Decentralized cooperative optimization method to enhance discharging efficiency of distributed energy storage system

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Abstract. A decentralized cooperative optimization method is proposed in this study to improve discharging efficiencies of distributed energy storage systems (DESSs) in a smart distribution network (SDN). The proposed method achieves global information or control coordination only through local information interaction between neighbour agents without centralized agents. It is accomplished by using the improved consensus-based information discovery and pinning algorithm of multi-agent system (MAS), which obviates the need for a central controller. Meanwhile, the proposed method coordinates DESSs and the corresponding discharging efficiencies using associated marginal costs in a decentralized way, that can maximize the discharging efficiency while reducing local power mismatch in a SDN. Representative simulation cases are carried on to verify the effectiveness and adaptability of the proposed approach.

1. Introduction

Various types of control schemes have been proposed to overcome the limitations and bottlenecks of previous schemes. For instance, DG control\(^1\), load control scheme, the local optimization control scheme of DGs and energy storage systems (ESSs) \(^2\), as well as the hierarchical control scheme \(^3-5\)have all been proposed and applied. The coordination control strategy of the ESSs was considered as an effective solution for stabilization of an ADS \(^6\). Due to the intermittency of the DGs and constantly load demand changing, the charging/discharging of various ESSs in an ADS needs to be properly coordinated to enhance the reliability, self-heating and efficiency of renewable energy utilization \(^7\).

The coordination control modes of the ESSs in a smart distribution network can be centralized or distributed. However, the centralized control strategies require a central controller, which easily suffers from a failure to handle the huge amount of data. Furthermore, taking the uncertainty of intermittent DGs into consideration, the fluctuation of DGs may result in unintentional structure changes, which will further increase the burden on centralized schemes\(^8-9\). Additionally, the distributed scheme, which uses a leader agent to gather information from all of the other local agents and sum it to obtain global information, raises similar concerns about the system.

The algorithm can be described in details as follows:

\[
x_i^{[k+1]} = \sum_{j=1}^{n} \omega_{ij} x_j^{[k]} \tag{1}
\]
Performance and reliability when possible malfunctions and attacks occur at the leader agent[10]. Advantages of a fully distributed scheme include the ability to survive uncertain disturbances and decentralized data updating, which leads to more efficient information sharing and eventually a faster decision-making process and operation[11-13].

Inspired from the two-layer consensus-based fully distributed method and the coordination of ESSs, this study proposes a novel distributed coordination Optimization (DCO) for the ADSs that achieves the same performance as standard centralized hierarchical ADS control. As the most distinguishing features of this work, the two-layer consensus algorithm and pinning based DCO, are systematically studied in this study. More specifically, the main contributions of this study are illustrated as:

1) Proposal of a new DCO by using a two-layer consensus algorithm, that gets global information in information discover layer and implements CDO fully in the coordination control layer.
2) Proposal of a pinning based DCO approach to coordinate the ESSs considering marginal charging costs (MCCs), and power mismatch solving, as well as local consumption of renewable energy and power transmission losses.
3) Proposal of two updating methods, including the communication coupling weight updating and participated agent identify updating methods, which can adaptively meet the requirements for communication topology changes.

The rest of this paper is organized as follows: Section 2 presents a brief introduction on two-layer consensus algorithm and formulates the problem of ESS coordination in an ADS; Section 3 elaborates on the DCO using a two-layer consensus in an ADS; the proposed DCO is simulated and investigated with the simulation system in Section 4; and finally, the conclusions are presented.

2. Decentralized consensus algorithm

2.1. Consensus-based information discovery algorithm

The consensus-based discovery algorithm is used to discover crucial global information in a decentralized manner without a central agent, and make sure the key global information is shared among all the agents, where an agent can only communicate with its immediate where, \( i = 1, 2, \ldots, n, j = 1, 2, \ldots, n \), \( n \) is the total number of the entire MAS, all means the number of all the agents that participate in the information discovery; \( x_i \) indicates the state variable of the \( i \)-th agent, which could represent the discharging efficiency or the discharging power of \( i \)-th DESS; \( k \) is the discrete-time index; \( x_i^{[k+1]} \), \( x_i^{[k]} \) indicate the information discovered by agent \( i \) at iteration \( k \) and \( k+1 \), respectively; \( x_j^{[k]} \) is the shared information of agent \( j \); \( \omega_{ij} \) express the communication coupling correlation coefficient between agent \( i \) and \( j \).

