sum_{j=-\infty}^{k} P_j^{\mathrm{req}} \Delta t = \Delta t \sum_{j=-\infty}^{k} \tilde{D}_j^{\mathrm{HP}}. \tag{5}$$

In a non-ideal scenario with inadequate reserves, the equalities (4) and (5) will not hold: the left hand sides will be decided by the installed capacity of the reserves which may fall short of the right-hand sides at certain times. Determining the reserve requirement to meet a certain reliability level is to ensure that (i) the probability of the shortfall is smaller than a given threshold, and (ii) the magnitude of the shortfall, when it occurs, is smaller than a threshold.

A probabilistic threshold α can be defined using the *Loss of Load Probability* (LOLP), also known as Loss of Load Expectation (LOLE) [23]. Used in traditional resource adequacy planning for bulk power systems, the LOLP is the probability of generation falling short of demand. A smaller value of α means the probability of failing to meet demand is lower, but high reserves will be needed to ensure a low α. A larger α will have the opposite effect.

Suppose the reserves come from an ESS with *power capacity* C_P (MW) and *energy capacity* C_E (MWh). One can then argue that the minimum values of the numbers C_P and C_E that achieve $\mathbb{P}(\max_k |P_k^{\mathrm{req}}| < C_P) \geq 1-\alpha$ and $\mathbb{P}(\max_k |E_k^{\mathrm{req}}| < C_E) \geq 1-\alpha$, where $\mathbb{P}(\cdot)$ denotes probability, is the smallest reserve size needed to meet a LOLP requirement of at least $1-\alpha$. Evaluation of the probabilities is quite challenging since they depend on the statistics of $\tilde{D}_k^{\mathrm{HP}}$, which is likely to be a complicated non-stationary stochastic process. Obtaining a model of such a process to compute the relevant probabilities may be intractable.

We therefore perform a time aggregation so the resulting process can be modeled as stationary and ergodic. The necessary probabilities can then be estimated from time series data. To facilitate this development, two intermediate stochastic processes are introduced. The *daily required reserve power* and *daily required reserve energy* are defined as

$$P_i^{\mathrm{dreq}} := \max_{k \in \mathcal{K}^{(i)}} |P_k^{\mathrm{req}}| \qquad E_i^{\mathrm{dreq}} := \max_{k \in \mathcal{K}^{(i)}} |E_k^{\mathrm{req}}| \tag{6}$$

where $\mathcal{K}^{(i)}$ is the set of time indices corresponding to the i-th day. In other words, $(P_i^{\mathrm{dreq}}, E_i^{\mathrm{dreq}})$ is the minimum reserve

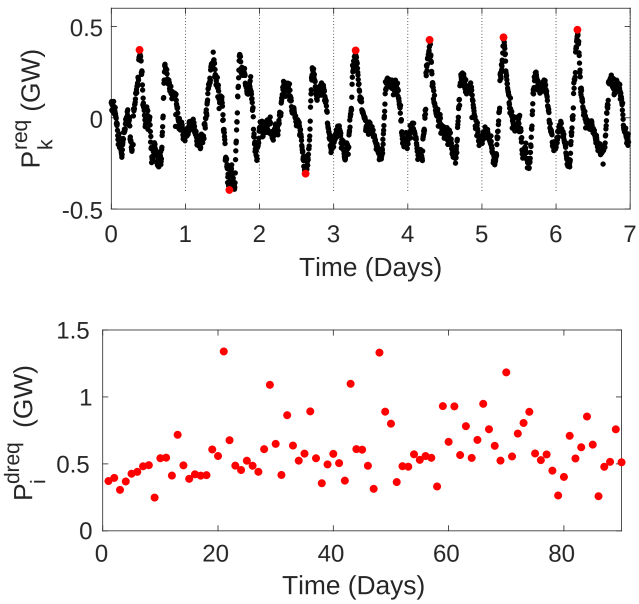

Fig. 1. Example of (top) P_k^{req} and (bottom) daily required reserve power capacity P_i^{dreq}. (Data: BPA, 2016)

capacity that can fulfill the requirements on the i-th day. Let us introduce two random variables, $P^{\mathrm{dreq}}, E^{\mathrm{dreq}}$, as the power and energy needed to be delivered by the reserve on an arbitrary day. The values $(P_i^{\mathrm{dreq}}, E_i^{\mathrm{dreq}})$ for $i = 1, 2, \ldots$ are to be treated as independent realizations of these two random variables.

