

Received August 20, 2019, accepted September 2, 2019, date of publication September 5, 2019, date of current version September 20, 2019.

*Digital Object Identifier 10.1109/ACCESS.2019.2939626*

# A Hierarchical Control Structure for Distributed Energy Storage System in DC Micro-Grid

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This work was supported in part by the National Natural Science Foundation of China under Grant 51877041, and in part by the Science and Technology Foundation of State Grid Jiangsu Electric Power Company, China, under Grant J2019092.

**ABSTRACT** To adapt to the rapid development of the renewable generations, DC micro-grid has been becoming an attractive technical route. Energy storages are widely employed in DC micro-grid to balance the power generation and usage. Therefore, the coordination and energy control among these distributed energy storage systems are critical technical issues to guarantee the overall efficiency and security. In this paper, the concept and characteristic of the distributed energy storage system in DC micro-grid are first analyzed. A hierarchical control system for power sharing is proposed to achieve the state-of-charge (SOC) balancing among energy storage units (ESU). In the lower layer of the control system, the DC droop control is applied to allocate the output power of each ESU based on its maximum output power. In the upper layer, consensus algorithm is utilized to adjust the output power reference of each ESU to reduce the SOC difference. Finally, a Matlab/Simulink model is built to verify the proposed approaches. The simulation results indicate that the proposed method can achieve the SOC balancing robust operation in distributed energy storage system.

**INDEX TERMS** DC micro-grid, distributed energy storage system, droop control, consensus control, SOC balancing.

#### **I. INTRODUCTION**

Micro-grid provides an effective solution to integrate distributed energy resource, including renewable generations, controllable loads and energy storage systems, into power system. Since the primary sources of most generations and energy storages in micro-grid are DC based, while considering there is no phase, harmonic and reactive power problem in DC system, DC micro-grid deservedly become an attractive technical route in recent years [1], [2].

Meanwhile, in order to overcome the uncertainty and volatility of the renewable generations, energy storage system is widely employed in DC micro-grid, playing the roles of power buffering, peak load shifting and backup power. Respect to the spatial distribution of renewable generations, energy storage unit (ESUs) are usually distributed installed to meet local power demand. However, to satisfy the power demand of the overall micro-grid coordinately, the output of each ESU should be allocated reasonably to maintain its

The associate editor coordinating the review of this manuscript and approving it for publication was Salvatore Favuzza.

optimal state and to extend the operation duration. Usually, there lays diversities in capacities and initial state-of-charges (SOC) among distributed ESUs, which would cause some units with low SOC quit operation before others. When the power output of the remaining ESUs are not enough to fill the overall gap between power supply and demand, the stability of the system is in danger. Therefore, the SOC balancing in distributed energy storage system is critical to the safety of the micro-grid [3], [4].

The power allocation SOC balancing scheme among distributed generations and ESUs in micro-grid is realized through the control methods of power converters, which can be roughly divided into three categories: centralized, decentralized and distributed [5]. Centralized approaches need a special topology, or a centralized controller as a master to determine the specific output power of each ESU [6]–[8]. Since the centralized communication is needed, these approaches have strict distance and topology requirements. Decentralized approaches do not demand complex communication networks [9]–[11]. The droop control and its variants are one of the most popular decentralized methods to

integrate multiple energy sources in a micro-grid [12]–[15]. Generally, it is a control method which regulates the voltage and current references of the converter according to certain droop curves.

Distributed approaches only need local and low-band communication. Distributed control based on consensus theory for network of dynamic agents was first introduced in 2003 [16]. To the control in power system, a feedback linearization-based consensus control design for inverters in islanded micro-grids is proposed to synchronize the inverter voltages in [17]. In [18], a consensus based droop control is proposed for real and reactive power sharing in micro-grids. Distributed multi-agent control strategies for SOC balancing in distributed energy storage systems have been presented for AC micro-grids [19]–[21] and DC micro-grids [22]–[26]. In [19], a dynamic energy level balancing strategy is proposed to improve frequency regulation and reliability between ES devices. In [20], distributed multi-agent SOC balancing with robustness to communication delays is presented. In [22], a multi-agent sliding mode control strategy is designed for SOC balancing in DC micro-grid. In [25], distributed controllers for voltage restoration are introduced. Compared with centralized approaches, the distributed approaches can ensure the flexibility when topology changes and the robustness of the system under communication failure situations.

