Electric Storage for Optimal Frequency Control

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***Abstract*—Frequency control by energy storage units has been extensively promoted during the last years due to development in energy storage and power electronics technologies. The outstanding ramping capabilities of storage units makes them attractive for fast response services. However, performance metrics of such services are not always obvious and the true benefit of using storage is hard to assess. In the present manuscript we have developed an easy-to-use method for performance assessment and control design for energy storage, participating in frequency control under stochastic load perturbations. As a demonstration of our method, we perform a control design for single area system with energy storage and show that even storage with a very modest power capacity is sufficient to completely take over the primary frequency control duty. Since our method does not require explicit dynamic simulations over stochastic model, it is easily generalizable on more complex systems.**

***Index Terms*—Droop control, frequency control, electric storage.**

I. Introduction

Reduction in prices for energy storage lead to the fast increase of the grid-connected storage capacity over the last years. One of the obvious choices for energy storage is the mitigation of the intermittency in power demand and supply, especially the one caused by renewable sources. There exist a number of possible types of application of storage, a very comprehensive overview is given in an excellent report [1].

Compared to conventional synchronous generators, power electronics interfaced storage units have outstanding ramping capabilities which makes them an excellent choice for any grid applications where fast response is required. Over the last several years there was significant progress in development of policies for storage participation in ancillary service markets, especially in frequency regulation. In United States, the, so-called, pay-for-performance policy has been already implemented by most ISO's, the review of current policies is given in [2]. In Great Britain the special service called Enhanced Frequency Response was designed [3] to be delivered specifically by energy storage systems.

The interest of scientific community is mainly focused on optimal planning and operation of energy storage units. Sophisticated strategies are being developed for maximizing profit during storage participation in frequency control [4], [5]. A common approach in a lot of studies is based on running a number of scenarios based on available real-life data (such as PJM regulation signals, or National Grid frequency data) and then define the range of control settings that provide satisfactory performance. Such an approach, however, provides little insight into the role of each system parameter and is not always easy to generalize on larger systems.

In the present manuscript we develop an easy-to-use scalable method for assessing the performance of energy storage units and optimizing their control parameters for primary frequency control. We define the control performance metrics based on average values of system states and derive closed-form expression for these metrics in terms of system parameters and control settings. We then illustrate our method on a simple, yet representative example of a single-area power system and discuss it's generalization for more complex systems. We then demonstrate the performance of designed control by running explicit numerical simulation over non-linear model with control deadbands.

II. Modeling Approach

In this section we establish basic models that we use to study frequency fluctuations and develop new control methods. In the present manuscript we will consider an aggregated dynamics of a power system which can also be thought of as dynamics of it's center of inertia (COI), more detailed models of systems with multiple areas are a subject of ongoing research. Since the subject of our study is deviation of system frequency from nominal value, we consider dynamics of the system on top of some steady-state operating point.

A. Frequency Dynamics

We assume that both primary and secondary frequency controls are realized in the system, and additional control by energy storage units is present. Since we are only considering dynamics of the system's COI we can approximate the system by a one-bus dynamic equivalent. We assume, that an aggregate inertia time-constant of the system H and an aggregate one-stage turbine time constant τ_T. Frequency

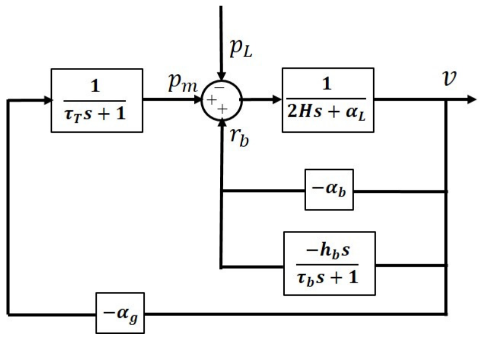

Fig. 1. Block diagram of the system (1) (without secondary control and deadbands), with additional frequency control by storage unit (4).

