Intelligent control scheme for participation of aggregated energy storage in grid frequency regulation

Oshnoei, Arman; Sorouri, Hoda; Kulkarni, Abhijit; Teodorescu, Remus; Blaabjerg, Frede

Published in:
Energy Storage Conference 2023 (ESC 2023) 2023

Publication date:
2024

Citation for published version (APA):
Oshnoei, A., Sorouri, H., Kulkarni, A., Teodorescu, R., & Blaabjerg, F. (2024). Intelligent control scheme for participation of aggregated energy storage in grid frequency regulation. In *Energy Storage Conference 2023 (ESC 2023) 2023*

Intelligent control scheme for participation of aggregated energy storage in grid frequency regulation

Conference Paper · January 2023

DOI: 10.1049/icp.2023.3104

5 authors, including:

Arman Oshnoei
Aalborg University
66 PUBLICATIONS **1,048** CITATIONS

Hoda Sorouri
Aalborg University
8 PUBLICATIONS **42** CITATIONS

Remus Teodorescu
Aalborg University
308 PUBLICATIONS **8,692** CITATIONS

F. Blaabjerg
Aalborg University
3,425 PUBLICATIONS **159,579** CITATIONS

Intelligent Control Scheme for Participation of Aggregated Energy Storage in Grid Frequency Regulation

Arman Oshnoei[1], Hoda Sorouri[1], Abhijit Kulkarni[1], Remus Teodorescu[1], Frede Blaabjerg[1]

[1]Department of Energy, Aalborg University, Aalborg, Denmark
**E-mail: aros@energy.aau.dk*

Keywords: Artificial neural network, battery energy storage system, dynamic performance, grid frequency regulation

Abstract

Battery Energy Storage Systems (BESSs) have proved to be efficient in frequency regulation by providing flexible charging/discharging powers. This paper proposes an artificial neural network (ANN)-based intelligent control scheme to provide the aggregated BESS with control signals to be efficiently involved in the frequency regulation in a power system. The ANN is proposed to provide online correction for proportional-integral controller gains in the control loop of aggregated BESS, passing the control system's reliance on operating point conditions. Then, the steady state power distributions are evaluated, showing that BESSs can facilitate a fast contribution to frequency regulation and smooth removal from the regulation process. Eventually, the OPAL-RT real-time digital simulator is used to perform real-time verifications on the simulated power grid to demonstrate the proposed control scheme's effectiveness.

1 Introduction

Renewable Energy Sources (RESs), such as solar panels and wind turbines, are increasingly utilized worldwide to address energy scarcity and support efforts to lower carbon emissions. These types of energy sources are largely influenced by environmental factors and can be inconsistent and unpredictable. As a result, when these energy sources are incorporated into power systems, they can create serious stability problems, like frequency regulation issues [1]. Therefore, power systems that heavily utilize RESs will need larger backup power supplies and complex control strategies. Battery Energy Storage Systems (BESSs) are a promising solution to supply this additional backup power. With their quick reaction time and ability to control the rate at which power is produced, BESSs react faster than traditional generation units [2]. This rapid response is vital in decreasing the rate of change of frequency deviation.

There have been extensive studies on the role of Battery Energy Storage Systems (BESSs) in frequency regulation markets. Refs. [3] and [4] consider the integration of BESSs into the system for primary frequency control reserves. The issue of sizing BESS aggregators at various penetration levels for frequency regulation is investigated in [5]. An optimal coordinated strategy to increase the potential profits from multiple BESSs participating in the frequency regulation service is proposed in [6]. In [7], a decentralized droop control scheme is presented to enhance frequency performance while optimally maintaining the State-of-Charge (SoC) of BESSs. While these studies are focused on the modeling and dispatch methods of BESSs, the development of efficient controllers that can provide BESSs with regulation commands for effective participation in frequency regulation services has not been sufficiently addressed.

In terms of designing control methods for BESSs, a robust control strategy for distributed BESSs is proposed in [8], considering the uncertainty in wind generation. In [9], a dual-consensus-based control method is introduced to enable BESSs to participate in frequency regulation in a standalone power grid. Ref. [10] offers a disturbance observer coupled with a two-layer model predictive control for electric vehicles as mobile energy storage systems in regulation service, leveraging their rapid response to charge/discharge signals. Nonetheless, these control strategies rely heavily on the system's operating conditions. Consequently, uncertainties or unexpected variations in the system's parameters can affect the controller's performance.