This paper focuses on exploring an effective control method to achieve SOC balance among distributed ESUs in a micro-grid. A hierarchical control structure is proposed to allocate power rationally to realize the SOC balancing while meet the overall power demand for the energy storage system. The control structure contains two layers. In the lower layer, droop control is adopted to share the output power among ESUs based on their maximum output power abilities. In the upper layer, consensus algorithm is used to further adjust the output power of the ESUs according to their SOC level to reduce the difference. One highlight of the proposed scheme is that it only require limited local communications between neighbors ESUs rather than the centralized communication network with a central controller.

The rest of this paper is organized as follows. Section II introduces the characteristics of distributed energy storage system and the concept of droop control. Section III introduces the proposed hierarchical control structure and the principle of the control strategy of the two layers. The simulation results are given and analyzed in Section IV. Section V draws the conclusion.

### **II. DISTRIBUTED ENERGY STORAGE SYSTEM IN DC MICRO-GRID AND ITS WORK MODE**

#### A. ENERGY STORAGE SYSTEM IN DC MICRO-GRID

A typical DC micro-grid with distributed energy storage system is shown in Fig. 1. Various distributed power sources, ESUs and loads are parallel connected to the DC bus through independent converters.

Each ESU has the local control targets associated with the generations and loads it installed with. For examples,



**FIGURE 1.** Distributed energy storage system in DC micro-grid.

ESUs installed with renewable generations usually play the role of energy buffer to constrict the power fluctuation by output or absorb energy, which means local control targets at maintaining stable power output coordinately with renewable generations; ESUs installed with critical loads often act as backup power and the local control target is keeping remain energy (or SOC) at an adequate level.

Meanwhile, if the distributed deployed ESUs are treated as a whole, meeting the power demands of the micro-grid can be set as their overall target. Thus, the ESUs forms a distributed energy storage system when they operate coordinately.

To realize the effective coordination among distributed ESUs, there will be limited communication connections among ESUs. The requirement of the communication network will be discussed in section III.

#### B. MODEL OF DISTRIBUTED ENERGY SYSTEM

To simplify the analysis, the equivalent model of the distributed energy storage system is shown in Fig. 2. In this model, *n* ESUs are parallel connected to the DC bus through respective DC converters. Meanwhile, the two-way communication are set between certain neighbor ESUs. A single DC



**FIGURE 2.** Simplified structure of distributed energy storage system.

load is also connected to the DC bust to represent the overall power demand inside the micro-grid.

The ESU model has four key parameters: capacity *Ce*, maximum power  $P_{max}$ , output power  $P_o$  and SOC (%). *E* and  $P_{max}$  are the inherent parameters while  $P_o$  and SOC are dynamic parameters in operation.

Ignoring the power loss of converters, the relationship between *P<sup>o</sup>* and SOC can be expressed as:

<span id="page-2-4"></span>
$$
SOC = SOC_0 - \int \frac{\eta P_o}{V_{Bat} C_e} dt
$$
 (1)

where  $SOC<sub>0</sub>$  is the initial value of SOC,  $\eta$  is charge-discharge efficiency and *VBat* is the battery output voltage.

#### C. DROOP CONTROL IN DC MICRO-GRID

Droop control is a power allocation method which does not require any communication, thus is widely adopted in microgrid control.



**FIGURE 3.** Block diagram of DC droop control.

The basic concept of droop control for DC micro-grid is illustrated in Fig. 3. The *I-V* droop control is given as follows:

<span id="page-2-0"></span>
$$
U_o = U_{rated} - R_d I_o \tag{2}
$$

where  $U<sub>o</sub>$  is the output voltage of the converter connected to DC bus,  $U_{rated}$  is the rated voltage of the converter,  $R_d$  is the droop coefficient (virtual resistance), and  $I<sub>o</sub>$  is the output current of the converter.