dynamics equations for such a system under load perturbations p_L have the following form:

$$\dot{\theta} = v \tag{1a}$$

$$2H\dot{v} = p_m - p_L - \alpha_L v + r_b \tag{1b}$$

$$\tau_T \dot{p}_m = - p_m + \mathcal{K}(v) - K_i\theta \tag{1c}$$

where the rest of the denotations are as follows: $v = \Delta\omega/\omega_0$ is the per unit frequency deviation from the nominal, p_m - mechanical power perturbation in per unit (as a result of control actions in response to frequency deviations), α_L - is the load sensitivity coefficient, θ - is the integral of frequency deviation, that is used to execute the action of secondary frequency control with the gain K_i, r_b - is the energy storage contribution to frequency control (described in details in the next subsection), $\mathcal{K}(v)$ - is the primary frequency response by generators. We assume $\mathcal{K}(v)$ to be a droop-based proportional control with certain governor deadbands $\pm v_{db}$:

$$\mathcal{K}(v) = \begin{cases} -\alpha_g(v + v_{db}) & v \leq -v_{db} \\ 0 & v_{db} < v < v_{db} \\ -\alpha_g(v - v_{db}) & v \geq v_{db} \end{cases} \tag{2}$$

where α_g is the aggregate inverse droop of all the generators in the system. We note, that the presence of deadbands makes the system (1) non-linear and difficult to analyze.

B. Frequency Response from Energy Storage

The term r_b in equation (1b) represents frequency response actions from energy storage units. Unlike synchronous machines, power-electronics interfaced storage units can provide almost instantaneous power response and can be assumed to operate without deadbands. We assume that the energy storage units provide proportional control in the form of droop (we denote the inverse storage droop as α_b), and derivative control in the form of virtual inertia (which we denote as h_b). Thus, a desired storage output (in Laplace domain) is $r_b(s) = -\alpha_b v(s) - h_b s v(s)$. However, the second term in this expression can not be implemented due to its a-causality. Therefore, a low frequency approximation should be used for derivative. We use the standard low-pass representation with time constant τ_b:

$$sv(s) \to \frac{s}{\tau_b s + 1} v(s) \tag{3}$$

Finally, we get the following dynamic equations describing the energy storage participation in frequency control:

$$r_b = -\alpha_b v - \frac{h_b}{\tau_b} v + \frac{h_b}{\tau_b} w \tag{4a}$$

$$\tau_b \dot{w} = v - w \tag{4b}$$

where w is an auxiliary variable responsible for the low frequency derivative approximation. A block diagram of the system described by equations (1) and (4) is given by Fig.1.

C. Load Fluctuations

The loading term p_L in equation (1b) represents stochastic load fluctuations. In this manuscript we will assume that it can be modelled as an Ornstein-Uhlenbeck Process (OUP) [6]:

$$\dot{p}_L = -\frac{1}{\tau_p} p_L + b\xi(t) \tag{5}$$

where τ_p and $D = b^2/2$ are parameters called load mean reversal time and diffusion coefficient respectively. The term $\xi(t)$ represents a standard white noise with the following properties:

$$\mathbb{E}[\xi(t)] = 0; \qquad \mathbb{E}[\xi(t_1)\xi(t_2)] = \delta(t_1 - t_2) \tag{6}$$

The advantage of representation (5) is that while being rather general, it allows for closed form solutions to be obtained for linear systems. Parameters τ_p and b can, in principle, be inferred from frequency measurement data, however, detailed analysis of some actual data is the subject of subsequent research. For the purpose of the present manuscript we will assume both τ_p and b to be known. We will use the values of $\tau_p = 30s$ and $b^2 = 3 \cdot 10^{-6}$. The load mean reversal time can be approximately inferred from duration of frequency variation events from real-life data [7], [8] and then the diffusion coefficient can be determined from mean frequency deviation

III. Frequency Response Performance Metrics

Since the goal of this manuscript is the study of the possible benefits of using energy storage for frequency response we first need to formulate specific metrics to evaluate the system performance. According to the so-called Control Performance Standard (CPS1) developed by NERC [9], standard deviation of the system frequency over a calendar year should not exceed certain target value. Therefore, we will use the frequency standard deviation σ_u as one of the performance indicators:

$$\sigma_v = \sqrt{\mathbb{E}[v^2]} \tag{7}$$

where $\mathbb{E}$ denote the expected value, and we will use σ_x to denote the standard deviation of variable x throughout the manuscript.

The second performance metrics that we will use, is the standard deviation of the rate of change of system frequency (ROCOF):

$$\sigma_{\dot{v}} = \sqrt{\mathbb{E}[\dot{v}^2]} \tag{8}$$

This can be thought of as a measure of a generator wear-and-tear, since most of the mechanical stress on the generator equipment is associated with sudden accelerations or decelerations of it's turbine.