This paper proposes an intelligent control scheme based on an artificial neural network (ANN) that equips aggregated BESSs with control signals. This enables efficient participation in frequency regulation within a standalone power system. The ANN is designed to adaptively tune the BESS controller online, an advantage that allows it to generate control actions that are responsive to uncertainties and external disturbances, in contrast to conventional controllers. Assessments of steady-state power distributions are also conducted, illustrating that BESSs can withdraw from participating in the frequency regulation process once system balance is attained.

2 System Modeling

2.1 System overview

Through the aggregator, a group of BESSs are integrated into the grid. Distributed BESSs are coordinated to drive the frequency deviation Δf to zero, with control demand divided among BESSs based on their rated power. The communication network transports control and measurements. The control

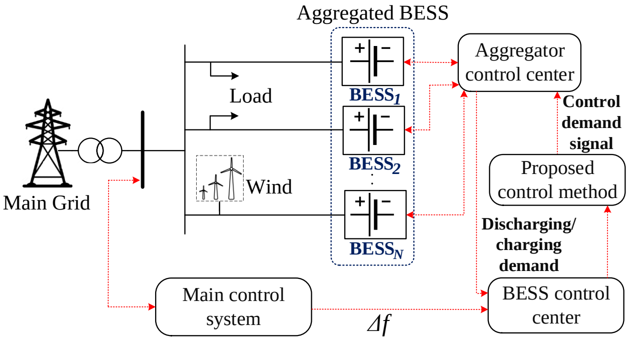

Fig. 1 Schematic view of the contribution of BESSs in frequency regulation.

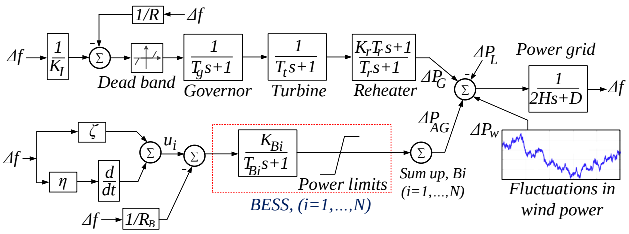

Fig. 2. Frequency response model of the system.

center located at the power grid dispatching center sends commands to the BESS aggregation center, which in turn sends charge or discharge signals to each BESS and relays power data back to the control center via a remote terminal unit. This process is described in Fig. 1.

The block diagram of the BESS control for the frequency regulation service is shown in Fig. 2. As can be seen, the system comprises a reheated thermal generator, a renewable energy production, and a BESS aggregator together with the load demand. The production of the wind farm as the renewable unit is assumed to be the source of uncertainty in the system. The frequency deviation dynamics can be described as follows:

$$\dot{\Delta f} = -\frac{D}{2H}\Delta f - \frac{1}{2H}(\Delta P_L - \Delta P_G - \Delta P_w - \Delta P_{AG}) \quad (1)$$

where

$$\Delta P_{AG} = \sum_{i=1}^{N} \Delta P_{B_i} \quad (2)$$

where ΔP_G, ΔP_w, and ΔP_L represent the variation in the output power of the thermal generator, wind farm, and in load value, respectively; ΔP_{AG} denotes the output power change of the BESS aggregator that manages N distributed BESSs. ; M is the inertia constant of the thermal generator; and D represents the load damping coefficient.

2.2 *BESS model*

The change in output power of i-th BESS can be modeled using a first-order transfer function, expressed as follows:

$$\Delta \dot{P}_{B_i} = -\frac{1}{T_{B_i}}\Delta P_{B_i} + \frac{K_{B_i}}{T_{B_i}}u_i - \frac{K_{B_i}}{T_{B_i}R_B}\Delta f \quad (3)$$

where K_{B_i} and T_{B_i} are the charging/discharging coefficient and the time constant, respectively; R_B is the droop coefficient of the aggregator model; and u_i is the control command to the i-th BESS. The change in the SoC for the i-th BESS at time t is written as follows:

$$SoC_{B_i}(t) = SoC_{B_i}(0) - \int \frac{P_{c_i}(t)}{3600 \times Q_{B_i}} \quad (4)$$

where

$$P_{c_i}(t) = \begin{cases} P_{B_i}(t)/\beta & \text{if} \quad P_{B_i}(t) > 0 \\ \beta P_{B_i}(t) & \text{if} \quad P_{B_i}(t) < 0 \end{cases} \quad (5)$$

where Q_{B_i} denotes the capacity measured in MWh and $SoC_{B_i}(0)$ refers to the initial SoC for the i-th BESS. To achieve unit conversion from hours to seconds, Q_{B_i} is multiplied by 3600; and $0 < \beta \leq 1$ denotes the charging/discharging efficiency. For the preservation of battery life, it is crucial to keep the SoC of each BESS within specified upper and lower limits, expressed as $SoC_{B_i} \in, [SoC_{min}, SoC_{max}]$. These limits are set to be 10% and 90%, respectively [8].