The value of \( \omega_{ij} \) is determined according to the local information, and it can adjust locally to better adapt to the communication topology change or fault conditions. The specific calculation process of the \( \omega_{ij} \) can be described as follows:

\[ \omega_{ij} = \begin{cases} \frac{2\gamma}{\sum_{k \in N_{i,j}} n_{i,j} + n_{j,i}} & k \in N_{i,j} \\ 1 - \frac{2\gamma}{\sum_{k \in N_{i,j}} n_{i,j} + n_{j,i}} & j = i \\ 0 & \text{otherwise} \end{cases} \]  

where, \( S(t) \) is defined to describe the changes of the communication topology in a SDN; \( \gamma \) is a constant, and \( 0 < \gamma < 1 \); \( n_{i,S(t)} \) and \( n_{j,S(t)} \) respectively indicate the number of agents in the neighborhood of agents \( i \) and \( j \), both \( n_{i,S(t)} \) and \( n_{j,S(t)} \) are local information which can be detected locally and can adaptively adjust when the communication topology changes.

For all the DESSs in a SDN, the whole consensus process can be described using a matrix format as in (3)

\[ X^{(i+1)} = \Omega \cdot X^{(i)} \]

\[ \Omega = [\omega_{ij}] \]
where $X^{[k]}$ is the information matrix, and $\Omega$ is the communication updating matrix that is determined according to the communication topology.

### 2.2. Consensus-based pinning algorithm

Another algorithm using in this study is the consensus-based pinning method, which preset pinned consensus values according to the power mismatch in the SDN, the calculation process is described as follows:

$$x_i^{[k+1]} = \sum_{j=1}^{n} \alpha_{ij} x_j^{[k]} - d_i \left( x_i^{[k]} - x^* \right)$$  \hspace{1cm} (4)

where, $x^*$ is the preset pinning consensus value determined based on the discovered global information; $d_i$ is the pinning gain for the $i$-th agent, generally, $1 \geq d_i \geq 0$. and $d_i=0$ indicates that there is no control over the agent.

Accordingly, the consensus process of all the DESSs in a SDN can then be described using the matrix format as in (5) neighboring agents in the communication topology.

$$X^{[k+1]} = [\Omega - (D \otimes I_n)]x^{[k]} = \Omega_x x^{[k]}$$ \hspace{1cm} (5)

where $\Omega_P$ is the communication updating matrix considering pinning.

### 3. Decentralized cooperative optimization discharging method

In this study, a decentralized cooperative optimization method is proposed to enhance discharging efficiency of DESSs. Firstly, the global information (power mismatch information and network topology information) is discovered and Shared through the Consensus-based information discovery algorithm. Then, set the pinning consensus value $x^*$ through global information, complete distributed coordination optimization by consensus-based pinning algorithm. Figure 1 illustrates the flowchart of the proposed method as follows:

![Flowchart of the proposed method.](image)

#### 3.1. Decentralized optimization objective formulation

Firstly, a localized discharging function is established locally for a single DESS under the MAS-based decentralized architecture without a central controller as follows:

$$\varphi_{E_j} = \alpha_i - \beta_i P_{E_j} \hspace{1cm} (6)$$
Where, \( i = 1, 2, \ldots, n \), which is used to identify the DESS in the SDN system; \( PC,i \) indicates the power of the \( i \)-th DESS. And \( PE,i \) indicates the actual output of the \( i \)-th DESS to the power of the system; while \( \phi_{E,i} \) indicates the discharging efficiencies, which have remarkable dependence on the discharging power and is the critical factor for improving the discharging efficiency of DESS. Generally, the relationship between the discharging efficiency coefficient \( \phi_{E,i} \) of DESS and its discharging power can be described as:

\[
\phi_{E,i} = \alpha_i + \beta_i P_{E,i}
\]

(7)

Where, \( \alpha_i, \beta_i \) are the discharging coefficients of the \( i \)-th DESS, both \( \alpha_i \) and \( \beta_i \) are the constants, and the values are generally between 0 and 1.

Then, to fully cooperate all the DESSs in the SDN, the optimization objective function can be derived according to the localized discharging function (6) and (7) as

\[
\begin{align*}
\text{Min} & \quad \sum_{i \in N_i} P_{C,i} = \sum_{i \in N_i} (\alpha_i + \beta_i P_{E,i})P_{E,i} \\
& \quad P_t = \sum_{i \in N_i} P_{E,i} \\
& \quad P_{t,j} = \left( \frac{U_{E,j}}{U_{E,j}^*} \right)^\gamma P_{E,j} \\
& \quad P_{C,j}^{\text{max}} < P_{C,j} < P_{C,j}^{\text{min}}
\end{align*}
\]

(8)