Assuming the rated voltage of all parallel converters are identical. For any two ESUs *i*, *j*, there is:

<span id="page-2-1"></span>
$$
\begin{cases}\nU_{oi} = U_{rated} - R_{di}I_{oi} \\
U_{oj} = U_{rated} - R_{dj}I_{oj}\n\end{cases}
$$
\n(3)

Ignoring line impedance, it yields:

$$
U_{oi} \approx U_{oj} \approx U_{bus} \tag{4}
$$

Combining [\(2\)](#page-2-0) and [\(3\)](#page-2-1), it can be derived:

<span id="page-2-2"></span>
$$
I_{oi}: I_{oj} = \frac{1}{R_{di}} : \frac{1}{R_{dj}}
$$
 (5)

Eq. [\(5\)](#page-2-2) indicates that the output current allocation is related to the droop coefficient. It can be further derived that the output power allocation of all ESUs in the whole system is as follows:

$$
P_{o1}: P_{o2}: \ldots: P_{on} = \frac{1}{R_{d1}}: \frac{1}{R_{d2}}: \ldots: \frac{1}{R_{dn}} \qquad (6)
$$

If the droop coefficient is set by the ratio of the maximum power *Pmax* of each ESU, the dynamic out power of ESUs can be allocated proportionally:

$$
\frac{P_{o1}}{P_{\text{max1}}} = \frac{P_{o2}}{P_{\text{max2}}} = \dots = \frac{P_{on}}{P_{\text{maxn}}} = k_d \tag{7}
$$

where  $k_d$  is the ratio of output power allocated to maximum output power.

Due to the virtual resistance, the increase of output current will lead to the decline of output voltage, and the voltage variation must satisfy:

<span id="page-2-3"></span>
$$
\Delta U = R_d I_o \le \Delta U_{\text{max}} \tag{8}
$$

where  $\Delta U_{\text{max}}$  is the acceptable maximum voltage variation, usually taking 5% of the rated voltage of DC bus.

According to [\(8\)](#page-2-3), the droop coefficient for ESU can be obtained by:

$$
R_d = k_r \frac{\Delta U_{\text{max}} \cdot U_{\text{rated}}}{P_{\text{max}}}
$$
 (9)

where  $k_r$  is a droop coefficient factor that satisfies  $0 < k_r < 1$ . It also means that the maximum output power is reached with maximum voltage drop.

#### **III. SOC CONSENSUS CONTROL SCHEME**

#### A. FRAMEWORK OF HIERARCHICAL CONTROL STRUCTURE

Although droop control can achieve the rational power allocation among ESUs, the global control objectives of system are hardly realize with no communication.

In the situation that initial SOC differs or several ESUs fail, the allocation by droop control will lead to SOC difference between asymmetric ESUs during the operation. Therefore, a hierarchical control structure is designed to solve the problem of SOC balancing, as shown in Fig. 4.

The droop control introduced in the last section is adopted in the lower layer. Therefore, the output power of ESU*<sup>i</sup>* is allocated by droop control based on its maximum output power, and no communication is needed.

In the upper layer, a current correction block is included and its reference is generated by a novel SOC consensus control, which is based on limited communication. The current correction is added to the current command of the droop control for a secondary SOC-balancing adjustment. The detailed SOC consensus control will be illustrated in the next paragraph.

#### B. CONSENSUS THEORY

In distributed system, there is no central controller and all units play equal roles. A basic unit with full self-control and



**FIGURE 4.** Framework of control strategy.

communication functions are defined as an agent. The consensus algorithm is a distributed control strategy to achieve agreement in a multi-agents system.

The average consensus theorem relies on local information of local agents to guarantee that the important information are shared in a distributed manner.

