Hierarchical Control Strategy for Microgrid Based on Finite-time Consensus Algorithm

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Abstract—In order to overcome the shortcomings of centralized control strategy for microgrid, a hierarchical control strategy based on finite-time consensus algorithm is proposed in this paper. Based on the droop control, the control strategy uses the finite-time consensus theory of multi-agent system to solve the optimal power generation value of the system, and adjusts the droop coefficient to make the power generation power of the power supply the optimal value. Then the compensation of frequency and voltage is introduced by multi-agent technology to stabilize the system frequency and voltage at rated value.

1. Introduction

In recent years, due to the increasingly prominent environmental problems, the depletion of fossil energy and the increase of energy demand, distributed generation (DG) has developed rapidly[1]. Due to the difference of power generation cost characteristics and working characteristics of each DG, it is necessary to study the economic dispatch and operation control of the microgrid system[2]. The Economic Dispatch Problem (EDP) of microgrid is to minimize the total power generation cost of the system by coordinating the output between DGs under the condition of meeting the system and equipment level constraints. At present, many achievements have been made in the research on the optimization strategy to solve the micro grid EDP: Ref.[3] uses an improved particle swarm optimization algorithm to solve the EDP. This algorithms belong to centralized optimization algorithms, relying too much on the control center, and their failure will lead to system paralysis. In view of the shortcomings of centralized optimization algorithms, some scholars have proposed using distributed algorithm to solve the EDP of microgrid. Ref.[4] proposed a distributed control strategy of DC microgrid based on finite time consistency algorithm; Ref.[5] proposed a distributed microgrid algorithm based on multi agent system consistency theory, and used the incremental cost of each power generation unit as a consistent variable. The above documents do not consider the system response convergence time, which has some problems, such as slow convergence time, low control accuracy or no optimization of AC microgrid.

The MAS finite-time consensus algorithm has been successfully applied in fields such as robot formation and swarming problems[7]. It is a distributed control method that can be achieved the purpose of global control by communicating with neighboring agents. Using the finite time theory of MAS, aiming at the problem of optimal operation control of micro-grid, this paper proposes a distributed hierarchical control strategy for micro-grid based on MAS finite-time consistency algorithm. The control strategy includes three contributions: First, the finite-time consistency algorithm is applied to make the micro-increase rate of each DG consistent, and the optimal value of each DG power generation is solved, so that the total power generation cost of the system is minimized; Secondly, introduce
frequency and voltage compensation, and apply MAS technology to achieve frequency and voltage stability; Finally, based on the optimal value of each DG power generation, the actual power generation of each DG is consistent with the optimal value by adjusting the droop coefficient of each DG.

2. MAS

2.1. Graph theory
Generally, for a microgrid system containing \( n \) DG's, if the DG is regarded as a node in the agent communication network, its communication topology can be represented by an undirected graph \( G = \{ V, E, A \} \). Where, \( V = \{ v_1, v_2, v_3, \ldots, v_n \} \) represents the set of nodes, \( n \) is the number of nodes in the graph; \( E \subseteq V \times V \) represents a set of edges, \( e_{ij} = (v_i, v_j) \) represents the edges of the graph; In the graph \( G \), the adjacency matrix \( A = (a_{ij})_{n \times n} \) is usually used to describe the relationship between nodes, where \( a_{ij} \) is the connection weight from node \( i \) to node \( j \). If the node \( i \) can receive the information of the node \( j \), then \( a_{ij} > 0 \), otherwise \( a_{ij} = 0 \). For any node \( v_i \), define its neighbor node set as \( N(v_i) = \{ v_j \in V : (v_i, v_j) \in E \} \). In agent communication, Laplacian matrix is generally used to describe the communication between agents, that is \( L = (l_{ij}) \in \mathbb{R}^{n \times n} \), where \( l_{ij} = -a_{ij} \), \( l_{ii} = \sum_{j \neq i} a_{ij} \).