Aggregation over a day is performed since sample paths of the process P_k^{req} are highly non-stationary due to the intra-day periodicity inherent in demand and renewable generation. Such trends get suppressed when aggregated, making a stationary model more justifiable for the process P_i^{dreq}. Evidence is shown in Figure 1. It becomes easier to estimate probabilities from samples $(P_i^{\mathrm{dreq}}, E_i^{\mathrm{dreq}})$ if the underlying stochastic processes can be modeled as stationary.

If the installed capacity of the reserve is (C_P, C_E), then the LOLP achieved is $\mathrm{P}(P^{\mathrm{dreq}} \geq C_P \cup E^{\mathrm{dreq}} \geq C_E)$. We now define the *minimum reserve capacity* (P_{res}, E_{res}) *for a given probabilistic threshold* α as

$$P_{res} := \min_{C_P} \{C_P | \Pr(P^{dreq} \leq C_P) \geq 1-\alpha\} \tag{7}$$

$$E_{res} := \min_{C_E} \{C_E | \Pr(E^{dreq} \leq C_E) \geq 1-\alpha\}. \tag{8}$$

The proposed sizing method simply consists of fitting a probabilistic model to data so that the right hand side of the equations above can be computed.

Reserves sized based on the probability of generation plus storage falling short of demand alone has the weakness that the magnitude of the shortfall is not considered. The magnitude of shortfall can be quantified using the *energy index of reliability* (EIR) [24]. To define EIR, we need to define two quantities. The first is the *expected energy demand*, which is the average energy demand over a specific time period:

$$E_D := \frac{1}{n_{days}} \sum_{i=1}^{n_{days}} E_i^{dreq} \tag{9}$$

where n_{days} is the number of days. The second is the *Expected Energy Not Served* [24], which is the average energy shortfall over the same time period:

$$E_{NS} := \frac{1}{n_{days}} \sum_{i=1}^{n_{days}} (E_i^{\text{dreq}} - E_{res}) \mathbb{1}_{(E_i^{\text{dreq}} > E_{res})} \tag{10}$$

where $\mathbb{1}_{(x>y)} = 1$ if $x > y$ and 0 if $x \leq y$. The energy index of reliability E_{IR} is then defined as

$$E_{IR} = 1 - \frac{E_{NS}}{E_D}. \tag{11}$$

A value of E_{IR} closer to 1 means higher reliability. In contrast to LOLP which only quantifies the risk of reserve capacity (both W and Wh) being too small, EIR quantifies the consequence of the shortfall in energy supply that occurs as a result of inadequate reserves.

The process of computing all the necessary quantities from power system time series data of demand and renewable generation are summarized below; details of the steps are provided in the next sections.

1) By filtering the net-load data, samples of $\tilde{D}_k^{\text{HP}}$ are obtained. Power spectrum analysis of controllable generation is used to determine the cutoff frequency ω_c of the filter.
2) By using (4), (5), and (6), samples of the two random variables P^{dreq}, E^{dreq} are obtained. A year's worth of time series data leads to 365 samples. Probability density functions (pdf) of P^{dreq} and E^{dreq} are estimated from these samples.
3) Reserve capacities are then determined with estimated pdfs by using (7)-(8).

Data from BPA is used to illustrate the steps above in the subsequent sections.

B. Step I: Obtaining $\tilde{D}_k^{\text{HP}}$ From Available Time Series Data

Since bulk power systems employ many conventional generators, each with a distinct characteristic, the cutoff frequency ω_c is an aggregate quantity that cannot be identified from any generator's characteristics. In our analysis, we estimate the cutoff frequency ω_c from a Fourier analysis of conventional generation data G_k^c, in particular power spectral density (PSD). The frequency where amplitude becomes significantly small is selected as ω_c. As an illustration, Figure 2 shows the PSD of conventional generation estimated from a year's worth of 5-minute sampled data of thermal generation from BPA. From this dataset, a nominal cutoff frequency is chosen to be 3×10^{-5} Hz, or roughly $\frac{1}{9\text{ hours}}$. This is equivalent to assuming that conventional generators will not be asked to change their setpoints much more quickly than once every 9 hours. Later we will study the effect of having faster generators. A second order, high-pass Butterworth filter with the above cutoff frequency is then used to determine $\tilde{D}_k^{HP}$ and thus P_k^{req}. The quantity E_k^{req} is computed from (5).