In the absence of deadbands the system of equations (1), (4), and (5) becomes linear and σ_v and $\sigma_{\dot{v}}$ can be directly calculated from the system parameters without the need to run stochastic simulations. In order to do this, we first re-write equations (1), (4), and (5) in a standard input-output form:

$$\dot{x} = Ax + Bu \tag{9a}$$

$$y = Cx, \tag{9b}$$

Here x is the vector of system states, for example, for equations (1), (4), and (5) one has $x = [\theta, v, p_m, w, p_L]^T$. The term Bu represents the external input to the system, in our case $B = [0, 0, 0, 0, b]$ and $u = \xi$. The output $y = Cx$ can be one- or multi-dimensional.

For linear systems driven by white noise, the probability density function for its states or outputs is Gaussian. According to standard rules, the expected value of the square of the output $y^T y$ can be calculated by the following formula:

$$\mathbb{E}[y^T y] = \mathrm{Tr}\big[CQC^T\big] \tag{10}$$

where Q is the system co-variance matrix that satisfies the following Lyapunov equation:

$$AQ + QA^T = -BB^T \tag{11}$$

If the output y is scalar, then equation (10) gives it's variance σ_y^2.

IV. Battery Control Design

Let us illustrate the use of the framework described in the previous section for the actual design of energy storage controller. For this purpose we first consider a simplified version of the system (1) without secondary control and deadbands. We assume that the parameters of the system from (1) are known, their values (and dimensions) are given in the Table. I. For this case the state vector is three-dimensional - $x = [v, p_m, p_L]^T$, and the state and input matrices A and B are:

$$A = \begin{bmatrix} -\frac{\alpha_L}{2H} & \frac{1}{2H} & -\frac{1}{2H} \\ -\frac{\alpha_g}{\tau_T} & -\frac{1}{\tau_T} & 0 \\ 0 & 0 & -\frac{1}{\tau_p} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ b \end{bmatrix} \tag{12}$$

It is now straightforward to calculate the co-variance matrix Q according to equation (11), the explicit expressions for components of Q are rather cumbersome, we do not present them here. Now, if we use $C = [1, 0, 0]$, in equation (9), this corresponds to the output $y = v$ and using formula (10) and parameters from the Table I we get $\sigma_v = 3.3 \cdot 10^{-7}$ per

TABLE I
Basic values of power system parameters

Parameter	Description	Value
H	Inertia time-constant	$5\,\mathrm{s}$
α_g	Inverse droop of generators	$12.5\,\mathrm{p\,u}$
τ_p	Load mean reversal time	$30\,\mathrm{s}$
$D = b^2/2$	Load diffusion coefficient	$1.5 \cdot 10^{-6}\,\mathrm{s}^{-1}$
τ_T	Mean turbine time-constant	$3\,\mathrm{s}$
K_i	Secondary control gain	$0.05\,\mathrm{s}^{-1}$
ω_{db}	Governor deadbands	$\pm 15\,\mathrm{mHz}$

unit. This corresponds to a standard frequency deviation of approximately 35 mHz - a typical value for conventional power systems. In order to get the expected value of ROCOF we use $C = [-\alpha_L/2H, 1/2H, -1/2H]$, so that now $y = \dot{v}$ and the formula (10) gives $\sigma_{\dot{v}} = 2.07 \cdot 10^{-4}$ p.u./s corresponding to 12.4 mHz/s in initial units.

Let us now design a control system for storage unit that will perform frequency response instead of turbine, so that the generator is operating at a constant power output - $p_m = 0$ (we remind that p_m is the mechanical power deviation from the steady state). Using the control system from (4) and generator dynamics (1) with $p_m = 0$ and in the absence of secondary control and deadbands, we again get a 3-rd order linear system with the vector of states now being $x = [v, w, p_L]^T$, and the state and input matrices A and B given by:

$$A = \begin{bmatrix} -\frac{\alpha + h_b/\tau_b}{2H} & \frac{h_b}{2H\tau_b} & -\frac{1}{2H} \\ \frac{1}{\tau_b} & -\frac{1}{\tau_b} & 0 \\ 0 & 0 & -\frac{1}{\tau_p} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ b \end{bmatrix} \tag{13}$$

where we have made the denotation for the full load and storage inverse droop $\alpha = \alpha_L + \alpha_b$.