2.2. Finite-time consensus algorithm
For a MAS composed of \( n \) agents, the state of each agent can be expressed as:

\[
\dot{x}_i(t) = u_i(t)
\]

Where, \( x_i \) is the state variable of the \( i \)-th agent; \( u_i(t) \) is the control variable;

Each agent can only communicate with its surrounding neighbors. The state of the agent depends on its current state and the current state of its neighboring agents. The following finite-time consistency protocol is designed.

\[
u_i(t) = \sum_{j=1}^{n} a_{ij}(x_j - x_i) + \alpha \sum_{j=1}^{n} a_{ij} \text{sign}(x_j - x_i)(x_j - x_i)
\]

Where, \( \alpha \) is the control parameter, usually \( 0 < \alpha < 1 \), \( \text{sign}(x) \) is a symbolic function.

Under the control of \( u_i(t) \), each agent exchanges information with neighboring agents through its current state, and when the communication topology satisfies the condition of undirected connectivity, all agents finally reach the same state.

**Theorem**[9]: Assuming that the MAS is undirected connected and its corresponding Laplacian matrix must be a real symmetric matrix, then agreement (2) can achieve the finite time average consistency of the system, that is:

\[
x_{i,\infty} = x_{2,\infty} = \ldots = x_{n,\infty} = \frac{1}{n} \sum_{i=1}^{n} x_{i,0}
\]

Where, \( x_{i,0} \) is the state quantity of the final convergence of the \( i \)-th agent; \( x_{i,0} \) is the initial state quantity.

3. Hierarchical control Based on Finite-time Consistency Algorithm
The traditional hierarchical control mostly adopts centralized control, its failure is likely to lead to the paralysis of the whole system, so the reliability is not high. The distributed control algorithm based on finite-time consistency can achieve the consistency of global state only by communicating with its adjacent agents[7], so as to realize global control and better adapt to the needs of microgrid in terms of rapidity and economy. So, a hierarchical optimization strategy based on finite-time consensus algorithm is proposed in this paper. This strategy overall control block diagram is shown in Fig.1.

The primary control layer is based on droop control strategy to perform \( P-f \) and \( Q-V \) control to realize DG power control and voltage and frequency adjustment. The secondary control layer is to eliminate the deviation of frequency and voltage generated by the primary control layer, and maintain the
frequency and voltage of the system at the rated value. The three-level control layer is the economic optimization layer, which solves the optimal value of each DG power generation during the economic optimal operation of the system, so that the total power generation cost is the lowest.

$$\Delta f = f_s - m_i (P_i - P_s), \Delta u = u_s - n_i (Q_i - Q_s)$$  \hspace{1cm} (4)

Where, $f_s$, $u_s$, $P_s$, $Q_s$ are the frequency, voltage, active and reactive power under rated conditions; $m_i$, $n_i$ is the droop control coefficient; $P_i$, $Q_i$ is the active and reactive power output; Generally, $m_i = m$, the settings are the same. For a microgrid composed of multiple DGs in parallel, the frequency of each DG is equal. Then, the expression of output power of each DG can be obtained as follows:

$$P_i = K / m$$ \hspace{1cm} (5)

Where, $K$ is a constant; It can be seen from Eq.(5) that the output power of each DG can be adjusted by adjusting the droop coefficient of the droop equation. In the primary control layer, the inverter droop control is adopted to realize the power control of each DG. However, since droop control is a kind of differential control, it will produce frequency and voltage deviations, so it is necessary to correct the frequency and voltage deviation in the secondary control layer.

3.2. Secondary control layer

In order to make the frequency and voltage of each DG reach the rated value of the system, the frequency and voltage compensation required for the introduction of the $i$-th DG are $\Delta f_i = m_i (P_i - P_s)$ and $\Delta u_i = n_i (Q_i - Q_s)$. In order to avoid the inconsistency between the frequency and voltage compensation of each DG during the operation of the microgrid, the average value of the compensation of each DG is taken as the frequency and voltage compensation of each DG, that is:

$$\Delta f = \frac{1}{n} \sum_{i=1}^{n} \Delta f_i = \frac{1}{n} \sum_{i=1}^{n} (m_i (P_i - P_s)), \Delta u = \frac{1}{n} \sum_{i=1}^{n} (n_i (Q_i - Q_s))$$ \hspace{1cm} (6)

