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SoC-Based Dynamic Droop Control for Battery Energy Storage Systems in DC Microgrids Feeding CPLs

Jianmin Wang^{1*}

¹Collage of Automation Engineering, Shanghai University of Electric Power, Shanghai, Shanghai, 200090, China

*Corresponding author's e-mail: wangjianm@mail.shiep.edu.cn

Abstract. In this paper, a dynamic state-of-charge (SoC)-based droop control and bus voltage stabilization strategy has been proposed for battery energy storage systems (BESSs) feeding constant power loads (CPLs). Firstly, a SoC-based dynamic droop control is proposed to realize proportional distribution of power. Secondly, a dynamic average consensus (DAC) algorithm is adopted to ensure that all SoC converge to the same value simultaneously. Thirdly, a nonlinear disturbance observer (NDO) and a backstepping controller are integrated to stabilize the DC bus voltage. In this way, the rapid voltage recovery and power distribution are obtained when droop coefficient is time-varying. Simulation results verify the feasibility and effectiveness of the proposed control strategy.

1. Introduction

In recent years, DC microgrids have been widely applied to power generations. The distributed DC generation becomes a critical research direction with the utilization of renewable energy sources (RESs), such as solar PV, wind turbine, water, and tidal. A typical DC microgrid is illustrated in Fig. 1. In general, RESs, BESSs, and loads are typically connected to the common DC bus through AC/DC or DC/DC converters. The intermittence of RESs and uncertainties of the loads cause certain destabilizing effects for DC microgrids. Given these conditions, the battery energy storage systems (BESSs) are widely deployed in DC microgrids to improve system stability and reliability[1].

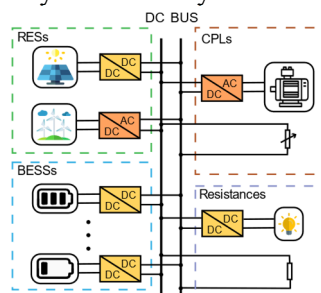


Figure 1. A typical DC Microgrid with RESs, BESSs, and loads.

Although BESSs can maintain the bus voltage at a desirable value and buffer the RES power, it should also consider the power distribution between BESSs to improve the batteries' lifetime and efficiency. There are many research results been proposed to solve the power distribution issue in the literature. See for example, [2-5]. In [2-3], the sources and loads power management problem was dealt with by tuning the fuzzy logic parameters. Meanwhile, droop control is widely used for power



distribution in the decentralized control. The droop control is a simple and effective control method in DC microgrids[4]. However, the traditional droop control coefficient is a constant, it cannot adapt to state-of-charge (SoC) variations of BESSs. Therefore, the BESSs with low SoC may run out of their energy, which will cause the system to become unstable.

To solve problem of BESS over-discharging, the SoC of battery has been considered in many energy storage strategies. The SoC balance issue is addressed in [6] by proper energy sharing through adjusting charging and discharging rates. An SoC-based adaptive droop control is reported to ensure SoC balance with an adjustable convergence speed. The SoC of each battery needs to be estimated and controlled. Reference [7] proposed mode switching strategies to adjust the SoC of the energy storage devices. This method can flexibly adjust the control strategy according to SoC real-time value, while it has strict requirements for seamless mode transition. In [8], with the intention of solving the problem of unbalanced output power of multiple energy storage batteries, dynamic droop control strategy based on the SoC of battery has been used.

The BESSs need to keep power distribution and SoC balance to stabilize DC bus voltage. Meanwhile, the load variations will affect system stability. For example, constant power load (CPL) variations may cause instability of DC microgrids. Multiple types of research have been conducted for stabilizing DC bus voltage with CPLs. In [9], a decentralized composite controller (DCC) is proposed to realize global system large signal stability of the DC microgrids. In [10], backstepping control is also used for large signal stability. Considering that the nonlinear disturbance observer (NDO) estimates parameters faster and more accurate than traditional ones, this paper uses NDO and backstepping controller to regulate the DC bus voltage. The contributions of this paper can be summarized as follows.