Where, \( N_i \) is the index set of all the DESSs. \( P_{C,j}^{\text{max}} \) is the maximum output power of the \( i \)-th ESS, \( PM_{C,j} \) is the Minimum output power of the \( i \)-th DESS, \( P_t \) is the estimated value of the power that the ESS should provide to the system, \( P_{t,j} \) is the estimated value of the power that \( i \)-th DESS should provide to the local load, \( U_{E,j} \) is the actual output voltage of the \( i \)-th DESS, \( U_{E,j}^* \) is the expected value of the voltage output of the \( i \)-th ESS. When \( U_{E,j} = U_{E,j}^* \), We deem the system runs in the desired state, the power that the ESS should provide to the system is equal to the power that the ESS actual provides to the load, and both of these are equal to \( P_t \). In a smart distribution network, due to the constantly changing power demands of individual users, and the intermittency of the DGs, the imbalance between power supply and demand is constantly changing, it is difficult to get an accurate value of the total power imbalance of the entire SDN in real-time. In (9), DESS measures its own output voltage value and its own output power to estimate \( P_{t,j} \). When the system is running in expectation state, all load is running in the rated state, and the output voltage of each ESS is equal to \( U_{E,i}^* \). When the power demand of SDN increases, such as sudden load, the output voltage of DESS become less than the expected value, causing \( P_t \) to increase. Then, control system starting, making \( P_{E,i} \) increase, Make the system return in expectation state. When the power demand of SDN decreases, the adjustment process is similar to above. Considering the line drop, \( U_{E,i}^* \) should be slightly larger than the rated voltage of the line. The value can be selected according to the actual line. As can be seen in (8), the objective for coordinating multiple DESSs in discharging mode is to minimize the total discharging power.

### 3.2. Global key information discovery

According to the optimization function and information discovery algorithm in Section III.A, the key information required for maximizing the discharging efficiencies of multiple DESSs is determined, which mainly includes the total number of agents participating in the information discovery \( n \), the total power imbalance of the entire SDN \( PI \), And the number of each ESS that is working at this time. By using the key information discovery algorithm based on local information interaction, each DESS participating in the collaboration can master the required global information for decision making, and the discovery process is described as follows:

\[
\begin{align*}
\sum_{i=1}^{n} P_{E,i} = \frac{P_t}{n} \quad \Rightarrow \quad n = i \\
\Rightarrow \quad P_{E,j} = n \cdot P_{E,i}
\end{align*}
\]

(10)
where, the global key information about the consensus convergence is shared to each agent, and $n_{\text{mas}}, P_{\text{mas}}$ respectively indicate the discovered information through the consensus-based information discovery algorithm.

When the consensus-based information discovery algorithm is calculating $n_{\text{mas}}$, if the $i$-th DESS shares information $i$, the remaining DESS shares information $0$, so that $i$-th DESS can obtain $n$ through the consensus-based information discovery algorithm. After each ESS respectively finds the information $n$, in the next loop, they can find all the number of DESS, which running at this time.

So that each DESS can obtain the global information $n$ and $P$ according to the consistency of the shared information as shown in (10).

### 3.3 Decentralized optimization problem solution

In order to optimize the discharge efficiency of distributed energy storage system. We need to know how to minimize the discharge power when the load demand is inevitable. The solution formula is the formula (11)

$$\begin{align*}
\begin{cases}
\text{Min} & \sum_{i=1}^{n} P_{E,i} = \sum_{i=1}^{n} \left( \alpha_i + \beta_i P_{E,i} \right) P_{E,i} \\
\text{s.t.} & P_{h} = \sum_{i=1}^{n} P_{E,i}
\end{cases}
\end{align*}
$$

(11)

where, the PIS is the value of the power that the ESS should provide to the system.

The marginal cost of discharging of the DESS is introduced to solve the optimization problem in a decentralized manner. Assume that the marginal cost of the $i$-th DESS has a quadratic cost function and is derived as:

$$M_{C,i} = \frac{\partial^2 \left( \alpha_i + \beta_i P_{E,i} \right) P_{E,i}}{\partial P_{E,i}} = \alpha_i + 2\beta_i P_{E,i}$$

(12)

Where, MC,i indicates the marginal cost of the $i$-th DESS.