The BESSs are set to either charge or discharge following the instructions of frequency deviation signal Δf. The BESS will not respond to the received signal unless it deviates from a dead zone, restricted by a positive upper threshold and a negative lower threshold. Therefore, a typical design strategy for a BESS controller involves configuring the controller's output to be proportionate to a function of Δf, as follows.

$$u_i = (\zeta + \eta s).h(\Delta f) \quad (6)$$

where

$$h(\Delta f) = \begin{cases} 0 & \text{if} \quad \Delta f \in, [\Delta f_l, \Delta f_u] \\ \Delta f - \Delta f_u & \text{if} \quad \Delta f > \Delta f_u \\ \Delta f - \Delta f_l & \text{if} \quad \Delta f < \Delta f_l \end{cases} \quad (7)$$

As Eq. (6) implies, a proportional-derivative (PD) controller as an effective control method is used to achieve the adjustment of the BESS output power, and Δf_u and Δf_l are the dead zone's upper and lower thresholds for the BESS, which are assumed to be ± 0.003 Hz. Given that PD control includes constant gains, fluctuations in the operating point and the emergence of uncertainties, which act as additive disturbances to the dynamic model, could result in unsatisfactory outcomes in both performance and rate of convergence. Hence, a regulation scheme based on ANN is employed in this paper to provide an accurate online adaption of the control parameters, which will be addressed in section 3.

3 Proposed ANN-based tuner scheme

Generally, intelligent approaches can be used as supervisory tuners to enhance the performance of classic controllers in complex nonlinear power system models with uncertainties [11]. Accordingly, an ANN-based tuner strategy is used in this paper for online and fine-tuning of the PD controller embedded in the control loop of the BESS aggregator. In developing

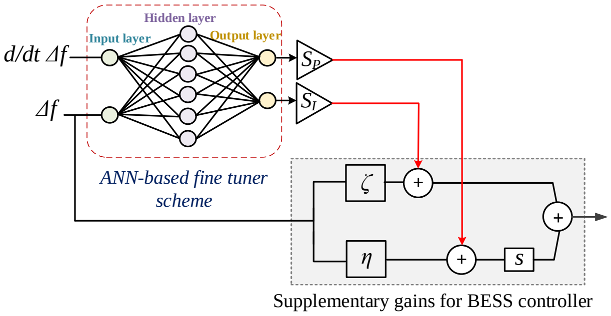

Fig. 3 ANN-based tuner strategy for online tuning of BESS aggregator controller.

the ANN-based tuner strategy, the frequency deviation signal as well as its derivative used as inputs to the ANN. Fig. 3 shows how the ANN-based approach is used in the control system of the BESS. The designed ANN comprises an input and an output layer with two hidden layers. The input layer of ANN contains ten linear neurons, and the hidden layers contain twenty nonlinear neurons. The nonlinear functions in the hidden layers can provide a smooth update of the neural network weights throughout the procedure. The output layer of ANN contains two linear neurons corresponding to the control variables, namely the proportional and integral gains of the PI controller.

4 Regulation capacity of the BESSs in steady-state

The primary frequency control is designed to react to a frequency deviation within the initial seconds. The secondary frequency control, provided by generators and BESS aggregator, contributes regulation capacities to return the frequency to its nominal value in a steady state. According to Fig. 1 (b), the generator output power can be written as

$$\Delta P_G(s) = \left(\frac{K_l}{s} - \frac{1}{R}\right).T(s)\Delta f(s) \tag{8}$$

where

$$T(s) = \frac{K_r T_r s + 1}{(T_g s + 1)(T_t s + 1)(T_r s + 1)} \tag{9}$$

where time constants T_g, T_t, and T_r are associated with the governor, turbine, and reheater, respectively; and K_r represents the reheater gain. The frequency dynamics illustrated in Eq. (1) to a change in load value can be expressed as follows:

$$\Delta f(s) = \frac{-L(s)}{1 + (V(s) + W(s))L(s)}.\Delta P_L(s) \tag{10}$$

where $V(s)$ and $W(s)$ denote the feedback gain of the control loop for the generator and the BESS, respectively, which are calculated as follows:

$$L(s) = \frac{1}{Ms + D} \tag{11}$$

$$V(s) = -\left(\frac{K_l}{s} - \frac{1}{R}\right).T(s) \tag{12}$$

$$W(s) = -\left(\zeta + \eta s - \frac{1}{R_B}\right).e^{-\zeta s}.\frac{K_B}{1 + T_B s} \tag{13}$$

where ζ refers to the time delay in transmitting control signals from the BESS aggregator to each BESS. Assuming that the system is subject to a step load change $\frac{\Delta P_L}{s}$, the steady state frequency deviation is obtained as follows:

$$\Delta f(\infty) = \lim_{s \to 0} s \times \Delta f = \frac{-1}{D + V(0) + W(0)}.\Delta P_L \tag{14}$$

