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Hybrid storage system sizing for minimum daily variability injection

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***Abstract*—Supercapacitors complement the limitations of battery storage technologies, and therefore, a battery-supercapacitor hybrid storage device (HSS) has established as a viable option for mitigating the renewable energy variability. For optimal sizing of both batteries and supercapacitors, batteries are treated as low-frequency variation mitigation device and supercapacitors as high-frequency variation mitigation device. However, the maximum amount of current injected or extracted from the battery for a given capacity rating is limited, failing which, supercapacitors would replace batteries to mitigate low-frequency variability. Both slow and fast varying components are defined respecting a cut-off frequency, and in this problem, the objective is to minimize the annualized cost of HSS with optimal cut-off frequency. The sizing of the HSS should also minimize the variability for a given statistical significance. The cut-off frequency is iterated over the solution space using mode pursuing sampling method to obtain the optima. The proposed method is illustrated with a sample dataset and results are discussed. Additionally, an additional problem where the frequency of operation of the supercapacitors is limited to two hours to limit the self-discharge rate of the supercapacitors is also discussed.**

I. Introduction

Typical battery technologies, such as, Lead-Acid, Lithium-ion, Sodium-Sulphide, Nickel-Cadmium, Vanadium-Redox, Zinc-Bromide, have a fast response time, low self-discharge rate, and high energy density, which make them suitable for mitigating the slow varying renewable energy (RE) generation [1]. However, most of the battery technologies suffer from limited cycling life, and low power density, which indicates that none of these technologies alone is capable of limiting the fast varying component of RE generation, without significantly increasing their capacity rating. Supercapacitors complement the disadvantages of battery technologies with the help of possessing a large number of cycling life, large maximum charging/discharging current limit for a given capacity rating and long shelf life.

However, supercapacitors suffer from low energy density, comparatively high self-discharge rate, and relatively higher capacity cost [2]. Furthermore, the capacity required to mitigate the variability of a given frequency and amplitude is inversely proportional to the signal frequency. And therefore, the capacity requirement for the mitigation of the high-frequency variability is comparatively lower. Like this, in the grid storage application, supercapacitors with low energy capacity and high power density, are often touted for being used in high-frequency variation mitigation application, while batteries are generally used for low-frequency energy application [3]. This idea is following hybrid energy storage (HES) devices, which is well established in electric vehicle applications, because of its low energy, high power demand during the charging process, and high energy demand during discharging process. In this regard, batteries and supercapacitors are the commonly used elements in vehicles [4].

Capacity sizing in grid energy storage application is a function of the operational objective, and, in this regard, the use of hybrid energy storage (HSS) systems, which is consisting of supercapacitors, batteries and associated power electronic converters, has been critically discussed in the existing literature. Frequency-based capacity sizing was first introduced in [5], with the objective to segregate low and high-frequency component in the historical RE dataset for sizing, and is considered in this paper. Subsequently, optimal capacity calculation of HSS devices, where, Lithium-ion battery and ultra-capacitor bank minimize short- and long-term fluctuation in the wind power production according to 1-min and 30-min fluctuation mitigation requirement using remaining energy level feedback control, have been discussed in [6]. Moving average filter based segregation of high and low-frequency wind generation variability and associated battery-supercapacitor HSS control strategy is considered in [7]. Different power-sharing strategy among battery and supercapacitor from the electricity grid injection is presented in [8]. For forecasts are never perfect, the objective of reference [9] is to mitigate the variation within the wind-generation forecast error signal by segregating different frequency components using discrete Fourier transform (DFT) technique, and mitigating each of the variability component using NaS batteries, compressed air energy storage, and conventional generators respectively. Maintaining grid frequency stability using battery-supercapacitor HSS with stochastic wind power fluctuation within an isolated grid is discussed in [10]. A ramp-rate and upper wind fluctuation rate limiting sizing of HSS is considered in [11] and [12] respectively. For RE generation is highly variable, sizing in a wind-diesel isolated system using a stochastic optimization technique is discussed in [13]. Sizing and design of energy storage, to simultaneously regulate wind generation variability and ensure grid voltage stability is presented in [14]. Determination of the capacity of battery storage as an energy buffer, thereby providing constant dispatch into the grid is carried out in [15] and [16]. For base-load dispatch strategy from RE-storage combination may not be viable for a finite capacity storage device, a 'minimum variability injection schedule' is discussed in [16]. In [16], the authors assumed the use of multiple storage devices, where, it was hypothesized that low-frequency components, will be mitigated by batteries with a smaller number of storage cycles and vice versa. However, it was shown that the use of a single battery type with the lowest unit cost to throughput ratio considering the whole frequency spectrum generally derives the minimum total annualized cost. In contrast to [15], the authors in [16] have also shown that statistical significance has a direct implication on sizing, and a proportional increment in statistical significance will exponentially reduce in the injection of variability. Optimum sizing of HES is also described in [17], where, pre-determined intra-day and intra-hour variability are mitigated by batteries and pumped-hydro respectively.