Using equation (10) we can calculate the mean frequency deviation as a function of parameters for this new system. Fig.2 shows σ_v as a function of battery droop α_b and virtual inertia h_b for a fixed value of $\tau_b = 1$s (we will assume this value further on). We can deduce, that the mean frequency deviation is not sensitive to virtual inertia, but sensitive to droop. The explicit expression for σ_v is rather cumbersome, however, for realistic values of system parameters the following conditions are satisfied:

$$\tau_p \gg \tau_b; \qquad \alpha\tau_p \gg H; \qquad \alpha\tau_p \gg h_b \tag{14}$$

where we have made a denotation $\alpha = \alpha_b + \alpha_L$. In this approximation σ_v has a very simple form:

$$\sigma_v = \frac{b}{\alpha_b + \alpha_L}\sqrt{\frac{\tau_p}{2}} \tag{15}$$

from which it is apparent that it doesn't depend on h_b and depends strongly on α_b [10], [11]. Thus, for determination of the needed battery droop one can set virtual inertia to zero in the original expression for σ_v. In order to have the mean frequency deviation of our new system not worse than the

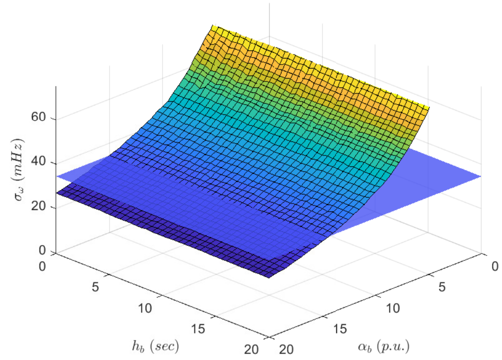

Fig. 2. Mean frequency deviation σ_v of a system with battery as a function of battery droop α_b and virtual inertia h_b. Mean frequency deviations of 35 mHz for the original system is shown as a flat plane.

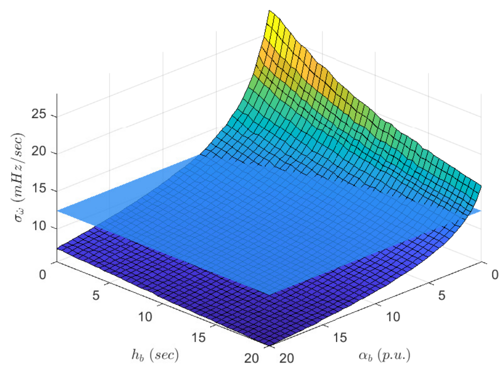

Fig. 3. Mean ROCOF of a system with battery as a function of battery droop α_b and virtual inertia h_b vs. the ROCOF of the original system (flat plane).

original one, we find that we have to set the value of the battery droop α_b of at least 10.49 p.u.

Having determined the needed amount of droop we can now consider the effects of virtual inertia. For this we write the expression for $\sigma_{\dot v}$ with (14) taken into account:

$$\sigma_{\dot v} = \left(\frac{b^2 \tau_p}{4H(2H + h_b + \alpha\tau_b)} \right)^{1/2} \tag{16}$$

We see, that by tuning the virtual inertia we can decrease the mean value of ROCOF. However, even in the absence of virtual inertia the mean value of ROCOF is $\sigma_{\dot v} = 1.13 \cdot 10^{-4}$ (or 6.76 mHz/s) for the system with battery, which is almost two times lower than for the original system. The reason is that compared to a generator, the battery executes droop response faster - without any delays in turbines. Setting virtual inertia to a reasonable 5s allows to decrease the mean ROCOF even more, to $\sigma_{\dot v} = 10^{-4}$ or 6.07 mHz/s.

Let us now estimate the value of battery power that we need to execute the developed control. This can be done by calculating the standard deviation of r_b which is the battery power output. For this, we chose $C = [-\alpha_b - h_b/\tau_b, h_b/\tau_b, 0]$

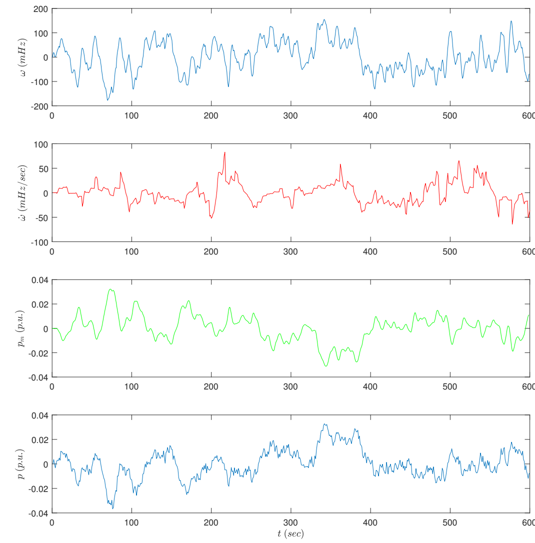

Fig. 4. Frequency, ROCOF, generator mechanical power variation and load fluctuations as functions of time for the initial system with parameters from Table I