Due to the integrator present in the control loop of the generator($V(0) = \infty$), the steady-state frequency deviation will disappear. The dynamics of variation in the aggregator output power to the load change is calculated as follows:

$$\Delta P_{AG}(s) = \frac{-W(s)}{Ms + D + V(s) + W(s)}.\Delta P_L(s) \tag{15}$$

The steady-state aggregator power is calculated as follows:

$$\begin{aligned} \Delta P_{AG}(\infty) &= \lim_{s \to 0} s \times \Delta P_{AG}(s) \\ &= \frac{-W(0)}{D + V(0) + W(0)}.\Delta P_L \end{aligned} \tag{16}$$

Similarly, the steady-state deviation in the aggregator power will vanish. This implies that the BESS power is effectively counteracted by the inbuilt controller (PD control) once the frequency deviation stabilizes at zero. The steady-state generator power can also be calculated as follows:

$$\begin{aligned} \Delta P_G(\infty) &= \lim_{s \to 0} s \times \Delta P_G(s) \\ &= \frac{V(0)}{D + V(0) + W(0)}.\Delta P_L = \Delta P_L \end{aligned} \tag{17}$$

This shows that the generator will be in charge of following the steady state load changes and the BESS makes no contribution to the steady state load change.

5 Real-time simulation results

The suggested LFC system is evaluated using the OPAL-RT real-time (RT) simulator. The simulation studies are conducted on an isolated power system. The system parameters are shown in Table I. The variation of the wind farm generation is shown in Fig. 4. It's assumed that the BESS aggregator will incorporate 5 distributed BESSs into the grid, with parameters sourced from [8]. The overall capacity of these distributed BESSs is 9.85 MWh. The BESSs have a rated power of ±2 MW in both the charge and discharge modes. The dynamic performance of the proposed control strategy is analyzed by applying

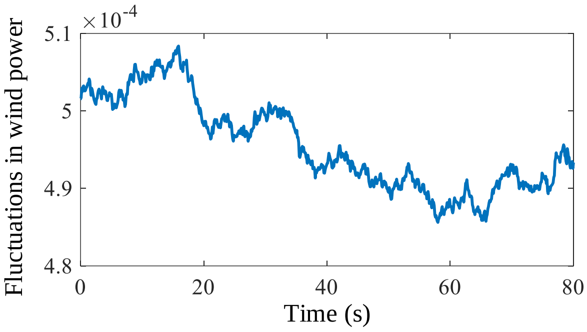

Fig. 4. Fluctuation in wind farm power.

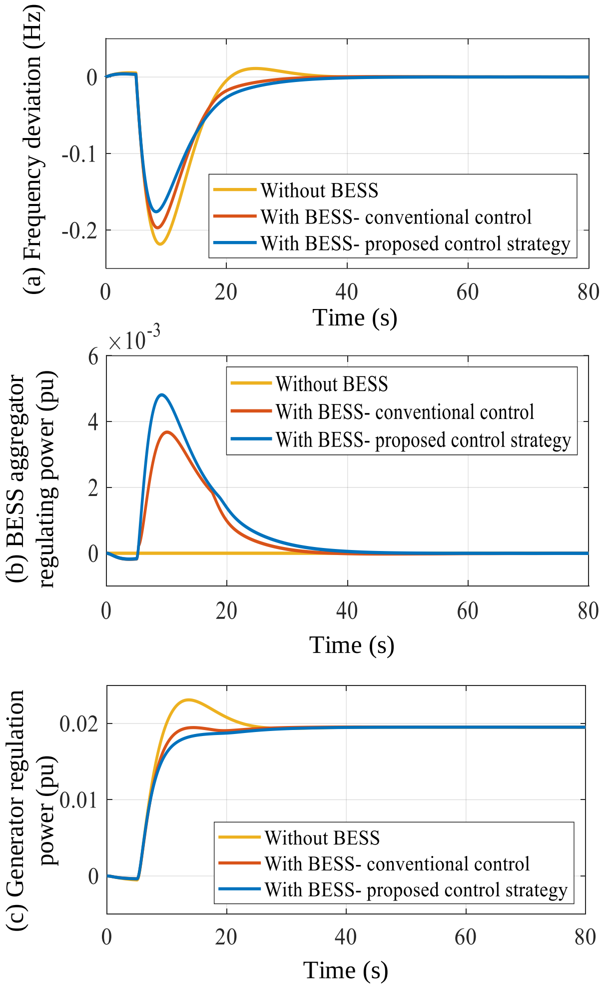

Fig. 5 (a) Frequency response ;(b) BESS aggregator regulating power ;(b) renerator output power.