In an extension to reference [16], the sizing of HSS to mitigate the RE generation variability has been discussed in this paper. The complete frequency spectrum of historical generation data used for sizing of storage devices is divided into low and high-frequency variabilities about a cut-off frequency, which is needed to be optimized while minimizing variation from deviating the daily base-load generation strategy in both high and low-frequency component to a given statistical significance. Independent of the cut-off frequency selected, the high-frequency variability is to be mitigated using supercapacitors. In addition to the converter rating, given a capacity rating of the battery, current drawn from or injected into the battery (called as C_{rate}) is generally limited [18]. So, there exist two choices in the selection of storage devices to mitigate the low-frequency variability: (i) install batteries and if the C_{rate} exceeds C_{rate} limit of the battery, increase capacity-rating of the battery, which was indicated in [16], or (ii) install batteries, but, if the C_{rate} exceeds C_{rate} limit of the battery, install supercapacitors. The second choice is the primary focus in formulating the optimization problem, while the first choice is dealt with as an extension and is presented in the illustrative example. The sizing result is calculated for different historical generation dataset for analysis. The impact of C_{rate} on optimal sizing is also studied.

II. Sizing of the HSS for a Given Cut-Off Frequency

To segregate the low and high-frequency segments, the frequency response of the historical generation data, $X(k)(k \in \mathbb{Z})$ can be calculated using DFT [19]. The cut-off frequency determining the design of low- and high pass filter can vary between $k = 1$ and the Nyquist frequency. If the frequency response is ranged within $[F_1, F_2]$, the low-pass and the high-pass filter response determined by the cut-off frequency, F can be given by, $[F_1, F) \cup (F_2 + F_1 - F, F_2]$ and $[F, F_2 + F_1 - F]$ respectively. Also consider, L and H be the suffix representing low and high-frequency variability respectively, about the cut-off frequency, F. In this section, the statistical sizing of the HSS is described with respect to a given cut-off frequency, F.

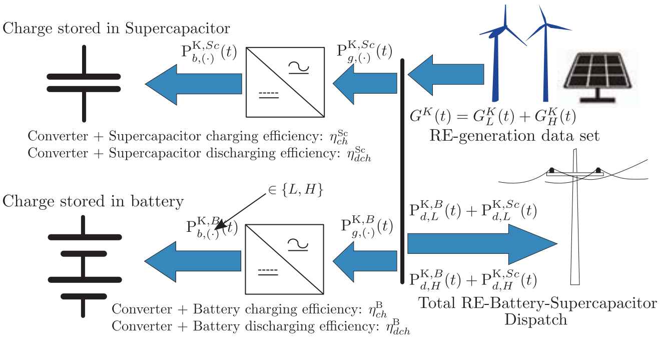


Fig. 1: System Configuration of Battery-Supercapacitor HSS

The availability of batteries and supercapacitors for mitigation of RE generation variability, such that the combined output mimics base-load generation strategy, is being studied in this paper. That signifies, combined output from the batteries, supercapacitors, and REGs to be constant for a given day. To maintain the independence of daily schedules during the day-ahead operation, the daily average of the total power injected into batteries must be zero. Fig. 1 depicts the typical combined operation of renewable energy generators (REGs), batteries and supercapacitors.

In an AC-grid, both batteries and supercapacitors are connected into the grid through converters, as shown in Fig. 1. Charging and discharging efficiency of both batteries and converters ($\eta^B_{ch}, \eta^B_{dch}$) and supercapacitors and converters ($\eta^{Sc}_{ch}, \eta^{Sc}_{dch}$) are not 100%. And, therefore, charge extracted during discharging will always be higher and the charge injected into both the storage devices during the charging process will always be lower than the grid end power.

A. HSS sizing for an arbitrarily selected day

"Minimum variability injection" discussed in [16] is applied for determining the capacity rating of the storage devices, throughput rating of the battery, and the power rating of the converter of a given day, K corresponding to both the low and high-frequency variability components, L and H respectively. Fig. 1 can be referred for the nomenclature. Optimization problem, (1)-(5) is shown to be solved for low frequency component, L using batteries, B. Similarly, "Minimum variability injection" optimization problem needs to be solved for high-frequency component, H using supercapacitors, Sc, or low-frequency component, L using supercapacitors, Sc.