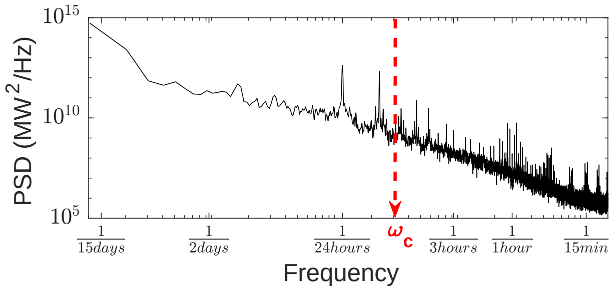

Fig. 2. Power spectral density (PSD) of conventional generation used to estimate conventional generation cutoff frequency ω_c. (Data: BPA 2016)

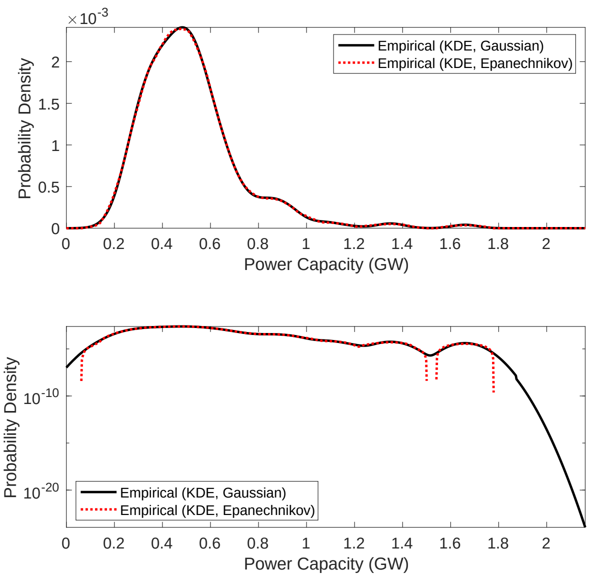

Fig. 3. (top) Comparison of daily required reserve power capacity P^{dreq} fit with a kernel density estimator (KDE), with two distinct kernels. (bottom) Same data in log-scale: the data-poor regions show the effect of the choice of kernel. Data: BPA (2016).

C. Step II: Estimating pdfs

A combination of non-parametric model fitting - using a kernel density estimator (KDE) - and a parametric model for the tail of the distribution that is sample poor is used. Figure 3 (top) shows two non-parametric density estimates for BPA data. The two pdfs are estimated with two distinct and commonly used kernels, Gaussian (that has an infinite support) and Epanechnikov (that has a finite support). For values in which there are enough samples, i.e., the density itself is large, the two pdf estimates match.

However, they differ significantly where there is not enough data, i.e., rare events. Thus, a non-parametric pdf obtained from data is not adequate for predicting rare events due to the lack of observations about such events. *Beyond values observed sufficiently in the data, any probability computed with the estimated pdf is determined more by the shape of the kernel used rather than by the (unknown) pdf.* Figure 3 (bottom) provides evidence in support of this claim. This is most clearly seen in the tail region, with extremely large values of power capacity that were not observed in the data.

The tail region is crucial because LOLP targets may fall in this range. For instance, North American Electric Reliability Corporation (NERC) suggests a LOLP of 0.1 days/year, which translates to $\alpha = 0.00027$ [23, pg. 9]. However, since the empirical probabilities are estimated from operational data in an operational power system, the number of data points in the tail region of the net-load that conventional generator will be unable to serve is necessarily small. In fact for BPA in 2016, the smallest probability we can reliably evaluate from the KDE of the pdf corresponds to $\alpha = 0.0043$ since that point is still within the observed data range.