and use equation (10). For the parameters we specified above - $\tau_b = 1$ s, $\alpha_b = 10.49$ p.u., and $h_b = 5$s - we find that the standard deviation of r_b is $\sigma_{r_b} = 6 \cdot 10^{-3}$ p.u. which corresponds to 0.6% of generator rated power. According to properties of standard distribution, r_b stays within the double standard deviation for 95% of time. Therefore, if we chose the battery of 1.2% of generator rated power we can supply full frequency response for 95% of time. In this derivations we have assumed that the battery is able to provide the effective droop response of 10.49 p.u. (on a generator base), which could mean a rather sharp power-frequency response for a small size battery. While there are no significant control delays for batteries and their droop settings are not significantly limited by stability considerations, proper tuning can still represent a challenge. Discussion of this topic, as well as determining the needed battery capacity, is the subject of subsequent research.

V. Numerical Evaluation

In this section we present a result of direct numerical simulations for the initial system and system with battery. For the simulations we take into account the presence of the secondary frequency control and governor deadbands. All the simulations are performed using Matlab ODE45 module. The parameters of the initial system are given in Table I. Fig.4 gives the generator frequency, ROCOF, variation of generator mechanical power output and load fluctuations as functions of time. It is obvious that the generator readjusts it's mechanical power output following the load variations.

Dynamics of the system under the same load fluctuations but with batteries executing most of frequency control is given by Fig.5. Again, the dynamics of frequency, ROCOF and

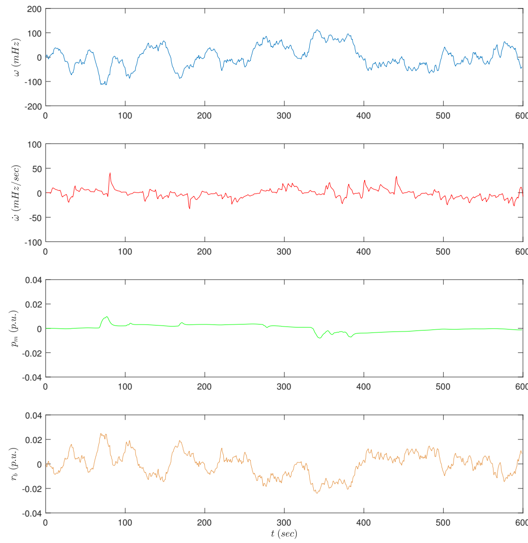

Fig. 5. Frequency, ROCOF, generator mechanical power variation and battery power output as functions of time for the system with frequency control realized by energy storage

generator mechanical power variations are shown. In addition, the battery power output is also given. For this system we have used the above discussed parameters - $\tau_b = 1$ s, $\alpha_b = 10.49$ p.u., and $h_b = 5$s - and also extended the deadbands of generator governor to 70 mHz (which is twice the standard deviation of frequency). It is obvious, that the presence of battery significantly reduces the ROCOF variations and allows for almost constant power output from generator, varying its mechanical power only occasionally, when the frequency deviates beyond the wide deadband region.

VI. Conclusions

We have developed a method for assessing the energy storage performance in primary frequency control under stochastic load perturbations. We used mean deviations of frequency and ROCOF as two main performance metrics and showed how the battery control settings can be tuned to achieve the desired values of two metrics. Our method allowed us to obtain closed-form solutions for performance metrics under realistic conditions on systems parameters. Further, we demonstrated that even a modest power capacity of storage units is enough to almost completely remove the need to perform primary frequency response by conventional generators.

The main advantage of the method is that explicit dynamic simulations on stochastic models are not required. A rather mild condition on the form of load perturbations allowed to obtain simple algebraic equations for performance metrics, and implement a control design based on them. The method can be easily generalized to more complex systems, such as multi-are power grids or more sophisticated dynamic models of power grid components.

The directions of further research include the optimal placing of storage units for frequency control and area-aware control settings [12], [13], generalization of the method for more sophisticated stochastic models of load [14], [15], load model inference from frequency measurement, role of frequency measurement noise and accuracy on the control performance, stability limits for control settings, etc.

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