Considering a multi-agents system, the communication topology can be described by an undirected graph  $G = \langle V, \rangle$  $E >$ . In the graphical model, node set  $V = \{1, \ldots, n\}$ represents agents in the system and edge set  $E = \{e_1, \ldots, e_m\}$ represents the two-way communication links between agents. If *G* is a connected graph, which means there is a path consisting of adjacent edges between every pair of nodes, consensus algorithm can be applied to the system.

The state variable of agent *i* at a certain moment is denoted by  $x_i(t)$  and the neighbors of agent *i* are denoted by  $N_i = \{j \in$  $V|(i, j) \in E$ . The first-order continuous consensus algorithm to obtain an average of the system is as follows:

<span id="page-3-0"></span>
$$
\dot{x}_i(t) = -\sum_{j \in N_i} a_{ij} [x_i(t) - x_j(t)], \quad i = 1...n \qquad (10)
$$

Eq. [\(10\)](#page-3-0) can be further written as:

$$
\dot{X} = -LX \tag{11}
$$

where *L* is the Laplacian of the network and its elements are defined as follows:

$$
l_{ij} = \begin{cases} -1, & j \in N_i \\ |N_i|, & j = i \end{cases}
$$
 (12)

where  $|N_i|$  is the number of neighbors of node *i*.

In the real-world distributed system, there is a delay existing in the sampling and communication processes among nodes and control systems are generally discrete systems. Therefore, the first-order discrete consensus algorithm is introduced:

<span id="page-3-1"></span>
$$
x_i[k+1] = \sum_{j=1}^n d_{ij}x_j[k], \quad i = 1...n \tag{13}
$$

Eq. [\(13\)](#page-3-1) can be written as:

$$
X^{k+1} = DX^k \tag{14}
$$

where  $\boldsymbol{D}$  is state transition matrix.

If matrix *D* satisfies:

[\(1\)](#page-2-4) The sum of the row vector or column vector is 1.

[\(2\)](#page-2-0) The maximum eigenvalue is a single root, while the modulus of the remaining eigenvalues is less than 1.

Then,  $x_i$  will converge to a certain equilibrium state:

$$
x_i^* = f^T X[0] \tag{15}
$$

where  $f$  is the left eigenvector with value 1 of  $D$  and  $X[0]$ is initial state of the system. In particular, if *D* is a doubly stochastic matrix (the sum of the row vector or column vector is 1),  $x_i$  will converge to average value of initial state:

$$
x_i^* = \frac{1}{n} \sum_{j=1}^n x_j [0], \quad i = 1...n
$$
 (16)

#### C. SOC CONSENSUS CONTROL

In order to solving the SOC imbalance problem in the distributed energy storage system, a control algorithm based on first-order discrete consensus algorithm is proposed.

Considering a distributed energy storage system containing *n* ESUs with limited communication connections, ESUs can be regarded as agents. The SOC of each ESU is denoted as state variables:

$$
S(k) = [SOC_1(k), SOC_2(k), ..., SOC_n(k)]^T
$$
 (17)

As to the state transition matrix in consensus iteration, a doubly stochastic matrix *D* by Metropolis–Hastings weights is constructed [27]:

$$
d_{ij} = \begin{cases} \frac{1}{\max (n_i, n_j) + 1}, & j \in N_i \\ 1 - \sum_{j \in N_i} \frac{1}{\max (n_i, n_j) + 1}, & i = j \\ 0, & \text{else} \end{cases}
$$
(18)

where  $n_i$  and  $n_j$  are the number of neighbors of  $ESU_i$ and ESU*<sup>j</sup>* .

With communication between neighbors, state variables will gradually average with iteration steps in the consensus algorithm

$$
\mathbf{S}^* = \mathbf{D}^m \mathbf{S} \left( k \right) \tag{19}
$$

$$
\lim_{m \to \infty} s_i^* = \frac{1}{n} \sum_{j=1}^n \text{SOC}_j(k) \tag{20}
$$

where *m* is the number of iterations, the value of which is related to the communication frequency. If needed, each agent can communicate repeatedly and calculate to get a nearly averaged value at high frequency.