When (11) reaches the optimal solution, the well-known solution of (9) is $\kappa_{\cdot}^*$, as also can be seen in (14).

$$\begin{align*}
\begin{cases}
\alpha_1 + 2\beta_1 P_{E,1} = \alpha_2 + 2\beta_2 P_{E,2} = \cdots = \alpha_n + 2\beta_n P_{E,n} \\
P_{h} = \sum_{i=1}^{n} P_{E,i}
\end{cases}
\end{align*}
$$

(13)

Therefore, we can calculate the value of PE,i when (10) takes the optimal solution:

$$P_{E,i} = \frac{P_{h} + \sum_{j=1}^{n} \frac{\alpha_j - \alpha_i}{2\beta_j}}{\sum_{j=1}^{n} \frac{\beta_j}{\beta_j}} \quad i \in N, i$$

(14)

the expected value of marginal cost can be obtained:

$$k_{C}^* = \alpha_i + 2\beta_i P_{E,i}$$

(15)

Hence, the optimal solution process to coordinate the marginal cost among the DESSs can be achieved by the consensus-based pinning algorithm described in Section III.B as follows:

$$k_{ij}^{k+1} = \sum_{j=1}^{n} \omega_{ij} k_{ij}^{k} - d_i \left( k_{ij}^{k} - k_{C}^* \right)$$

(16)

In (13), when all the marginal cost functions are controlled by the pinning control, the system reaches the optimal solution, that is, the multiple DESSs in the SDN achieve the optimal discharging efficiency under the current operating state.

By controlling the active power references of the DESSs, the total power really stored in the DESSs and the discharging efficiencies will be maximized.
4. Simulation results

A smart distribution network (SDN) is established based on the IEEE 33 bus system to verify the proposed decentralized optimization method for multiple DESSs. Figure 2 illustrates the communication architecture of the DESSs. Additionally, the installation location and capacity of the DESSs are shown in Table 1:

| Number | 1    | 2    | 3    | 4    |
|--------|------|------|------|------|
| Capacity/MV | 70   | 60   | 65   | 72   |

According to step 2, the local characterization function and global optimization objective function of discharging efficiency of a single distributed energy storage system are established. Then, according to (7), the discharging efficiency localization characterization function and the global optimization objective function of the single distributed energy storage system are established, and the value of the corresponding constant of the formula (13) is determined as shown in Table 2.

| DESS   | α    | β    |
|--------|------|------|
| DESS 1 | 4.3  | 0.08 |
| DESS 2 | 3.65 | 0.06 |
| DESS 3 | 3.4  | 0.07 |
| DESS 4 | 4.15 | 0.064|

4.1. Case A

At the beginning of the simulated period, the SDN system is in a stable condition. DESS is supplied to the load according to the initial power. When t=0.4 s, the system experiences an abrupt change of load. Before the load changes, a total output power of DESSs is 80KW, power ratings of the new load is 80KW. The change of DESS output power is shown in Figure 3:
MCC change process of each ESS is shown in Figure 4:
If the system simultaneously meets two conditions at a certain time: 1) MCC of each ESS is the same value. 2) system supply and demand power balance. We believe that the discharge efficiency of the distributed energy storage system is optimal. Figure 4 and Figure 5 shows that after an abrupt change of load, the system power supply and demand is re-balanced and the MCC of each ESS is the same value. So we say that the system reaches the optimal discharge efficiency of distributed energy storage system. The Decentralized cooperative optimization method is effective.

The change of the total output power of all ESS in the system is shown in Figure 5:

4.2. Case B
At the beginning of the simulated period, the SDN system is in a stable condition. Each battery is supplied to the load according to the initial power. At this point, the MCCs of each DESSs is not consistent, and the system has a small unbalance between supply and demand. The initial value of each ESS marginal cost is 7.5, 6.5, 5.5 and 4.5. The imbalance between power supply and demand is 18.5KW. When $t=0.4$ s, DCO starts work, the variation of the DESS output power in the model is shown in Figure 6:

![Figure 6. Output power of the DESSs.](image)

The MCC change curve of each DESS is shown in Figure 7:
At the initial stage, the MCC of each DESS is different, after distributed coordinated optimization, each MCC is pulled to the expected value.

![Figure 7. MCC of the DESSs.](image)

The imbalance value of supply and demand is shown in Figure 8:

![Figure 8. Imbalance value of supply and demand.](image)

After distributed coordinated optimization, the system's power imbalance value of supply and demand can be eliminated.

5. Conclusions
The present paper to establish the decentralization of the distributed collaborative optimization framework, without a centralized controller, only through the information interaction between the neighbor agent, can achieve global key crucial global information sharing, significantly reduce the complexity of the communication topology, improve the adaptability of the distributed power plug and play. And propose a distributed storage system discharging efficiency decentralization discharging
collaborative optimization method, based on the system voltage at this time estimate the power imbalance using distributed storage system discharging characteristics between marginal cost coefficient and the real-time discharging power convergence of iterative calculation, using multi-agent consistency convergence of iterative algorithm, decentralized framework in distributed collaborative improve the discharging efficiency of distributed energy storage system, effectively improve the efficiency of collaborative discharging multiple distributed energy storage systems.

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