Among them, $\Delta f$, $\Delta u$ is the average value of the frequency compensation amount and the voltage compensation; Simplify Eq.(6), which can be rewritten as:

$$\Delta f = m_s \left( \frac{1}{n} \sum_{i=1}^{n} \frac{P_i}{P_s} - 1 \right), \Delta u = n_s \left( \frac{1}{n} \sum_{i=1}^{n} \left( \frac{Q_i}{Q_s} - 1 \right) \right) = n_s \left( \frac{1}{n} \sum_{i=1}^{n} \left( \frac{Q_i}{Q_s} - 1 \right) \right)$$ \hspace{1cm} (7)

Where, $P'_i$, $Q'_i$ is the unit value of the actual output active and reactive power of the $i$-th DG; Taking $P'_s$ and $Q'_s$ as state variables, substituting into Eq.(1-2), the consensus algorithm for $P'_s$ and $Q'_s$ is:

![Fig.1 Overall block diagram of hierarchical control strategy for microgrid](image-url)
The final convergent value is substituted into Eq.(7) as the average value of the unit value of active and reactive power respectively to obtain the compensation amount of system frequency and voltage. After adding the compensation amount, the frequency and voltage are stabilized at the rated value.

3.3. Three-level control layer
The three-level control layer adjusts the power generation of each DG to make the total power generation cost of the system the lowest, and obtains the optimal value of the power generation of each DG at this time. The power generation cost of DG is composed of fuel cost and maintenance cost. Maintenance cost is a linear function of power generation, and fuel cost is a quadratic function of power generation. Assuming that the power generation $P_i$ of the $i$-th DG, $a_i, b_i, c_i$ are the power generation cost coefficient of the DG, the power generation cost function can be obtained as follows:

$$\sum_{i=1}^{n} a_i P_i + b_i P_i + c_i 
\text{Total power generation cost.}$$

(9)

Taking into account that the microgrid system should also meet a series of constraints such as the balance of supply and demand power and the limitation of DG power generation during the operation of the microgrid system, there are:

$$\sum_{i=1}^{n} P_i = P_{\text{total}}; P_{\text{min}} \leq P_i \leq P_{\text{max}}$$

(10)

Where, $P_{\text{min}}$ and $P_{\text{max}}$ are the minimum and maximum power generation of the $i$-th DG respectively; $P_{\text{total}}$ is the total active load of the system. For a microgrid system with $n$ DGs, the overall goal of economic optimal operation is to minimize the total power generation cost of all DGs, that is $\min \sum_{i=1}^{n} C_i(P_i)$.

In traditional power systems, the micro-increment rate is often used to solve the optimization problem of Eq.(12-14). By calculating the partial derivative of the active power from the power generation cost the micro-increment rate. When the micro-increment rate of each DG is equal, the total power generation cost of the system is the lowest. At this time, the relation between the system micro-increase rate and the optimal value of power generation is as follows:

$$\sum_{i=1}^{n} P_i = P_{\text{typ}}; P_{\text{typ}} \leq P_i \leq P_{\text{typ}}$$

(11)

Among them, $\lambda_{\text{typ}}, \lambda_{\text{typ}}, P_{\text{typ}}$ are respectively the optimal value of the system micro-increase rate, the optimal value of the $i$-th DG micro-increase rate and the optimal value of the generation power when there is no power generation limit. Eq.(11) is the optimal value obtained by the centralized algorithm. Because the actual total active power load of the system is related to the operating point of the system, it is difficult to obtain it directly. This paper substitutes $\lambda$ as a state variable into Eq.(1-2). Through local communication and calculation, the global optimal value of $\lambda$ can be obtained.

$$\lambda(t) = \sum_{i=1}^{n} a_i (\lambda_i(t) - \lambda_i(t)) + \sum_{i=1}^{n} a_i \text{sign}(\lambda_i(t) - \lambda_i(t)) \right| \lambda(t) - \lambda_i(t)$$