To go beyond the range allowed by observed data, we need to fit a parametric model of the pdfs to the observations. Empirical pdfs estimated from multiple years of data consistently showed non-symmetric behavior (Figure 3 is one example). Standard parametric models do not fit the entire range of data. We therefore choose power laws in the form of (12) as parametric models of the pdfs to fit the tail region:

$$f_{P^{dreq}}(x) = c(x)^d \quad f_{E^{dreq}}(y) = c(y)^d, \quad x, y \in \Omega \quad (12)$$

where c, d are unknown constants and $f_{P^{dreq}}$, $f_{E^{dreq}}$ are cumulative distribution functions based on their respective KDE. The tail region is chosen as $\Omega(x) = \{x | 1 - F_X(x) \leq 0.1\}$. The pdf estimate used in the rest of the paper consists of a KDE estimate with a Gaussian kernel up to the tail region, and the power law estimate in the tail region.

An assessment of the log-log plot of the complementary cdf versus the daily required reserve capacities showed linear behavior in the tail region. This suggested a power-law was a good fit for the right tail of the pdf. With a parametric fit to the pdf of the daily reserve needs, one can extrapolate the required capacities to satisfy very small LOLP. The quality of the resulting power law fits can be assessed from the comparison in Figure 4.

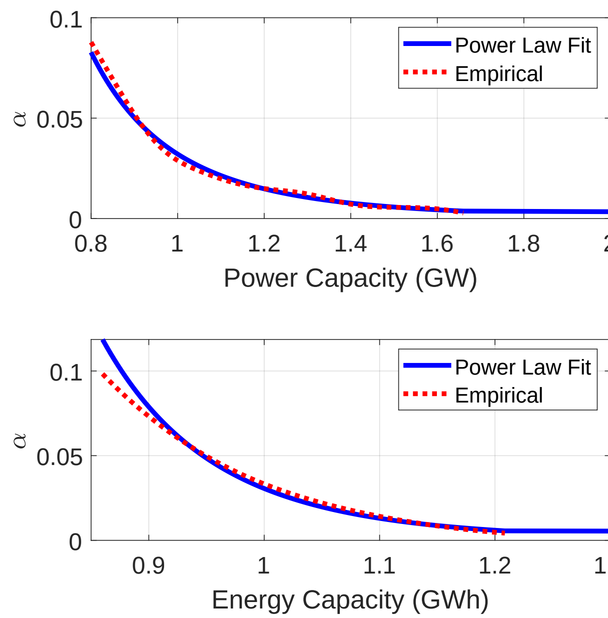

Fig. 4. Power law results for (top) P^{dreq} and (bottom) E^{dreq} along with KDEs show that this parametric model can be used to find reserve needs beyond the range of observable data. (Data: BPA, 2016)

III. Results

To illustrate how the proposed method in Section II can be applied to an existing power system, we provide two case studies by applying the method to data from Bonneville Power Administration (BPA) and California Independent System Operator (CAISO). The data is sampled at 5-minute intervals in both cases.

A. Case Study I: Bonneville Power Administration (BPA)

As mentioned in Section II-B, the cutoff frequency ω_c was determined to be $\frac{1}{9 \text{ hours}}$. Figure 5 shows the reserve requirements of power and energy computed from the proposed method for NERC's recommended $\alpha = 0.00027$. We also compute the power reserve requirements using two other methods: the deterministic method of Makarov *et al.* [16], and BPA's current reserve sizing method[1]. The reserve sizes obtained by [16]'s method, 1.62 GW, and by BPA's own method, 0.8 GW, correspond to $\alpha = 0.0043$ (1.5 days/year) and 0.0893 (32 days/year), respectively. One can back-calculate the LOLP corresponding to a given reserve size using the cumulative distribution function of P^{dreq}, which is computed from the pdf shown in Figure 3. The LOLP obtained by each of the three methods can now be compared, which is shown in Figure 5.

The reserve requirements calculated by the deterministic method in [16] are much lower than that obtained by the proposed method with $\alpha = 0.00027$, since the former is based purely on observed data. Extreme events that correspond to $\alpha = 0.00027$ are not observed in this dataset. The explanation for the reserve requirements from BPA's method is similar.