(1) To regulate the power distribution of BESSs, the local SoC information can be shared through the dynamic average consensus (DAC) algorithm, which ensures the dynamic allocation of the preserved capacity of all batteries.

(2) By employing a compound stabilizer to regulate the DC bus voltage, the system large signal stability is enhanced with fast voltage convergence rate. The voltage deviation caused by the droop control can be compensated by a consensus algorithm.

The remaining of this paper is organized as follows: Section II describes the method of dynamic droop control and BESSs configuration. Section III presents a distributed control strategy with CPL. In Section IV, case studies are verified with Simulink. Finally, the conclusions are drawn in Section V.

2. THE PROPOSED DYNAMIC DROOP CONTROL

The architecture of distributed control for voltage regulation in a DC microgrid with multiple BESSs is shown in Fig. 2. The energy storage devices consist of batteries and bidirectional DC/DC converters, which mainly use boost converters. Batteries are connected to the common bus by DC/DC converters respectively. They will supply power to load and maintain the DC bus voltage. In this section, a dynamic power management strategy is proposed to effectively distribute power between BESSs.

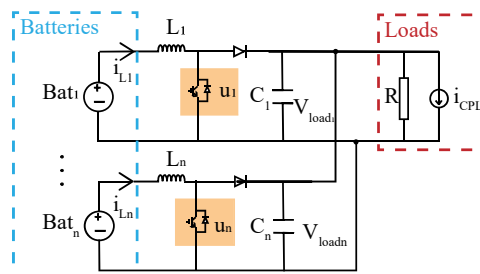


Figure 2. The simple architecture of distributed BESSs.

2.1. SoC-Based Droop Control

This section proposes a dynamic power distribution method. By employing basic droop control, the voltage reference of i th converter is expressed as

$$V_{loadi} = V_{ref} - m_i \times P_{outi} \quad (1)$$

where V_{ref} is the nominal voltage, V_{loadi} and P_{outi} are output voltage and load power of the converter for the i th battery, and m is the corresponding droop coefficient. The subscript i ($i = 1, 2, 3, 4$) is the variable associated with the i th BESS.

Let $SoC_i(t)$ be the SoC of the i th BESS at time t and $SoC_i(0)$ be the initial SoC value. Also, let Q_i and I_{Bi} be the battery capacity and output current, respectively. $SoC_i(t)$ is estimated by using the basic Coulomb counting method as

$$SoC_i(t) = SoC_i(0) - \frac{1}{Q_i} \int I_{Bi} dt. \quad (2)$$

To achieve SoC balancing among BESSs, higher SoC supply higher power while lower SoC batteries provide less power in discharging mode. Inspired by [11], the droop coefficient which is based on i th SoC is expressed as

$$m_i = m_0 \left(1 + \frac{SoC_i(t) - SoC_{ave}}{SoC_{ave}} \right)^n \quad (3)$$

where m_0 is a positive constant, n represents the equalization velocity adjustment coefficient, SoC_{ave} is the average value of $SoC_i(t)$.

$$SoC_{ave} = \frac{1}{i} \sum_1^i SoC_i(t). \quad (4)$$

The ratio relation between power and droop coefficient is

$$P_{out1} : P_{out2} : \dots : P_{outi} = \frac{1}{m_1} : \frac{1}{m_2} : \dots : \frac{1}{m_i}. \quad (5)$$

2.2. Dynamic SoC Consensus

The dynamic average consensus algorithm has been used to balance all SoC of BESSs. In addition, in order to obtain i th local SoC information for dynamic droop coefficient, the dynamic average consensus algorithm is designed as

$$\begin{cases} \dot{\omega}_i = -\gamma_1 \omega_i - \sum_{i \neq j} a_{ij}(t)(\hat{\theta}_i - \hat{\theta}_j), \\ \hat{\theta}_i = \omega_i + \theta_i \end{cases} \quad (6)$$

where $i, j = 1, 2, 3, 4$. $\theta_i = SoC_i(t)$ is the i th local measurement data, ω_i is an internal state, and $\gamma_1 > 0$ is a constant.

$$a_{ij} = \begin{cases} 1, & i \neq j, \\ 0, & i = j. \end{cases} \quad (7)$$

The dynamic consensus algorithm shown in (6) is adopted, and each local communication agent can exchange information without a central controller. In order to obtain average consensus, the error vector is obtained as $e_i(t) = \hat{\theta} - \frac{11^T}{n} \theta_i$, where $i = 1, 2, \dots, n$. As time goes to infinity, the $e_i(t)$ goes to zero. The (6) can be achieved in [13].