(12)

The final convergence value of Eq.(12) is taken as the optimal value $\lambda_{\text{typ}}$ of the system's marginal increase rate under the condition of no generation power limitation, and it is substituted into Eq.(11) to obtain the optimal value of the $i$-th DG generation power:

$$P_{\text{typ}} = \frac{\lambda_{\text{typ}} - b_i}{2a_i}$$

(13)

If the limitation of DG generation power is considered, the DG exceeding or below the limited output power can only operate at the maximum or minimum power. It is assumed that $\Omega$ represents all DG sets.
where the optimal value of generation power does not reach the generation power limit under the condition of no generation power limit; \( \lambda^m_i \) and \( P_i^m \) are respectively the optimal value of the \( i \)-th DG micro increment rate and the optimal value of generation power under the condition of generation power limitation. According to the balance of total power supply and demand of the system:

\[
\sum_{i=1}^{n} P_i^m + \sum_{i=1}^{n} P_i^m = P_0 \tag{14}
\]

It can be seen from Eq.(13) that in order to make the system economically and optimally run, DG that does not reach the power limit should satisfy Eq.(15):

\[
P_i^m = \frac{\lambda_i^m - b_i}{2a_i}, \quad i \in \Omega; \quad \lambda_i^m = \lambda_j^m = \lambda^m, \quad i, j \in \Omega,
\]

Among them, \( \lambda^m \) is the micro-increase rate when the system is economically optimal under the condition of limited power generation; Substituting Eq.(13) into Eq.(10), we know:

\[
P_p = \sum_{i=1}^{n} P_i^m = \sum_{i=1}^{n} \frac{\lambda_i^m - b_i}{2a_i} = \sum_{i=1}^{n} \frac{\lambda_i^m - b_i}{2a_i} + \sum_{i=1}^{n} \frac{\lambda_i^m - b_i}{2a_i}
\]

As part of the power that exceeds or falls below the power limit is still provided by the DG that has not reached the power limit, there are:

\[
P_p = \sum_{i=1}^{n} P_i^m + \sum_{i=1}^{n} P_i^m = \sum_{i=1}^{n} \frac{\lambda_i^m - b_i}{2a_i} + \sum_{i=1}^{n} P_i^m
\]

Combining Eq.(16-17), it can be obtained that when the system economy is optimal under the condition of power limitation, the optimal value of the system micro-increase rate is shown in Eq.(18):

\[
\text{if } i \in \Omega, \lambda_i^m = \lambda_i^m; \text{else } \lambda_i^m = \left(2a_i P_{i,\text{max}} + b_i\right) \text{ or } \left(2a_i P_{i,\text{max}} + b_i\right)
\]

From Eq.(10) and Eq.(15), the optimal power generation of each DG under the condition of power generation power limitation can be obtained as:

\[
P_i^m = \frac{\lambda_i^m - b_i}{2a_i}, \quad \text{else } P_i^m = P_{i,\text{min}} \text{ or } P_{i,\text{max}}
\]

In the three-level control layer, the optimal value of each DG’s power generation is obtained by Eq.(13) and Eq.(19), and it is output to the primary control layer.

| Tab.1 Simulation parameters and cost coefficients of DGs |
|---|---|---|---|---|---|---|---|---|---|---|
| \( P_{i,\text{in}} \)/kW | \( Q_{i,\text{in}} \)/kvar | \( m_i \) \times 10^3 | \( n_i \) \times 10^3 | Load_i | \( a_i \) \times 10^3 | \( b_i \) \times 10^{-2} | \( c_i \) | \( P_{i,\text{min}} \)/kW | \( P_{i,\text{max}} \)/kW |
|\begin{tabular}{c|c|c|c|c|c|c|c|c|c|}
DG1 & 80 & 50 & 1 & 1.2 & 60kW+j10kvar & 1.6 & 2.03 & 0.85 & 50 & 120 \\
DG2 & 70 & 40 & 1.14 & 1.5 & 70kW+j20kvar & 1.2 & 5.66 & 0.52 & 50 & 100 \\
DG3 & 60 & 30 & 1.33 & 2 & 80kW+j0kvar & 1.74 & 4.2 & 1.295 & 40 & 80 \\
DG4 & 50 & 20 & 1.6 & 3 & 90kW+j0kvar & 1.36 & 6.7 & 0.7 & 30 & 60 \\
\end{tabular} | Others parameters: \( L=1\text{mH} \) | \( C=500\mu\text{F} \) | \( V_0 = 311V \) | \( f = 50\text{Hz} \) | \( k_{ps} = 10 \) | \( k_{pv} = 5 \) |

