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Keywords

« AC microgrid », « Operation cost minimization », « Droop control », « Incremental cost consensus », « Multiagent ».

Abstract

Microgrid, as a promising technology to integrate renewable energy resources in the distribution system, is gaining increasing research interests recently. Although many previous works have been done based on the droop control in a microgrid, they mainly focus on achieving proportional power sharing based on the power rating. With various types of distributed generator (DG) units in the system, factors that closely related to the operation cost, such as fuel cost and efficiencies of the generator should be taken into account in order to improve the efficiency of the whole system. In this paper, a multiagent based distributed method is proposed to minimize operation cost of the AC microgrid. Each DG is acting as an agent which regulates the power individually using proposed frequency scheduling method. Optimal power command is obtained through carefully designed consensus algorithm with only light communication between neighboring agents. Case studies verified that the proposed control strategy can effectively reduce the operation cost.

Introduction

With distributed energy resources (DER), energy storage and dispersed loads clustered as a mini power system, microgrid is becoming a promising technology to meet the challenge of integrating diverse distributed generators (DGs). Similar with bulk power system, reducing total generation cost through economic dispatch is essential for improving the efficiency of the system, especially when different types of DGs exist in the system. However, the major concern of the most previous works are focused on sharing the power among the DGs based on their respective kVA ratings, through virtual impedance [1], [2], adaptive tuning [3], etc.

There are few works trying to dispatch the power considering generation cost. In [4], reduced gradient method is adapted to minimize the operation cost, but they are using a centralized controller which relies on heavy communication. In [5], an adaptive droop has been proposed according to the generation cost. However, it calibrates the droop coefficients based the maximum generation cost of each DG, which will not guarantee the optimal economic dispatch during the full range of operation capacity. In [6], incremental cost consensus is used in a smart grid context, but the details of power regulation realization are not given.

In this paper, a multiagent based distributed operation cost minimization method is proposed to dispatch the power economically based on generation cost of different DGs. Each DG is acting as an agent which regulates the power according to the command obtained through consensus algorithm with only light communication with direct neighbors. Details of proposed power regulation strategy based on frequency scheduling are firstly introduced. The proposed control strategy based on the multiagent system is then presented to set the optimal power command. A case study of AC microgrid with three different DG units is carried out to test the proposed control methodology.

Frequency scheduling for power regulation of droop controlled AC microgrid

Droop control is widely used in the microgrid to achieve the power sharing autonomously without communication. Conventional droop controller in an AC microgrid is expressed as

$$\omega_i = \omega_{0i} - K_{P_i} P_{G,i} \tag{1}$$

$$E_i = E_{0i} - K_{Q_i} Q_{G,i} \tag{2}$$

where ω_i, ω_{0i}, K_{Pi}, $P_{G,i}$, E_i, E_{0i}, K_{Qi}, and $Q_{G,i}$ are output voltage frequency, nominal frequency, proportional frequency droop voltage, proportional amplitude droop parameter, and reactive power of the DG unit i, respectively.

There are two possibilities to change the way how real power is shared among different DG units. According to (1), it can be seen from Fig. 1, that either changing the frequency droop gain or changing nominal frequency can change the real power sharing.

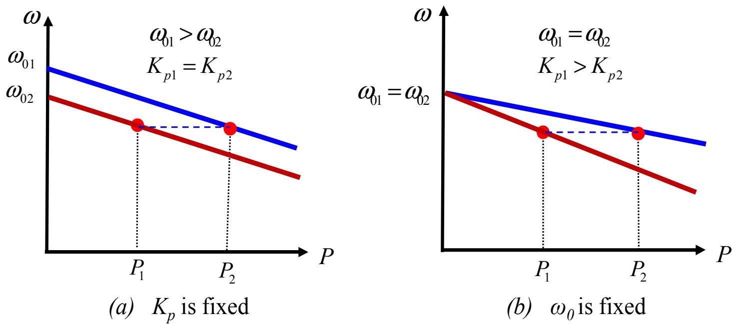

Fig. 1 Two way of real power regulation using frequency droop

Previous work [5] has employed adaptive frequency droop gain to reduce operation cost. Instead of adjusting the droop gain, the possibility of frequency scheduling is investigated in the paper. The control scheme of each DG is illustrated in Fig. 2.