2.3. System Model

The simplified DC/DC boost converters diagram is demonstrated in Fig. 2. The DC/DC boost converter circuits dynamic model is expressed as

$$\begin{cases} L_i \frac{dI_{Bi}}{dt} = V_{Bi} - (1 - d_i)v_{loadi}, \\ C_i \frac{dv_{loadi}}{dt} = (1 - d_i)I_{Bi} - \frac{P_{CPL}}{v_{loadi}} \end{cases} \quad (8)$$

where V_B is the battery output voltage, P_{CPL} represents the power of CPL, and d is the duty ratio.

The control objective is v_{loadi} , by setting v_{ref} to make v_{loadi} track v_{ref} . In order to observe immeasurable quantities, through feedback linearization of DC/DC converters, the system model in (8) has been transformed into the standard form as

$$\begin{cases} \dot{x}_{i1} = x_{i2} + h_{i1}, \\ \dot{x}_{i2} = v_i + h_{i2} \end{cases} \quad (9)$$

where x_{i1} , x_{i2} are state variables, h_{i1} , h_{i2} are uncertain items.

Design intermediate control rate v_i , making x_{i1} tracking its desired x_{i1d} ,

$$x_{i1d} = 0.5L_i \left(\frac{P_{ref}}{V_{Bi}} \right)^2 + 0.5C_i v_{loadi}^2 \quad (10)$$

where P_{ref} is total load power.

According to (9), h_i can get as

$$h_i = 1 - \frac{\frac{V_{Bi}^2}{L_i} - v_i}{\frac{V_{Bi} v_{loadi}}{L_i} + \frac{2I_{Bi} v_{loadi}}{R_0 C_i}}. \quad (11)$$

3. Distributed Controller with CPLs

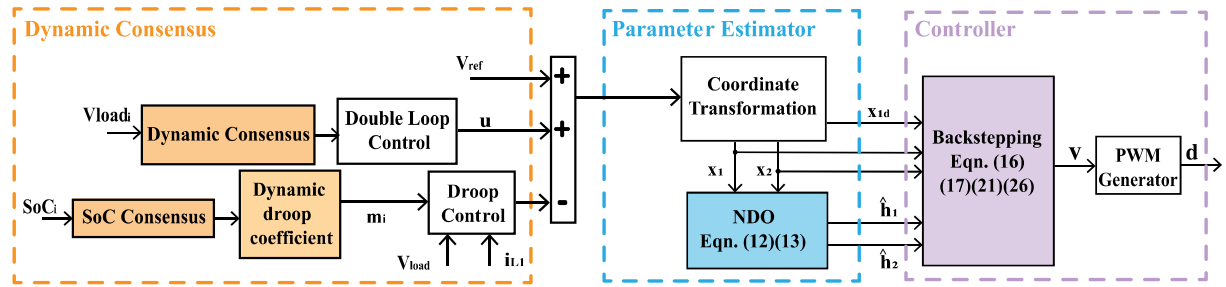


Figure 3. Control architecture of the proposed controller.

3.1. Nonlinear Disturbance Observer design

In (10), it can be observed that reference value x_{i1d} is an uncertain value, which varies with load power and may affect the stability of the system. Due to this cause, the NDO is employed to estimate uncertain items h_{i1} , h_{i2} and P_{ref} to achieve accurate tracking and fast dynamic response.