*S* ∗ is an ideal averaged state of the system. However, in the real-world system, due to the system level power demand, the ESU should maintain power output and the SOC of each ESU cannot be controlled in accordance with the ideal state. In the proposed control strategy, according to the difference between  $S^*$  and  $S(k)$ , the output current adjustment value of  $ESU<sub>i</sub>$  is calculated as follows:

$$
\Delta I_{i-i} = -k_p \left[ s_i^* - s_i(k) \right] I_{oi}^* \tag{21}
$$

where  $I_{oi}^*$  is the output current reference of the droop control.  $k_p$  is the proportional gain. The range of  $k_p$  follows:

$$
0 < k_p < \frac{0.6n\left(\frac{1}{k_d} - 1\right)}{\Delta \text{SOC}_{\text{max}}} \tag{22}
$$

When the output current of ESU*<sup>i</sup>* changes, in order to meet the power demand of the system, the adjustment value  $\Delta I_{i-i}$ should be compensated by its neighbor ESUs:

$$
\Delta I_{i-j} = -\frac{\text{SOC}_j(k)/R_{dj}}{\sum_{t \in N_i} \text{SOC}_i(k)/R_{dt}} \Delta I_{i-i}, \quad j \in N_i \tag{23}
$$

The allocation of compensation  $\Delta I_{i-j}$  is determined by current SOC and output capability (1/*R<sup>d</sup>* ) of each neighboring ESU. It should be noted that because the adjustment values of ESUs are different, the compensation is not symmetrical:

$$
\Delta I_{i-j} \neq \Delta I_{j-i} \tag{24}
$$

To sum up, the current correction of the  $ESU_i$  is the sum of its own adjustment value and compensation for neighboring ESUs.

$$
I_{dei} = \Delta I_{i-i} + \sum_{j \in N_i} \Delta I_{j-i}
$$
 (25)

It is obvious that:

$$
\sum_{i=1}^{n} I_{dei} = 0 \tag{26}
$$

which means the output power of the system can be maintained.

#### D. COMMUNICATION PROCESS

SOC consensus control relies on local communication among neighbor ESUs. In a single step of the current correction, there are *m*+1 times of communications process.

As shown in Fig. 5, in the 1st ∼ *m* th communication processes, ESU*<sup>i</sup>* exchanges its state variable in consensus



**FIGURE 5.** Information flow of ESUi.

iterations with neighbor ESUs to calculate their averaged SOC. In the  $m+1$ <sup>th</sup>, after acquiring the iteration result  $s_i^*$ , ESU<sub>i</sub> send out  $\Delta I_{i-i}$  and receive  $\Delta I_{j-i}$ . Finally, the current correction of the ESU*<sup>i</sup>* is obtained.

In the real-world control system, each ESU contains a synchronous clock for generating periodic pulses to drive the consensus control. Within each pulse, ESU*<sup>i</sup>* obtains a new current correction *Ide*\_*<sup>i</sup>* . The sequence flow chart of this consensus control process is shown in Fig. 6.

#### **IV. CASES STUDY**

#### A. SIMULATION MODEL AND PARAMETERS

As shown in Fig. 7, a DC micro-grid model consisting 5 ESUs is built in Matlab/Simulink. Its communication topology is shown in Fig. 8.

The parameters of ESUs and DC micro-grid is shown in Tab. 1.

#### B. CASE 1-SOC BALANCING

The SOC balancing performance is first simulated. In order to reveal the effect of consensus control, only lower layer (droop control) is enabled at the beginning of simulation. Then, the upper layer (consensus control) is enabled at *t*1. The simulation result is shown in Fig. 9 and the analysis is provide as follows:

 $t_0 \sim t_1$ : The output power is allocated only by droop control based on the maximum output power of each ESU. However, due to the difference of capacity and the initial SOCs, the SOC difference among ESUs is maintained around 30%.