Figure 5 shows how required reserves vary with α. Not surprisingly, reserve needs are reduced as α is increases since a higher α corresponds to lower reliability. Figure 6 shows how α relates to EIR. The relationship between EIR and α is similar to that between α and reserve capacity needs, indicating that reserve planning based on LOLP alone is adequate (at least in this case study); low probability of not meeting power demand leads to a small energy demand shortfall. Also, the results

[1]According to [25], BPA has adopted NERC standard BAL-002-WECC-2a as their current reserve sizing strategy. It requires "...the greater of either three percent of hourly integrated load plus three percent of hourly integrated generation or the loss of the most severe single contingency (MSSC)..." to be carried as reserves. In terms of this paper's definitions, this can be thought of as the sum of 3.0% of D_k and 3.0% of G_k. The maximum of the average reserve need each hour over a yearlong interval is assigned as the reserve requirement, P_{res}. Applying this method to BPA's data, the reserve need for 2016 turns out to be 796 MW. BPA's current reserve sizing strategy does not specify needs in terms of energy capacity. Thus, we could not make comparisons for the energy reserve requirements.

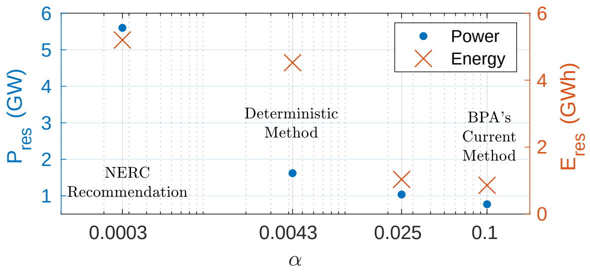

Fig. 5. Observing reserve requirements versus α shows reserve needs decrease as α increases. (Data: BPA, 2016)

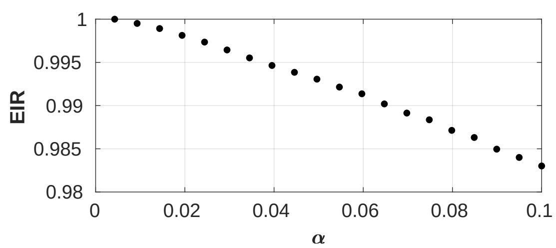

Fig. 6. EIR and α are inversely proportional indicating that a low probability of not meeting power demand leads to small shortfall of energy demand. (Data: BPA, 2016)

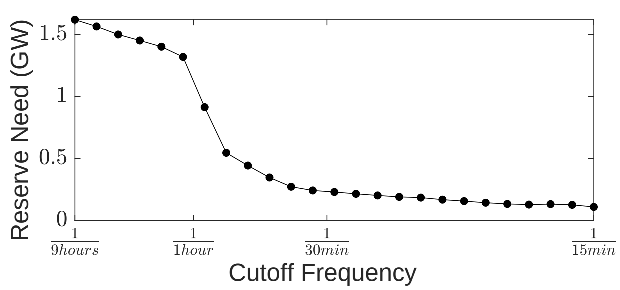

Fig. 7. Power reserve requirements at $\alpha = 0.0043$ as a function of cutoff frequency ω_c show a drop at $\frac{1}{1hour}$ that may indicate generators capable of ramping up and down faster have little benefit. (Data: BPA, 2016)

show that EIR decreases almost linearly with α.

Figure 7 shows how varying the cutoff frequency ω_c affects reserve requirements. Increasing ω_c means more of the higher frequency part of the net-load is met by conventional generators, i.e., presence of faster ramping generators. As expected, increasing the cutoff frequency decreases reserve needs. Interestingly, there is a sharp drop around $\frac{1}{1hours}$, and then a leveling off for frequencies higher than that. This indicates the largest benefit of fast ramping generators are likely to come from generators capable of ramping up or down at an hourly time scale. Faster, or intra-hourly ramping, seems to have diminishing return.