Due to the h_{i1} , h_{i2} are uncertain items, the uncertain item h_{i1} can be estimated based on NDO of the following form[10]

$$\begin{cases} \hat{h}_{i1} = l_{i1}(x_{i1} - r_{i1}), \\ \dot{r}_{i1} = x_{i2} + \hat{h}_{i1} \end{cases} \quad (12)$$

where r_{i1} is an auxiliary state of the NDO, $l_{i1} > 0$ is the NDO gain.

Similarly, the uncertain item h_{i2} is estimated by

$$\begin{cases} \hat{h}_{i2} = l_{i2}(x_{i2} - r_{i2}), \\ \dot{r}_{i2} = v_i + \hat{h}_{i2} \end{cases} \quad (13)$$

where r_{i2} is an auxiliary state of the NDO, $l_{i2} > 0$ is the NDO gain.

According to (12) and (13), the estimation error of h_{i1} , h_{i2} and their derivative are expressed as

$$\begin{cases} \tilde{h}_i = h_i - \hat{h}_i, \\ \dot{\tilde{h}}_i = \dot{h}_i - \dot{\hat{h}}_i = \dot{h}_i - l_i \tilde{h}_i. \end{cases} \quad (14)$$

Considering accuracy and stability of the observer, NDO-based tracking control is designed for uncertain systems (9), the uncertainties h_{i1} , h_{i2} are related to v_{loadi} and P_{CPL} . Thus, the rate of disturbances change must be bounded. The following assumption is required:

Assumption 1: The uncertain state h_i , $\dot{h}_i$ for the system (9) satisfy the following two conditions:

$$h_i(t) \in L_\infty, \dot{h}_i(t) \in L_\infty, \lim_{t \rightarrow 0} \dot{h}_i(t) = 0. \quad (15)$$

3.2. Backstepping Control Design

In this part, a nonlinear backstepping control is designed to obtain an optimized tracking performance of the main DC-DC bus voltage. Based on the standard form (9) and load power estimated by NDO, the backstepping algorithm can be used to enforce the state variables x_{i1} , x_{i2} to track their desired value x_{i1d} , x_{i2d} respectively.

The state variable x_{i1} state errors is e_i . The state variable x_{i2} state errors is δ_i .

$$e_i = x_{i1d} - x_{i1}. \quad (16)$$

$$\delta_i = x_{i2d} - x_{i2}. \quad (17)$$

Taking derivative of e_i yields

$$\dot{e}_i = \dot{x}_{i1d} - \dot{x}_{i1} = \dot{x}_{i1d} - (x_{i2} + h_{i1}) = \dot{x}_{i1d} + \delta_i - x_{i2d} - h_{i1}. \quad (18)$$

According to Lyapunov's second method, the scalar function is defined as

$$V_{i1} = \frac{1}{2}e_i^2 + \frac{1}{2}\tilde{h}_{i1}^2. \quad (19)$$

Then $\dot{V}_{i1}$ is obtained as

$$\dot{V}_{i1} = e_i(\dot{x}_{i1d} + \delta_i - x_{i2d} - \hat{h}_{i1}) - e_i\tilde{h}_{i1} + \tilde{h}_{i1}\dot{h}_{i1} - l_{i1}\tilde{h}_{i1}^2. \quad (20)$$

To stabilize (19) with the Lyapunov function (20), the virtual control law x_{i2d} is designed as

$$x_{i2d} = k_{i1}e_i + \dot{x}_{i1d} - \hat{h}_{i1}. \quad (21)$$

Then $\dot{V}_{i1}$ is obtained as

$$\dot{V}_{i1} = -k_{i1}e_i^2 + e_i\delta_i - e_i\tilde{h}_{i1} + \tilde{h}_{i1}\dot{h}_{i1} - l_{i1}\tilde{h}_{i1}^2. \quad (22)$$

Taking derivative of δ_i yields

$$\dot{\delta}_i = k_{i1}\dot{e}_i + \ddot{x}_{i1d} - l_i\tilde{h}_{i1} - v_i - h_{i2}. \quad (23)$$