$$\min_{\mathrm{P}^{\mathrm{K},B}_{d,L}(t), \mathrm{P}^{\mathrm{K},B}_{b,L}(t), \mathrm{P}^{\mathrm{K},B}_{g,L}(t)} \sum_{1 \leqslant t \leqslant N_D} \left(\mathrm{P}^{\mathrm{K},B}_{d,L}(t) - \overline{\{\mathrm{P}^{\mathrm{K},B}_{d,L}(t)\}} \right)^2 \quad (1)$$

subject to,

$$\mathrm{G}^{\mathrm{K}}_L(t) - \mathrm{P}^{\mathrm{K},B}_{g,L}(t) - \mathrm{P}^{\mathrm{K},B}_{d,L}(t) = 0 \quad (2)$$

$$\Lambda^{\mathrm{K}}_L(t) = \frac{\mathrm{P}^{\mathrm{K},B}_{g,L}(t)}{|(\mathrm{P}^{\mathrm{K},B}_{g,L}(t))| + \epsilon} \quad (3)$$

$$\left(\mathrm{P}^{\mathrm{K},B}_{b,L}(t) - \eta^B_{ch} \cdot \mathrm{P}^{\mathrm{K},B}_{g,L}(t) \right) \cdot (1 + \Lambda(t)) + \left(\mathrm{P}^{\mathrm{K},B}_{b,L}(t) - \frac{\mathrm{P}^{\mathrm{K},B}_{g,L}(t)}{\eta^B_{dch}} \right) \cdot (1 - \Lambda(t)) = 0 \quad (4)$$

$$k_h \sum_{1 \leqslant t \leqslant N_D} \mathrm{P}^{\mathrm{K},B}_{b,L}(t) = 0 \quad (5)$$

ϵ is a small positive integer to calculate the sign variable $\Lambda^{\mathrm{K}}_L(t)$. k_h refers to an hour equivalent of the sampling frequency. In objective function (1), the variability is defined as, squared sum of the error in daily injection $\mathrm{P}^{\mathrm{K},B}_{d,L}(t)$ from its average. N_D is the number of instants in a day. The optimization problem, (1)-(5) is solved for an arbitrary number of days, K, for both high and low-frequency component, considering batteries, B or supercapacitors, Sc as necessary. $\mathrm{G}^{\mathrm{K}}_L(t)$ refers to historical generation dataset for the low-frequency variability. Eq. (2) refers to the power balance equation. Eq. (3) refers to whether the storage device is charging or discharging. Equation (4) refers to the amount of charge being stored into the battery (or, the storage type of concern in relevant case). Equation (5) refers to the amount of charge stored in an operating horizon is zero, while ignoring the self-discharge rate.

Because, either of batteries, B, and supercapacitors, Sc are used to mitigate can be used to mitigate low, L or high, H frequency variability, generic conventions in the representation of the variables are resorted to. Let, $\mathrm{P}^{\mathrm{K},(\cdot)}_{b,(\cdot)}(t)$ and $\mathrm{P}^{\mathrm{K},(\cdot)}_{g,(\cdot)}(t)$ indicate total power injected into the storage and total power injected into the converter from the grid respectively at time

t of K^{th} day, corresponding to both low or high frequency component, for batteries or supercapacitors.

Given a historical dataset, the peak charged and peak discharged condition may not be symmetric. And therefore, for ensuring the charge injected into the battery for a day to be zero, appropriate selection of residual charge will be essential, necessitating, incorporation of the two-battery model as introduced in [16] for capacity determination. Unlike typical Li-ion batteries, supercapacitors can be treated as a deeply cycled energy storage device. Therefore, if the allowable terminal voltage of the supercapacitors lies within $[V_{max},\ V_{min}]$, then, the usable energy available within supercapacitors can be given by $0.5C(V_{max}^2 - V_{min}^2)/3600$ Wh. Rated V_{max} and V_{min} and the capacitance C is obtained from manufacturers data-sheet [2]. However, for simplicity, it can be assumed that the total charge stored within the supercapacitor is squared proportional to its terminal voltage. Furthermore, the total charge stored within the supercapacitor in a day assumed to be zero as well. The similar two-battery model can be used for determining the residual charge to be stored in the supercapacitors and the capacity rating. The charge stored within the storage $Q_{(\cdot)}^{\mathrm{K},(\cdot)}(t)$, capacity of $\mathrm{C}_{+,(\cdot)}^{\mathrm{K},(\cdot)}$, and $\mathrm{C}_{-,(\cdot)}^{\mathrm{K},(\cdot)}$ of the two-battery model for both the batteries and supercapacitors, for both low and high frequency variability can be given by,

$$Q_{(\cdot)}^{\mathrm{K},(\cdot)}(\tau) = k_h \sum_{1\leqslant t\leqslant \tau} \mathrm{P}_{b,(\cdot)}^{\mathrm{K},(\cdot)}(t) \quad ,\tau \leqslant N_D \tag{6}$$

$$\mathrm{C}_{+,(\cdot)}^{\mathrm{K},(\cdot)} = \left|\max\{Q_{(\cdot)}^{\mathrm{K},(\cdot)}(\tau);\ \ 1 \leqslant \tau \leqslant N_D\}\right| \tag{7}$$

$$\mathrm{C}_{-,(\cdot)}^{\mathrm{K},(\cdot)} = \left|\min\{Q_{(\cdot)}^{\mathrm{K},(\cdot)}(\tau);\ \ 1 \leqslant \tau \leqslant N_D\}\right| \tag{8}$$

$t, \tau \in \{1, \cdots N_D\}$ symbolizes daily operating horizon. As indicated in [16], while converters and supercapacitors (owing to their large number of cycles) require replacement only at the end of their operating life-cycle, batteries with limited cycle life need to be replaced frequently throughout the lifetime of the project. Both batteries and supercapacitors can be modular, and a series-parallel combination of the modules can be ensured. Assuming each of module charges and discharges uniformly, total current extracted or injected into the battery or supercapacitor will be uniformly divided into each of the parallel branches, ensuring uniform degradation of each of the battery and supercapacitor module.