TABLE I
CAISO RESERVE NEEDS (2016)

	Deterministic Method ($\alpha = 0.0028$)	NERC Suggestion ($\alpha = 0.00027$)	CAISO's Method ($\alpha = 0.0081$)
P_{res}	2.51 GW	6.5 GW	2.31 GW
E_{res}	1.50 GWh	5.51 GWh	not defined

B. Case Study II: California Independent System Operator (CAISO)

The proposed method was also applied to CAISO data from 2016. The nominal cutoff frequency ω_c was decided to be roughly $\frac{1}{5 \text{ hours}}$ by the method described in II-B. This is slower than what was obtained for BPA, which is consistent with the higher fraction of fast hydro generators in BPA compared to the slow nuclear and gas generators in CAISO. We omit the intermediate results in this case study.

Table I shows the reserve needs determined by the proposed method for the NERC suggestion ($\alpha = 0.00027$). The third column of the table also compares the reserve needs computed according to CAISO's current reserve sizing strategy defined in [26][2]. The result is a reserve requirement of 2.31 GW which corresponds to $\alpha = 0.0081$ (about 3 days/year). The power reserve needs predicted by [16]'s deterministic method is 2.51 GW, which corresponds to $\alpha = 0.0028$ (1 day/year), about 10 times larger than NERC's suggested value of LOLP.

As in the case of BPA, it was observed that higher α (lower reliability) and higher ω_c (faster conventional generators) lead to lower reserve requirement and lower EIR.

IV. PREDICTING FUTURE RESERVE NEEDS

In this section, we explore ways to use the previously developed method to predict future reserve requirements. During planning for a bulk power system to, for instance, determine the future reserve requirements, time series data for demand and renewable generation is not available. In that case, one can use time series forecasts in place of actual data. A second option is to fit models of reserve requirements as a function of quantities that are more easily predicted than time series of demand and generation, such as installed capacities of renewable generation. The implication of these two options is discussed next.

A. With Time Series Forecasts

We use the method adopted by CAISO to generate 5-minute resolution forecasts of demand and renewable generation [27].

[2]Here, spinning reserve is outlined in a slightly different manner than [1]: "Spinning reserve is the on-line reserve capacity that is synchronized to the grid system and ready to meet electric demand within 10 minutes of a dispatch instruction by the ISO". Therefore, we equate CAISO's spinning reserve definition to the reserves we size in this work. CAISO defines their spinning reserves as equal to "... 5% of the demand to be met by generation from hydroelectric (hydro) resources, plus 7% of the demand to be met by generation from other resources, plus 100% of any interruptible imports, or the single largest contingency (if the latter is greater)". Ignoring interruptible imports due to lack of clarification in the definition, we estimate the upper bound of CAISO's reserve strategy to be 5% of the total demand. With this, the maximum of the 10-minute reserve allocations for 2016 is used to compare with our method.

TABLE II
CAISO 2018 Forecast Reserve Needs at $\alpha = 0.005$

	Forecast data	True Data	Percent Difference
Power Capacity	2.04 GW	2.38 GW	15.4%
Energy Capacity	1.74 GWh	1.75 GWh	0.6%

TABLE III
BPA 2018 Forecast Reserve Needs at $\alpha = 0.005$

	Forecast data	True Data	Percent Difference
Power Capacity	1.55 GW	1.72 GW	10.4%
Energy Capacity	1.28 GWh	1.15 GWh	29.7%

Hourly demand forecast method developed by California Energy Commission (CEC) are used for the demand prediction. Wind generation at time instant k of the subsequent year is forecasted using

$$G_k^{w,nextyear} = G_k^{w,lastyear} \frac{C^{w,nextyear}}{C^{w,lastyear}} \quad (13)$$

where $C^{w,nextyear}$ is a prediction of the subsequent year's installed capacity. Forecasted solar generation computed in the same manner is termed $G_k^{s,nextyear}$. The total forecast of renewable generation is

$$\hat{G}_k^r = G_k^{w,nextyear} + G_k^{s,nextyear}. \quad (14)$$

This approach maintains load-wind, load-solar, and wind-solar correlations from year to year. After computing these forecasts, we interpolate to the needed time interval, and then apply the proposed method.