Design V_{i2} function as

$$V_{i2} = V_{i1} + \frac{1}{2}\delta_i^2 + \frac{1}{2}\tilde{h}_{i2}^2. \quad (24)$$

Taking derivative of V_{i2} yields

$$\dot{V}_{i2} = -k_{i1}e_i^2 + e_i\delta_i - e_i\tilde{h}_{i1} + \tilde{h}_{i1}\dot{h}_{i1} - l_{i1}\tilde{h}_{i1}^2 + \delta_i(-v_i - h_{i2} + k_{i1}\dot{e}_i - l_{i1}\tilde{h}_{i1} + \ddot{x}_{i1d}) + \tilde{h}_{i2}\dot{h}_{i2} - l_{i2}\tilde{h}_{i2}^2. \quad (25)$$

To stabilize (24) with the Lyapunov function (25), the intermediate control law v_i is designed as

$$v_i = k_{i2}\delta_i - \hat{h}_{i2} + \ddot{x}_{i1d}. \quad (26)$$

According to (25) and (26), the derivative of V_{i2} is expressed as

$$\dot{V}_{i2} = -k_{i1}e_i^2 - k_{i2}\delta_i^2 + e_i\delta_i - e_i\tilde{h}_{i1} + \tilde{h}_{i1}\dot{h}_{i1} + \delta_i k_{i1}\dot{e}_i - l_{i1}\tilde{h}_{i1}^2 - \delta_i\tilde{h}_{i2} - \delta_i l_{i1}\tilde{h}_{i1} + \tilde{h}_{i2}\dot{h}_{i2} - l_{i2}\tilde{h}_{i2}^2. \quad (27)$$

Theorem 1: The closed-loop system consisting of (8), (9), (16), (17), (21) and (26) is globally asymptotically stable and DC bus voltage v_{loadi} can track its reference value v_{ref} asymptotically. According to [10], eqn. (27) can be derived as

$$\dot{V}_{i2} \leq -(k_{i1} - 1.5)e_i^2 - \left[k_{i2} - \left(\frac{k_{i1}^4}{2} + \frac{1}{2k_{i1}^2} \right) - \frac{(k_{i1} + l_{i1})^2}{2} - 1 \right] \delta_i^2 - (l_{i1} - 1.5)\tilde{h}_{i1}^2 - (l_{i2} - 1)h_{i2}^2 + 0.5\dot{h}_{i1}^2 + 0.5\dot{h}_{i2}^2. \quad (28)$$

By selecting $l_{i1} \geq 2.5$, $l_{i2} \geq 2$, $k_{i1} \geq 2.5$ and $k_{i2} \geq \frac{k_{i1}^4}{2} + \frac{1}{2k_{i1}^2} + \frac{(k_{i1} + l_{i1})^2}{2} + 2$, the system is globally input to state stable.

3.3. Voltage Consensus Algorithm

The DC bus voltage cannot back to the voltage reference due to the virtual impedance. To improve the power distribution quality, the voltage of each agent should be consistent. From Eqn. (3), the droop coefficient can be achieved. By adopting consensus algorithm to get the error between V_{loadi} and V_{loadj} , voltage state can be expressed as

$$\begin{cases} \dot{\alpha}_i = -\gamma_2 \alpha_i + \sum_{i \neq j} a_{ij}(t)(\bar{V}_{loadj} - \bar{V}_{loadi}), \\ \bar{V}_{loadi} = V_{loadi} - \alpha_i \end{cases} \quad (29)$$

where $i, j = 1, 2, 3, 4$. α is an internal state, and $\gamma_2 > 0$ is a constant.

Define tracking error ϵ_i .

$$\epsilon_i = V_{ref} - \bar{V}_{loadi}. \quad (30)$$

In order to achieve global stability, the voltage compensation input is given by

$$u_i = k_{pi}\epsilon_i(t) + k_i \int_0^t \epsilon_i(t)dt. \quad (31)$$

A compensation control signal u_i is to be designed to add to the droop function (1). It's expressed as

$$V_{loadi} = V_{ref} + u_i - m_i P_{outi}. \quad (32)$$

According to global information, the DC bus voltage can track its reference value. Besides, local SoC information is adopted to regulate power distribution.