The depth of discharge determines the number of cycles executed by the battery. However, charging and discharging of the battery is a function of the historical dataset, and therefore, symmetric charging and discharging may not be ensured. The concept of the throughput of batteries [16] has been applied to this problem for simplicity to calculate battery life depreciation. Mathematically, daily throughput depreciation of the battery, B corresponding to the low-frequency variability, L , $\mathrm{T}_L^{\mathrm{K},B}$ can be given by,

$$\mathrm{T}_L^{\mathrm{K},B} = k_h \sum_{1\leqslant t\leqslant N_D} \left|\mathrm{P}_{b,L}^{\mathrm{K},B}(t)\right| \tag{9}$$

As indicated in [16], the rated lifetime throughput of the battery, Y can be given by the product of the 'throughput factor', $\mathcal{F}$ and the capacity rating of the battery, $\mathcal{C}$ ($Y = \mathcal{F}\cdot\mathcal{C}$). The throughput factor is unique for each type of battery. It can be observed that increasing capacity rating decreases the depth of discharge of the battery while increasing rated lifetime throughput. This signifies, increasing capacity increases the life of the battery as well. In contrast, because supercapacitors can execute a large number of cycles in contrast to the batteries, it can be safely assumed that their physical life will constrain the cycle-life. So, cycle life degradation of supercapacitors is not considered in this paper.

The rating of the converters $\mathrm{P}_{(\cdot)}^{\mathrm{K},(\cdot)}$ for both the storage device and both the frequency component can be given by assuming the similar converter can be used alongside both batteries and supercapacitors,

$$\mathrm{P}_{(\cdot)}^{\mathrm{K},(\cdot)} = \max\left\{\left|\mathrm{P}_{g,(\cdot)}^{\mathrm{K},(\cdot)}(t)\right|;\ \ 1 \leqslant t \leqslant N_D\right\} \tag{10}$$

B. Statistical sizing

Sizing of the batteries, supercapacitors and the converters corresponding to a given statistical significance of ρ, for the randomly sampled days (days are uniformly sampled) are given as follows:

$$\mathcal{C}_{+,(\cdot)}^{(\cdot)} = \mu\left(\left\{\mathbf{C}_{+,(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) + \rho\cdot\sigma\left(\left\{\mathbf{C}_{+,(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) \tag{11}$$

$$\mathcal{C}_{-,(\cdot)}^{(\cdot)} = \mu\left(\left\{\mathbf{C}_{-,(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) + \rho\cdot\sigma\left(\left\{\mathbf{C}_{-,(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) \tag{12}$$

$$\mathcal{P}_{(\cdot)}^{(\cdot)} = \mu\left(\left\{\mathbf{P}_{(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) + \rho\cdot\sigma\left(\left\{\mathbf{P}_{(\cdot)}^{K,(\cdot)} : \forall K\right\}\right) \tag{13}$$

$$\mathcal{T}_{(\cdot)}^{B} = \mu\left(\left\{\mathbf{T}_{(\cdot)}^{K,B} : \forall K\right\}\right) + \rho\cdot\sigma\left(\left\{\mathbf{T}_{(\cdot)}^{K,B} : \forall K\right\}\right) \tag{14}$$

Here, $\mathcal{C}_{+,(\cdot)}^{(\cdot)}$, $\mathcal{C}_{-,(\cdot)}^{(\cdot)}$, $\mathcal{P}_{(\cdot)}^{(\cdot)}$, $\mathcal{T}_{(\cdot)}^{B}$ are statistically calculated capacity ratings, power rating, of both battery and supercapacitors and throughput rating of the battery respectively. $\mathbf{C}_{+,(\cdot)}^{(\cdot)}$, $\mathbf{C}_{-,(\cdot)}^{(\cdot)}$, $\mathbf{P}_{(\cdot)}^{(\cdot)}$, $\mathbf{T}_{(\cdot)}^{B}$ are vector representing daily capacity ratings, power rating, of both battery and supercapacitors and throughput rating of the battery respectively for a large number of sampled days, based on an uniform distribution. $\mu(\cdot)$ and $\sigma(\cdot)$ are functions calculating mean and standard deviation. Overall capacity, $\mathcal{C}_{(\cdot)}^{(\cdot)}$ and residual state of charge, $\mathrm{SOC}_{avg,(\cdot)}^{(\cdot)}$ are calculated as follows:

$$\mathcal{C}_{(\cdot)}^{(\cdot)} = \frac{\mathcal{C}_{+,(\cdot)}^{(\cdot)} + \mathcal{C}_{-,(\cdot)}^{(\cdot)}}{\mathrm{SOC}_{max}^{(\cdot)} - \mathrm{SOC}_{min}^{(\cdot)}} \tag{15}$$

$$\begin{aligned}\mathrm{SOC}_{avg,(\cdot)}^{(\cdot)} &= \mathrm{SOC}_{min}^{(\cdot)} \\ &\quad + \frac{\mathcal{C}_{-,(\cdot)}^{(\cdot)}}{\mathcal{C}_{+,(\cdot)}^{(\cdot)} + \mathcal{C}_{-,(\cdot)}^{(\cdot)} + \epsilon}(\mathrm{SOC}_{max}^{(\cdot)} - \mathrm{SOC}_{min}^{(\cdot)})\end{aligned} \tag{16}$$

Derivation of (15), and (16) are calculated considering the capacity $\mathcal{C}_{+,(\cdot)}^{(\cdot)}$ corresponds to the SOC of $\mathrm{SOC}_{max}^{(\cdot)}$, and, the capacity $\mathcal{C}_{-,(\cdot)}^{(\cdot)}$ corresponds to SOC of $\mathrm{SOC}_{min}^{(\cdot)}$ respectively, and the SOC never exceeds these limits. $\mathrm{SOC}_{avg}^{(\cdot)}$ for the battery represents the residual charge to be maintained at the beginning and end, and $\mathrm{SOC}_{avg}^{(\cdot)}$ for the supercapacitors represent that an average squared voltage of $\sqrt{\mathrm{SOC}_{avg,(\cdot)}^{(\cdot)}}V_{rated}$ to be maintained it its terminal. V_{rated} is the rated terminal voltage of the supercapacitor.

C. Calculation of C_{rate}

Typical data-sheet of Li-ion battery [18] reveal that the maximum continuous current limit limits operation of batteries. Therefore, the maximum current limit can only be improved by increasing the capacity rating of the battery (this behavior was applied in equation (24) of reference [16]). Because the power drawn does not remain constant, C_{rate} is highly variable. But, the associated limit for the batteries must not be disregarded. However, unlike the batteries, a supercapacitor allows large non-repetitive maximum peak current rating [2], which will only be limited by the ratings of the associated converter. In day-ahead scheduling, C_{rate} varies throughout the day. Therefore, daily average C_{rate} can be used as a representative C_{rate}.

Observe, the C_{rate} can only be calculated, once the capacity of the battery is known. C_{rate} for a given day, $\mathrm{R}_{(\cdot)}^{\mathrm{K},B}$ and statistically calculated C_{rate}, $\mathcal{R}_{(\cdot)}^{B}$, for both low and high frequency component can be given by,

$$\mathrm{R}_{(\cdot)}^{\mathrm{K},B} = \frac{\overline{\left|\mathrm{P}_{b,(\cdot)}^{\mathrm{K},B}(t)\right|;\quad 1 \leqslant t \leqslant N_D}}{\mathcal{C}} \tag{17}$$

$$\mathcal{R}_{(\cdot)}^{B} = \mu\left(\left\{\mathbf{R}_{(\cdot)}^{\mathrm{K},B} : \forall K\right\}\right) + \rho \cdot \sigma\left(\left\{\mathbf{R}_{(\cdot)}^{\mathrm{K},B} : \forall K\right\}\right) \tag{18}$$

Where, $\mathbf{R}_{(\cdot)}^{\mathrm{K},B}$ are vector representing daily C_{rate} of the storage devices.

III. Optimum Cut-Off Frequency for the Sizing of HSS

The converters corresponding to both low and high-frequency component and supercapacitors requires replacement at the end of their physical life. Given their discount rate in the investment and allowable lifetime be given by, d and $n^{(\cdot)}$ respectively, the capital recovery factor (CRF) of the investment $K^{(\cdot)}$, can be used to calculate the respective annualized cost.

Although the rating of supercapacitors is provided in terms of its capacitance and terminal voltage rating, for simplicity, it has been assumed that the cost per unit capacity rating is given, and is provided by, Φ \$/kWh. Now, if the unit cost of converters be given by, U \$/kW, the annualized investment cost in supercapacitors, $\Gamma_H^S(F)$ to mitigate high frequency variability, H and the annualized investment cost in converters to mitigate both high and low frequency variability, $\Gamma_{(\cdot)}^P(F)$ will be given by,

$$\Gamma_H^S(F) = K^{Sc}\, \mathcal{C}_H^{Sc}\Phi, \qquad \Gamma_{(\cdot)}^P(F) = K^P\, \mathcal{P}_{(\cdot)}^{(\cdot)}U \tag{19}$$

$\mathcal{C}_H^{(\cdot)}$ is the statistically calculated capacity rating of the supercapacitor to mitigate high-frequency variability. The procedure of the statistical calculation is presented in Section II. $\mathcal{P}_{(\cdot)}^{(\cdot)}$ is the statistically calculated power rating of the converter. It is notable that, the power and the capacity rating corresponding to both high and low-frequency variability is a function of the type of storage devices. K^{Sc} and K^P are CRF corresponding to supercapacitor and converter respectively.