The first column of Table II shows the results for CAISO in 2018 predicted with 2017 data, for $\alpha = 0.005$. This value is chosen because it is large enough that the power-law fit to the pdf is unnecessary; the events corresponding to such an LOLP are seen in the data. To assess sensitivity to forecast errors, we also compute the reserve needs directly from 2018 data; results are shown in the second column of Table II. We see very good agreement between the estimates of energy capacity requirements obtained from the true data and forecasted data. There is however a large error in the power capacity.

Table III shows the results when the same method was used on BPA's data. The prediction for power reserve requirement is more accurate than at CAISO, though energy reserve requirement predictions are less accurate. BPA's forecasted demand data was not available, and a simple forecasting method from [27] was used to predict the load for 2018. The load prediction assumed trends from 2016 to 2017 were identical to those 2017 to 2018, which may not be the case for BPA. This assumption is likely the cause of the higher error in Table III than Table II.

B. Without Requiring Forecasts of Time Series Data

A simpler alternative to forecasting time series data is based on correlations of reserve requirements in past years determined from data to various likely predictors, such as installed renewable generation capacity or peak demand. If reserve needs are seen to be strongly correlated with such variables, then one could fit a simple regression model that predicts the reserve requirements from the values of these variables. Since grid operators typically have better predictions of variables such as installed renewable generation capacity than of renewable generation time series, this approach could provide a simple and straightforward method to predict reserve requirements.

TABLE IV
Correlation Coefficients at $\alpha = 0.005$

	BPA		CAISO	
	P_{res}	E_{res}	P_{res}	E_{res}
Peak Demand	-0.3278	0.0486	-0.7143	-0.0030
Installed Capacity	-0.8550	0.9664	0.9991	-0.7281

To assess this idea, we computed the reserve needs for $\alpha = 0.005$ using the proposed method for 2016, 2017, and 2018 with data from those years. Table IV presents the correlation coefficients between the reserve requirements in a year and their two possible predictors, installed renewable capacity and peak demand, during the same year. The installed renewable capacity is highly correlated with power reserve need for CAISO but is negatively correlated with energy reserve needs. In BPA, the opposite trend occurs. Overall, the trends in the correlations are not clear enough to predict reserve needs using a regressor model.

V. Conclusion

We propose a probabilistic method to compute both power and energy reserve requirements for a given LOLP from time series data on demand and renewable generation. Traditionally, reserve needs are specified in terms of power alone, assuming that the power is provided by a controllable generation with a limitless fuel supply, rendering the available energy infinite. If future grids rely on batteries to provide a significant part of the reserve, both power and energy requirements will need to be considered. Although power and energy reserve requirements are correlated in the two case studies presented here, one does not follow from the other.

The method in this work uses a probability density function fitted to the fast-varying component of the net-load, assuming that the slowly varying component is provided by controllable generation. Power law models of the pdfs used in the method allow planning for extreme events that have not been observed in the data. As intermittent renewables account for a larger share of total generation, extreme events are likely to occur with higher probability than they do now. Existing deterministic methods do not consider extreme events in the net-load that are not observed in the data though they are still possible and hence affect reliability. Methods that consider these probabilities in a principled manner, such as the proposed one, offer an advantage in planning for reliability in such a scenario. Moreover, the reliability provided by existing deterministic methods can be back calculated from the estimated pdf with the proposed method in terms of the LOLP, providing a common ground for comparison.

The reserve requirements computed did not show strong correlations to suspected predictors such as installed renewable capacity uniformly. This indicates simplistic reserve planning for the future based on such parameters, which are easier to predict than time series of demand and generation, may not provide adequate reliability. This presents an open problem: how to plan reserves for the future using easy-to-predict parameters for bulk power systems?

Applicability of the method described in this work spans many reserve types, i.e. spinning, non-spinning, etc. This is because the time response of reserve needs can be classified by the inverse of generating fleet cutoff frequency ω_c. Appropriate allocation of reserves to each class, however, is a separate problem that is not addressed in this work.

As well, in this work we have ignored transmission network constraints, aggregating an entire balancing authority into one node. Transmission network constraints will increase the size of required reserves, so our results can be taken as a lower bound. Extension of the sizing method to multi-area networks, which must be done together with siting of reserves, is another open problem.

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