4. Example and Simulation

4.1. Simulation model

In this section, the four-node microgrid system shown in Fig.2 will be simulated on the Matlab/Simulink platform to verify the layered control strategy proposed above. The microgrid system is composed of 4 DGs. The simulation parameters, cost coefficients and loads of each DG are shown in Tab.1. Next section analyzes and verifies the control strategy proposed in this paper through an example, and compares it with droop control. Assume that Load_1~Load_4 are put into the system.
4.2. Uses droop control
In droop control, the power distribution of each DG is distributed according to the ratio of the droop coefficient, which may result in the high power generation cost of the DG power generation, but the low power generation cost the low power generation of DG is not conducive to the economic operation of the power system. Fig. 3 shows the simulation results using droop control. From the figure, we can that the micro-increase rate of each DG is inconsistent, which does not meet the "equivalent micro-increment rate criterion" in the economic operation of the power system. Meanwhile, we can see that the system frequency and node voltage are 49.87Hz and 310.3V respectively, which also shows that droop control is a differential control.

(a) Micro-increase rate of DG  (b) Frequency change of DG  (c) Voltage change of DG
Fig.3 Simulation results using droop control

4.3. Uses hierarchical control strategy for microgrid based on finite-time consensus algorithm

(a) Convergence of Eq.(2)  (b) Convergence of Ref.[8]  (c) Output active power of DG
(d) Total cost comparison  (e) Frequency change of DG  (f) Voltage change of DG
Fig.4 Simulation results using hierarchical control

When the generation power limitation conditions are not considered, the economic optimal operation of the system is when the micro-increase rate of each DG are equal, as shown in Fig.4(a), the optimal value of the system increment rate is $\lambda_{\text{wp}}=0.246$/kWh. Fig.4(b) is the simulation result obtained by using the consensus algorithm proposed in the Ref.[8]. Compare Fig.4(a) with the Fig.4(b) It can be seen that the convergence time of the finite-time consensus algorithm proposed in this paper is nearly 60% faster. From Eq.(13), the optimal value of each DG is 63.81kW already exceeded its maximum power generation 60kW, so it is necessary to consider cost optimization under the conditions of power generation limitations. When considering the generation power limit, Fig.4(c) is the curve of the actual power generation of each DG. It can be seen that each DG can operate near the optimal value of the generation power and power generation is within the power limit, at this time the system economy is optimal. Fig.4(d) shows the comparison between the hierarchical control strategy proposed and the total power generation cost of the droop control system. The figure shows that the optimization of the total power generation cost of the system is effective. Fig.4(e) and Fig.4(f) show the frequency and voltage
changes of each DG. After adopting the layered optimization proposed, the frequency and voltage are stable at the rated value of the system.

5. Conclusion
This paper proposes a hierarchical control strategy for microgrid based on finite-time consensus algorithm, which realizes the economically optimal operation of the micro-grid system and ensures that the frequency and voltage of the system are stable at the rated value. This optimization algorithm only needs to communicate and exchange information between each distributed power source and its adjacent power source, which not only saves the investment of centralized control on communication equipment and lines, but also avoids that the failure of centralized control equipment will cause the entire system to be paralyzed. The control of the microgrid is more flexible and reliable. Finally, the simulation verification is carried out on the Matlab/Simulink platform, and the simulation results show the effectiveness of the optimization strategy proposed in this paper.

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