**FIGURE 6.** Sequence chart of consensus control.



**FIGURE 7.** Structure of simulation model.



**FIGURE 8.** Communication topology of simulation model.

After *t*1: At *t*1, the consensus control is enabled. After communication with neighboring ESUs, current correction *Ide* of each ESU is generated and added to the droop control

#### **TABLE 1.** Simulation parameters.



command in each consensus iteration. The output power is adjusted in order to reduce SOC difference. As shown in Fig. 9 (b) (c), at *t*1, due to the big SOC difference, the current correction is plays a dominant role in power allocation. Therefore, the SOC difference declines rapidly.

At  $t_2$  time: The SOC difference of system reduces to 1.51%. Consequently, the current correction drops to approaching 0. The droop control plays a dominant role in power allocation, and the power allocation ratio is similar to the beginning state.

Due to the limit of droop coefficient and current adjustment value, the bus voltage is always kept at an appropriate level as shown in Fig.  $9$  (a).

The simulation results show that the proposed hierarchical control structure can distribute the output power according to the output capacity of each ESU, while effectively reducing the SOC differences among them.

#### C. CASE 2-COMMUNICATION FAILURE

In this study, communication faults in distributed system is divided into two types: if the topology after failure still meets the requirement of connected graph, it is defined as a 'connected fault'. Otherwise, it is defined as an 'unconnected fault'. Fig. 10 shows the two types of communication faults by taking the simulation structure as an example.

Above two types communication faults are added to the simulation model in case 1, as shown in Fig. 10. The fault starts at  $t_2$  and ends at  $t_3$ .

Connected fault simulation result is shown in Fig. 11 and unconnected fault is shown in Fig. 12. The initial state of the two fault cases is the same. During  $t_0 \sim t_1$ , only the droop control is enabled. After *t*1, the hierarchical control strategy is fully activated. Thus, the SOC difference decreases from 30% to 14.11%.

In the connected fault case, only the communication link between ESU1 and ESU5 fails at  $t_2$ . The change in the communication topology leads to the change of available information of each ESU. Consequently, there is a sudden change



**FIGURE 9.** Simulation of SOC consensus control.



**FIGURE 10.** Two types communication faults.



**FIGURE 11.** Simulation of connected fault.

on the *Ide* and power allocation ratio as shown in Fig. 11 (a). However, because all ESUs are still connected, the average SOC can still converge with the consensus control. However, the convergence speed is affected. The SOC difference further decreased from 14.11% to 6.51%, as shown in Fig. 11 (b).

In the unconnected fault case, ESU1 lose all communication link with its neighbors and the communication network is no longer connected. Since ESU1 cannot communicate with any other ESU, its current correction cannot be generated. ESU1's output power is only determined by droop control as shown in Fig. 12 (a). The subsystem composed

of ESU2∼5 still meets the connectivity condition. Therefore, the SOC of these 4 ESUs gradually converges with the consensus control as shown in Fig. 12 (b). As a result of ESU1's absence, the SOC difference of the whole system decreases slowly from 14.11% to 11.44%.

After *t*<sub>3</sub>: The communication fault is recovered. Communication topology returns to normal and the SOC difference of the two cases both decreases rapidly.

To sum up, the connectivity of the communication topology after fault determines whether the system can



(a) Power allocation of ESUs



**FIGURE 12.** Simulation of unconnected fault.

work normally. Thus, the fault-tolerant operation of the distributed system in conditional.

## **V. CONCLUSION**

This paper introduces the characteristics of distributed energy storage system in DC micro-grid and establish the analysis model of it. In order to solve the SOC balancing problem, a hierarchical control strategy for distributed energy storage system is proposed. In the lower layer, droop control is adopted to allocate the output power of each energy storage unit, which is based on the maximum output power. In the upper layer, consensus algorithm is adopted to adjust output power of energy storage units in order to reduce the SOC difference in operation. Finally, a simulation model is built in Matlab/Simulink to verify the theoretical analysis. The result indicates that the proposed method can achieve the rational power allocation in distributed energy storage system and realize fault-tolerant operation in situation of connected communication fault.

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