If, d be the discount-rate of the installation of the battery, and, n_D be its operating life because of its cycling operation, Assuming, $n_D d \ll 1$, the CRF of the battery investment cost can be given by, $\frac{1}{n_D}$. Again if, the statistically calculated annual throughput expenditure of the batteries be given by Υ, and the throughput factor of $\mathcal{F}$, with rated capacity of the battery is given by $\mathcal{C}$, then the CRF of the battery can be approximated to be, $\frac{\Upsilon}{Y} = \frac{\Upsilon}{\mathcal{F}\mathcal{C}}$.

It can be observed that if multiple types of battery with different unit capacity cost, and throughput factor is provided, using Theorem 1 of reference [16], the battery type minimizing the unit-cost to throughput fraction minimizes the total cost. Let, the unit-cost and throughput of the battery minimizing unit-cost to throughput fraction be given by, Θ \$/kWh and $\mathcal{F}$ respectively. Now, if $\mathcal{R}_L^B$ of the low-frequency component is below the threshold, $C_{rate}^{B,lim}$, then, the low-frequency variability can be mitigated by the battery. Otherwise, installation of supercapacitors will be essential. The total annualized investment cost into the storage solution, $\Gamma_L^S(F)$ to mitigate the low-frequency variability can be given by,

$$\Gamma_L^S(F) = \begin{cases} \Theta\frac{\Upsilon_L^B}{\mathcal{F}} & \text{if} \quad \mathcal{R}_L^B \leq C_{rate}^{B,lim} \\ K^{Sc}\,\mathcal{C}_L^{Sc}\Phi & \text{otherwise} \end{cases} \tag{20}$$

Υ_L^B, and $\mathcal{C}_L^{Sc}$ are the statistically calculated daily throughput factor of the battery and capacity rating of the supercapacitor for the low-frequency component using Section II.

Because, the statistical significance is known a prior and is used in the calculation of the sizing for both high and low-frequency components, the benefit function is already known. Therefore, to maximize the total profit, the total annualized investment cost, $\Gamma_{Total}(F)$ is needed to be minimized, and, can be given by,

$$\Gamma_{Total}(F) = \Gamma_L^S(F) + \Gamma_H^S(F) + \sum_{Z\in\{L,H\}} \Gamma_Z^P(F) \tag{21}$$

It is notable that equation (21) is a function of the cut-off frequency, F, which is also one of the decision variables in the optimization problem. Since, to minimize the investment cost while ensuring that the variability injection into the grid is limited to indicated statistical significance, ρ is the objective, the minimum variability injection HSS sizing was carried out for different cut-off frequencies (using method mentioned in Section II) until an optimum is reached. Calculation of the rating of the storage solution for a given cut-off frequency is costly, and the solution space is discrete. Therefore, the annualized total cost (equation (21)) minimizing cut-off frequency is calculated using iterative, derivative-free mode-pursuing sampling (MPS) method (which is also used in [16]).

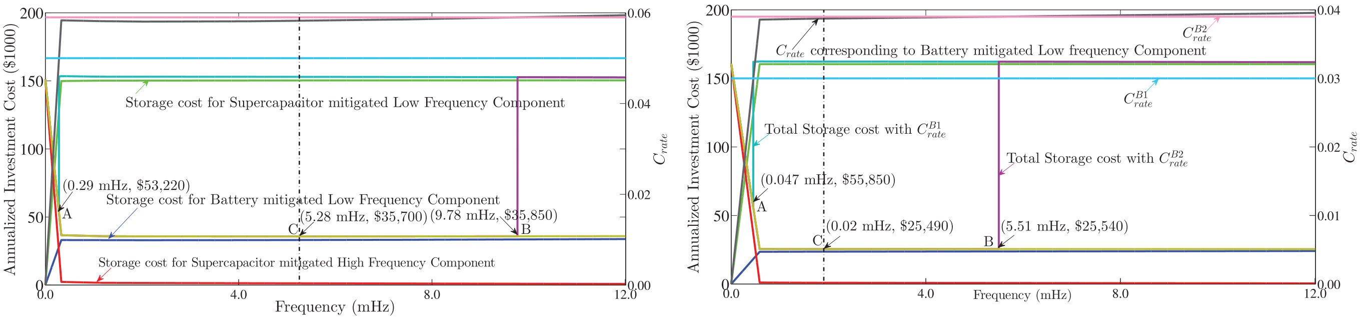
IV. Illustrative Example

Yearly historical generation data (consisting of 365 days) with the resolution of 30 seconds is used in this paper for analysis, which indicates that the Nyquist frequency of the historical generation dataset to be ≈16.67 mHz. Two datasets, one representing 20 kW solar generation plant, and the other representing 10kW solar + 10kW wind generation are used for analysis. The datasets that have been used in [16], are also used in this problem. For datasets used in [16] are of 10 minutes interval, datasets of 30 seconds resolution are obtained by linear interpolation while adding a uniform random variable representing 5kW and then truncating the resulting dataset to 20kW.