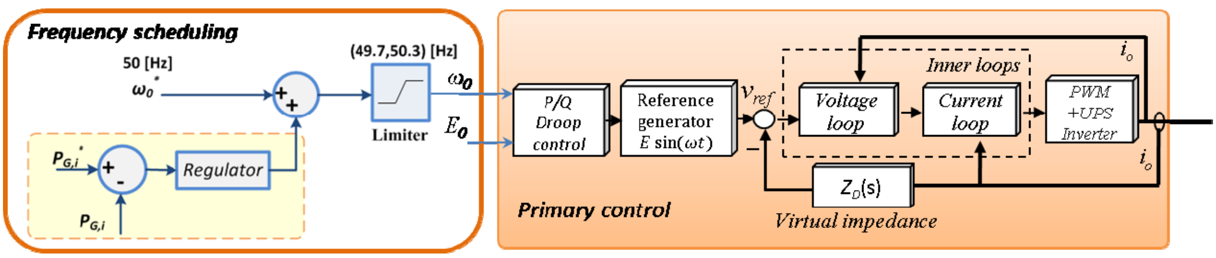

Fig. 2 Control scheme of frequency scheduling of each DG unit

In a single AC microgrid, one of the DG units sets the regulator as P controller and all the others as PI controller as shown in the block of frequency scheduling in Fig. 2, since for an islanded microgrid it must have at least one DG unit to balance the supply-demand mismatch.

Multiagent system for operation cost minimization using incremental cost consensus

In this session, the proposed distributed implementation of economic dispatch for operation cost minimization is introduced.

Problem statement

The generation costs of different DG units include many factors, which are surely not the same, but they might have a similar pattern which can be generalized as quadratic cost function [4]-[6].

$$C_i(P_{G,i}) = \alpha_i P_{G,i}{}^2 + \beta_i P_{G,i} + \gamma_i \tag{3}$$

where α_i, β_i and γ_i are the coefficients related to the cost function for generation *i*,

The total cost of operation of a microgrid with *n* generators can be expressed as,

$$C_{total} = \sum_{i=1}^{n} C_i(P_{G,i}) = \sum_{i=1}^{n} \alpha_i P_{G,i}{}^2 + \beta_i P_{G,i} + \gamma_i \tag{4}$$

Considering the constraints of power balance and power generation limitation, the objective to minimize the operation cost is to minimize the following function:

$$\begin{aligned} &Min \sum_{i=1}^{n} \alpha_i P_{G,i}{}^2 + \beta_i P_{G,i} + \gamma_i \\ &s.t. \\ &\sum_{i=1}^{n} P_{G,i} = P_D \\ &P_{G,i}^{\min} \le P_{G,i} \le P_{G,i}^{\max} \end{aligned} \tag{5}$$

where $P_{G,\ i}$ denotes the output power of DG unit *i*, and P_D denotes the total power demand of the system.

Incremental cost

In the conventional economic dispatch problem for the power system, the incremental cost of each DG unit is defined as

$$r_i = \frac{\partial C_i(P_{G,i})}{\partial P_{G,i}} = 2\alpha_i P_{G,i} + \beta_i \tag{6}$$

where r_i is the incremental cost of DG unit *i*,

Without generation capacity constraints, when the incremental cost reaches equality, it is the solution to (4) [7].

The common optimal r* can be expressed as

$$r^* = [\sum_{i=1}^{n} \frac{\beta_i}{2\alpha_i} + P_D] / (\sum_{i=1}^{n} \frac{1}{2\alpha_i}) \tag{7}$$

Conventionally, this optimal incremental cost is calculated by a centralized controller. However, this method suffers from single point of failure and relatively heavy communication overhead.

Incremental cost consensus

To overcome the inherent shortcomings of the centralized realization of economic dispatch, a distributed implementation without reliance on a single centralized controller is desired. Here we introduce the multiagent system into the system. Each local controller located in every DG unit can be taken as an agent, which communicates with their neighbors in the communication network. Each agent adopts the same consensus algorithm to discover the global variables, conducts the optimization, makes the decision and controls the local generation directly.

The difference of communication topology between consensus based multiagent system and conventional method can be illustrated in Fig.3. In this example, it assumes that there are four DG units in the microgrid. Fig.3 (b) only shows one possibility of the communication topology of the multiagent system, in which no centralized controller is needed and each local agent communicates with their neighboring agent in a connected graph.

Here, a graph G will be used to model the communication network of the multiagent system. Let $G = (V, E)$ be a undirected graph with a set of vertices $V = \{1, 2, \ldots, n\}$ and a set of edges $E \subseteq V \times V$. The undirected edge connects i and j is denoted by an unordered and distinct pair $(i, j) \in E$. The neighbors of vertices i is denoted as by $N_i = \{j \in V|(i, j) \in E\}$. An undirected graph is called connected if and only if there exists a path between any distinct pair of two vertices.