4. Simulation

In this section, simulations are conducted to verify the feasibility and effectiveness of the proposed control method with three cases. In this paper, the working range of BESS sets as [10%, 90%]. The system parameters are listed in Table I.

TABLE I: System parameters

Variables	Description	Value	Variables	Description	Value
V_{ref}	DC bus voltage reference	50V	l_{i1}	Observer gains	3000
V_B	Battery output voltage	25V	l_{i2}	Observer gains	1000
L	Inductance	2mH	k_{i1}	Controller gains	220
C	Capacitance	0.22mF	k_{i2}	Controller gains	1000

4.1. Case 1: Performance of proposed control approach with balanced SoC

Simulation results of the SoC-based droop control with balanced SoC are shown in Fig. 4. In this condition, the droop coefficient of each BESS is the same. From Fig. 4 (a), it is clear that each BESS offers the same power. The DC bus voltage transient value varies with the working condition. It can be observed from Fig. 4 (b) that the transient behaviour of V_{load} is improved compared to double loop control.

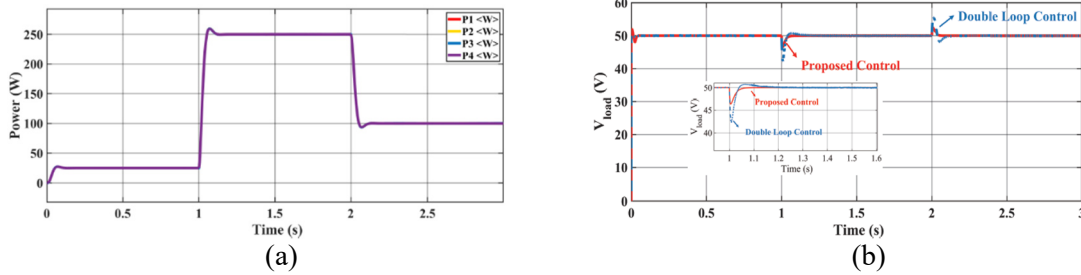


Figure 4. Simulation results with CPL variations under SoC balance condition.

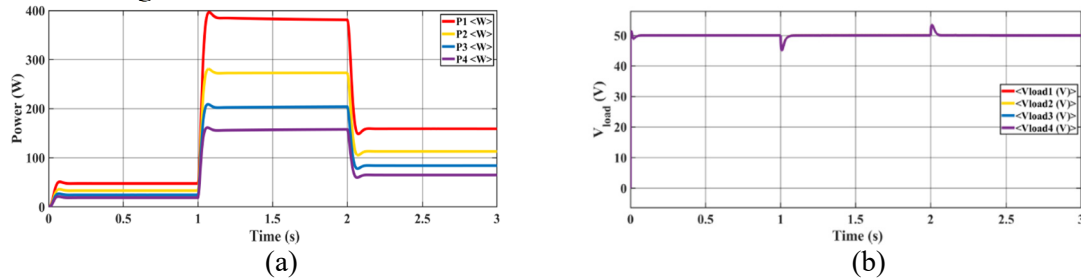


Figure 5. Simulation results with CPL variations under SoC imbalance conditions.

4.2. Case 2: Performance of SoC-based droop control with unbalanced SoC

It is assumed that the BESSs are working under different SoC values, the initial SoC values for 4 BESSs are respectively set as 90%, 88%, 86%, 84%. The CPL variations are the same with case 1. Fig. 5 shows that BESSs have different power distribution ratio. 1st Battery which has the highest SoC provides the most power under this case. The DC bus voltage will soon return to the steady state under the condition of CPL changes.

According to the dynamic consensus algorithm, the results are shown as Fig. 6. BESSs with unbalanced SoC will converge to the same value around 170s. All BESSs provide power in proportion to the preserved SoC of BESSs.

4.3. Case 3: Removal of BESS

The third case shows results with removal of BESS. Considering that if the SoC of BESS is less than 10%, this BESS should unplug to avoid over-discharging.