The cost and the specification of both the supercapacitor and the battery are presented in Table I. The parameters for

TABLE I: Specification of battery and supercapacitor modules

Parameters	Battery	Supercapacitor
Capacity Cost	\$1.12/Wh	\$14.74/Wh
Life	1500 (cycles) [18]	500000 (cycles) [2] 10 years DC-shelf [2]
Converter Specification	\$800/kW (cost), 20 years (life) [16]	
Charging and discharging efficiency (η_{ch}, η_{dch})	0.90 [1]	0.95 [1]
ϵ	1×10^{-10}	
	$\mathrm{SOC}_{max}^B = 0.9$ $\mathrm{SOC}_{min}^B = 0.1$	$V_{max} = 1.00V_{rated}$ $V_{min} = 0.45V_{rated}$
Discount rate of Converters and supercapacitors	3%	
Number of days for statistical sizing	146	



(a) With Wind generation only at 3σ significance

(b) With 50% Solar and 50% Wind generation at 3σ significance

Fig. 2: Variation in annualized cost for minimum variability injection (Legends in both the sub-figures must be referred together, legends and the associated arrows are color-coded)

the MPS algorithm for calculating the optimal frequency is given in Table II of reference [16]. Fig. 2 shows a graph of annualized cost function obtained using the MPS method.

The analysis presented here is based on the fact that in contrast to batteries, the theoretical maximum cycle life of the supercapacitors will not be achieved in during its operation, and therefore, will only need to be replaced at the end of its physical life. However, both cycle-life and the unit investment cost of batteries is minuscule compared to the supercapacitors. The cost of storage devices to mitigate high-frequency fluctuation is generally decreasing with increasing cut-off frequency (we observed this statement to be correct in the problem concerned), while that of low-frequency component is increasing. Because supercapacitor is needed to be used if C_{rate} limit is reached, such changes in the objective function will introduce a 'jump' in the annualized investment cost. Both in Fig. 2a and Fig. 2b, the 'jump' in the annualized total cost is observed at point 'A' and 'B' corresponding to C^{B1}_{rate} and C^{B2}_{rate} respectively. It is notable that in contrast to [16], where the optimal cut-off frequency minimizing the annualized cost of converters can be found at both the end of the solution space, in this problem, the cut-off frequency resides at an intermediate point.

Both in Fig. 2a, and Fig. 2b, if C_{rate} limit of the batteries are ignored, the annualized total cost minimizing optimal cut-off frequency lies at the Nyquist frequency. However, if C^{B2}_{rate} is the selected C_{rate} limit, the annualized cost function jumps at 'B', while, the optimal cut-off frequency minimizing the total cost lies at 'C', leading to, if C^{B2}_{rate} is the selected C_{rate} limit, the optimal cut-off frequency is located at 'C'. Contrarily, if C^{B1}_{rate} is the selected C_{rate} limit, the annualized cost jumps to 'A'. Which indicates that the optimal cut-off frequencies corresponding to C^{B1}_{rate} are located at 'A'. Therefore, if the cut-off frequency, at which, C_{rate} of the low-frequency component exceeding the C_{rate} limit of the battery, is greater the optimal cut-off frequency, C_{rate} limit will have no impact on the design of storage devices. On the contrary, if the C_{rate} of the low-frequency component is always lower than selected C_{rate} limit, one may find non-existence of the intermediate optimal point.

The results for the sizing of the HSS is also shown in Table II. Furthermore, reduction in statistical significance to be lower than 3σ will reduce the capacity and throughput requirement of storage devices and power rating of converters at the expense of increased injection of variability. For the sizing of both batteries and supercapacitors, SOC^{B}_{avg} and V^{Sc}_{avg} are not located at 0.50 and 0.71 (average charge stored to be 50%) respectively, implying, if residual charge stored in both batteries and supercapacitors are held at 50%, their capacity would not be fully utilized.

Instead of using a supercapacitor, if the capacity of the batteries is increased according to equation (24) of [16], in case the C_{rate} limit of the battery mitigating low-frequency variability is reached, the new optimal frequency will no longer be decided by C_{rate} limit. Accordingly, in Fig. 3, it has been considered that the supercapacitor will be used to mitigate high-frequency variability only if the cut-off frequency exceeds 0.54 mHz (period of less than approximately two hours). It is important to note that in contrast to the Lithium-ion battery [20] (considered in this work), supercapacitors have significantly higher self-discharge rate [21] which increases with increasing operating voltage. And, ensuring the supercapacitor mitigating the variability of the period less than or equal to two hours, in this problem, would ensure lower self-discharge rate. Beyond the operating cut-off frequency to be more than two hours, one needs to account for the self-discharge rate in the scheduling process, and, the discussed model to become invalid. Future work is required to obtain appropriate bound determining the limiting frequency that ensures operability of the supercapacitor. Alternatively, high-frequency variability will merely be mitigated by batteries, after adjusting its capacity to remain within allowable C_{rate}. Consequently, it can be seen in Fig. 3, within 0.00mHz to 0.54mHz, batteries are used to mitigate both high and low-frequency variabilities, and therefore, the total annualized cost of storage is increasing with increasing cut-off frequency as it was observed in [16].