Table 1 System Parameters

Parameters	Value	Parameter	Value
T_g	0.08s	M	0.1667 pu MW/Hz
T_t	0.3s	D	0.0084 pu MW/Hz
T_r	10s	R	5.6 Hz/pu MW
K_r	0.5	B	0.425 pu MW/Hz
K_I	-0.033		

a step load increase of 20 MW at t = 5 s. The frequency deviations are shown in Fig. 5 (a). As the results indicate, without the BESS aggregator, for a 0.02 pu load change at 5 s, the frequency will reach -0.22 Hz. In contrast, with the BESS aggregator, the frequency deviation remains below -0.2 Hz and below -0.18 Hz by using the proposed ANN-based PD control, demonstrating its superior performance compared to the PD control with fixed gains. The regulating power provided by the generator and BESS aggregator with the applied controllers is illustrated in Figs. 5 (b)-(c), respectively. The BESS aggregator regulating power shows a decreasing trend leveling off at zero with the recovery of the system frequency. The figures also illustrates that the BESS aggregator responds faster and charges/discharges more energy from/into the grid with the proposed controller; thus producing a further reduction in the frequency deviation.

6 Conclusion

This paper proposed an ANN-based intelligent control scheme to regulate the BESSs charging/discharging power to participate in the frequency regulation of an isolated power system. The ANN approach was proposed to provide online and adaptive tuning of the aggregated BESS controller. The main advantage of the proposed strategy was the ability to generate dynamic outputs for control objectives. This comprises producing the control actions concerning the uncertainties and external disturbances in contrast to the traditional controllers. The outcomes of real-time simulations indicate an enhancement in system frequency response when the proposed intelligent control scheme is employed. Steady-state power distributions also indicated that, following the restoration of system balance, the BESSs could smoothly terminate their involvement in the frequency regulation process.

7 References

[1] Final report to The European Commission, “Study on the effective integration of distributed energy recourses for providing flexibility to the electricity system,” 2015.

[2] G. He et al. “Cooperation of wind power and battery storage to provide frequency regulation in power markets,” *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3559–3568, 2016.

[3] D. Zhu et al."Optimal Coordinated Control of Multiple Battery Energy Storage Systems for Primary Frequency Regulation," in IEEE Transactions on Power Systems, vol. 34, no. 1, pp. 555-565, Jan. 2019, doi: 10.1109/TPWRS.2018.2868504.

[4] P. Mercier et al. “Optimizing a battery energy storage system for frequency control application in an isolated power system,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1469–1477, 2009.

[5] S. Chen et al. “Penetration rate and effectiveness studies of aggregated BESS for frequency regulation,”*IEEE Trans. Smart Grid.*, vol. 7, no. 1, pp. 167–177, 2016.

[6] D. Zhu et al. “Optimal coordinated control of multiple battery energy storage systems for primary frequency regulation,” *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 555–565, 2018.

[7] J. W. Shim et al. “Decentralized operation of multiple energy storage systems: Soc management for frequency regulation,” in *IEEE Int. Conf. Power Syst. Techn. (POWERCON)*, pp. 1–5, 2016.

[8] A. Oshnoei et al. “Robust control scheme for distributed battery energy storage systems in load frequency control,” *IEEE Trans. Power Syst.*, vol 35, no. 6, pp. 4781–4791, 2020.

[9] L. Xing et al. “Dual-consensus-based distributed frequency control for multiple energy storage systems,”*IEEE Trans. Smart Grid.*, vol 10, no. 6, pp. 6396–6403, Nov. 2019.

[10] A. Oshnoei et al. “Disturbance Observer and Tube-Based Model Predictive Controlled Electric Vehicles for Frequency Regulation of an Isolated Power Grid,”*IEEE Transactions on Smart Grid.*, vol. 12, no. 5, pp. 4351–4362, Sept. 2021.

[11] H. Sorouri, M. Sedighizadeh, A. Oshnoei, and R. Khezri, “An intelligent adaptive control of dc–dc power buck converters,” *Int. J. Electr. Power Energy Syst.*, vol. 141, p. 108099, 2022.