In this case, the initial SoC values for 4 BESSs are respectively set as 20%, 15%, 14%, 11%. As Fig. 7 shows, when the lowest BESS's SoC less than 10%, that BESS will stop supplying energy for load. At the same time, the remaining BESSs need to bear the demand power and dynamically distribute it in proportion.

5. Conclusion

A SoC-based dynamic droop control approach has been presented for power distribution and batteries' healthy in DC Microgrids with CPL. The proposed control scheme can share local SoC information with other BESSs by a dynamic average consensus algorithm. By adopting the NDO and backstepping controller, the system stability is improved. The stability and rapidity of the system are verified using Matlab / Simulink models, inferring that the proposed control algorithm is able to maintain good voltage regulation and appropriate power distribution.

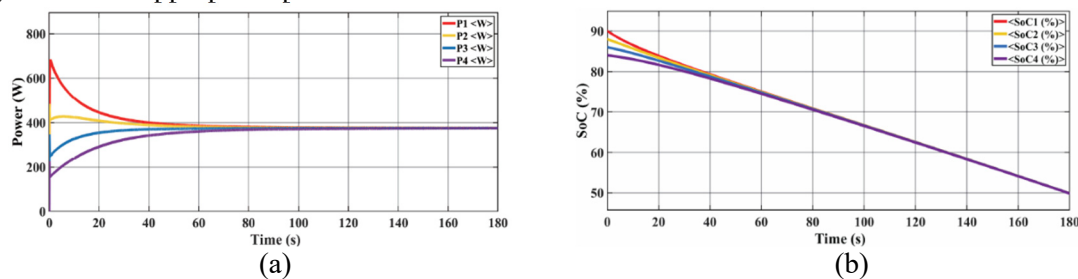


Figure 6. Simulation results of SOC convergence.

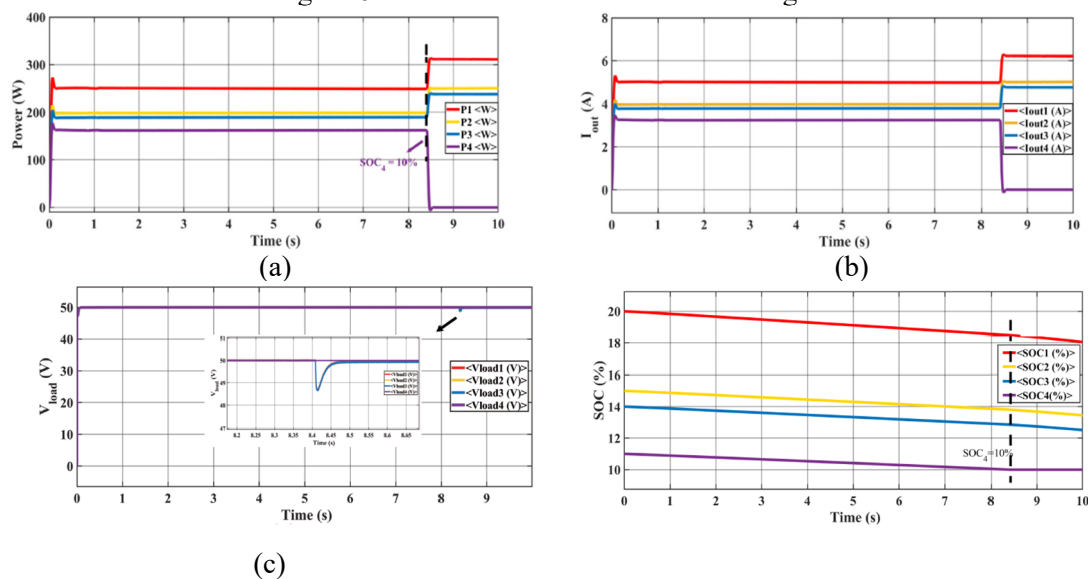


Figure 7. Simulation results with removal of BESS.

Acknowledgments

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