Nevertheless, the characteristics of the cost function within 0.30mHz-16.67mHz resemble Fig. 2a, with the exception that the jump in the total annualized cost does not exist. Comparing the cost functions, the cost of batteries to mitigate low-frequency component is monotonically increasing, while, that of supercapacitors mitigating the high-frequency component is monotonically decreasing. Ignoring the converter cost function, the cost of storage will have a minima if the marginal cost of batteries is equal to that of the supercapacitor, and consequently, a minima is observed at 4.78 mHz. However, from [16] it is understood that the cost of the converter is minimum at either extreme, increasing the total cost at 4.78 mHz, such that, the total cost is lower at the Nyquist frequency. As a result, the minima at 4.78 mHz no longer exists if the cost of PE-converters is included along with the cost of storage solutions.

Furthermore, from equations (19) and (20), one can observe that increasing or decreasing the parameters of the cost function, Φ, U and Θ, would only scale the associated underlying cost of batteries, supercapacitors and converters, while maintaining similar characteristics of the curve, guaranteeing, the existence of intermediate optimal cut-off frequency for suitable Φ, U and Θ. Nevertheless, the characteristics of the cost functions are driven by the historical dataset, the minimum

TABLE II: Comparison of the rating of the HSS for different historical datasets

	Battery				Supercapacitor		
	$\mathcal{C}$ (kWh)	Υ (kWh)	$\mathcal{P}$ (kW)	SOC^{B}_{avg}	$\mathcal{C}$ (kWh)	$\mathcal{P}$ (kW)	V^{Sc}_{avg}
With Wind generation only at 3σ significance and $0.059C$ Battery	86.74	120.860	16.14	0.45	0.89	8.04	0.80 V_{rated}
With 50% Solar and 50% Wind generation at 3σ significance and $0.039C$ Battery	93.27	86.66	10.93	0.51	0.56	6.01	0.78 V_{rated}

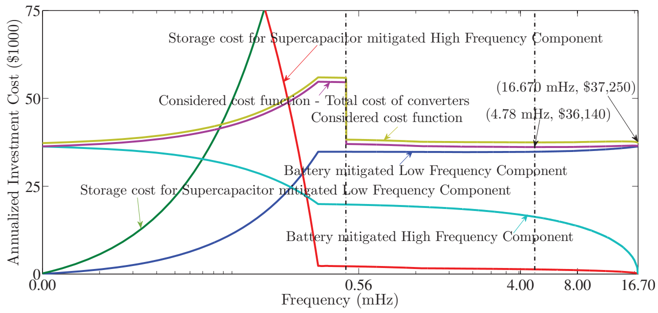


Fig. 3: Variation in annualized cost for wind variability mitigation upto 3σ (scale of frequency axis is in logarithmic scale, to magnify low cut-off frequency)

variability injection scheme, and the statistical significance selected. Sizing of HSS with different historical dataset and HSS parameters can also be calculated using the proposed methodology.

V. Conclusion

Use of Battery-Supercapacitor HSS in mitigation of variability is presented in this paper. Although constant dispatch level is desirable, existing literature shows that variability reduction is exponentially decreasing with increasing statistical significance. Therefore in this problem, the statistical significance is pre-specified in sizing calculation, and, the objective is to minimize the annualized investment cost. The historical RE generation data was divided into slow and fast-varying components, for each of the cut-off frequency. High-frequency variability is considered to be absorbed by supercapacitors, while low-frequency variability will be mitigated by batteries if the C_{rate} limit of the batteries are not hit. If, the C_{rate} limits of the batteries are reached, supercapacitors will be used to mitigate the low-frequency component as well. Because the annualized investment cost with batteries is significantly lower compared to investment cost with supercapacitors, installation of supercapacitors to mitigate low-frequency component when the C_{rate} requirement of low-frequency component equals pre-specified rate, would create a 'jump' in the annualized total cost in mitigating the low-frequency variability. It was also observed that the optima might not lie at either extreme of the solution space in HSS sizing. Furthermore, the location of the optimal cut-off frequency depends upon the relative location of optima, and the frequency at which C_{rate} requirement of low-frequency component equals a pre-specified rate, parameters of storage devices and converters, and dataset. Sizing of the HSS for the condition, where the use of supercapacitor to mitigate high-frequency variability is limited to the period of fewer than two hours to limit self-discharge rate, is also presented.

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