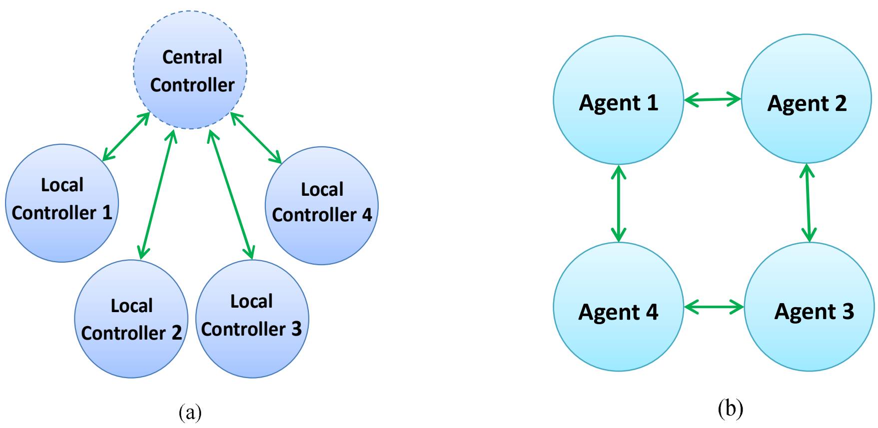

Fig. 3 Communication topology for two different control methodologies (a) communication topology for conventional centralized control (b) communication topology for multiagent based distributed control

In the communication network of multiagent system, each agent can be represented by a vertex, and the edge between any pair of two different agents means the bidirectional communication link between this pair of agent. The basis updating process of agent i can be written as

$$x_i[\mathrm{t+1}] = \sum_{j=1}^{n} d_{ij} x_j[\mathrm{t}] \tag{8}$$

where $x_j[\mathrm{t}]$ is the consensus variable discovered by agent j at iteration t, $x_i[\mathrm{t+1}]$ the consensus variable discovered by agent j at iteration t+1, and d_{ij} is the coefficient associated with edge ij. The coefficients need to be designed in the updating rule to make consensus converge.

There are several methods to determine the coefficients d_{ij} [8]-[11], e.g, Perron matrix [8], uniform method [9], metropolis method [10][11], where D is the coefficients matrix of the communication system, and to guarantee the convergence of the system, D should satisfies the following two constraints.

1. D is the double-stochastic matrix, i.e, the sum of D's row and columns are both one;
2. The eigenvalues of D should be within a close disk $|\lambda_i| \leq 1$.

Here the same method used by [12] is chosen in this paper to be adaptive to changes of communication topology and guarantee good convergence speed. The coefficients are defined as

$$d_{ij} = \begin{cases} 2/(n_i + n_j + 1) & j \in N_i \\ 1 - \sum_{j \in N_i} 2/(n_i + n_j + 1) & i = j \\ 0 & otherwise \end{cases} \tag{9}$$

The updating rule of the proposed incremental consensus algorithm is designed as follows.

$$r_i[t+1] = \sum_{i \in N_i} d_{ij} r_j[t] + \varepsilon P_{D,i}[t] \tag{10}$$

$$P_{G,i}[t+1] = \frac{r_i[t+1] - \beta_i}{2\alpha_i} \tag{11}$$

$$P'_{D,i}[t+1] = P_{D,i}[t] - (P_{G,i}[t+1] - P_{G,i}[t]) \tag{12}$$

$$P_{D,i}[t+1] = \sum_{i \in N_i} d_{ij} P'_{D,j}[t] \tag{13}$$

where $r_i[t]$ is the incremental cost of agent i at iteration t, ε is the feedback coefficients which controls the convergence of the consensus, $P_{D,i}[t]$ is the estimation of the global supply-demand mismatch, The initialization of the system can be set as follows:

$$\begin{cases} P_{G,i}[0] = 0 \\ P_{D,i}[0] = P_{L,i} \\ r_i[0] = \dfrac{\beta_i}{2\alpha_i} \end{cases} \tag{14}$$

Convergence analysis of the incremental cost consensus

In order to analyze the convergence of the designed consensus algorithm, the updating rule of each agent (9) to (13) can be rewritten in the matrix form:

$$\mathbf{R}[t+1] = \mathbf{D}\mathbf{R}[t] + \varepsilon \mathbf{P_D}[t] \tag{15}$$

$$\mathbf{P_G}[t+1] = \mathbf{H}\mathbf{R}[t+1] - \mathbf{W} \tag{16}$$

$$\mathbf{P_D}[t+1] = \mathbf{D}\mathbf{P_D}[t] - \mathbf{D}(\mathbf{P_G}[t+1] - \mathbf{P_G}[t]) \tag{17}$$

where $\mathbf{R}$, $\mathbf{P_D}$, and $\mathbf{P_B}$ are the column vectors of r_i, $P_{D,i}$, $P_{B,i}$, $\mathbf{W}$ is the column of $\frac{\beta_i}{2\alpha_i}$, and $\mathbf{H}$ = diag([$1/2\alpha_1$, $1/2\alpha_{2, \ldots,}$$1/2\alpha_n$]), The update rule can be further reduced into the following,

$$\begin{bmatrix} \mathbf{R}[\mathrm{t}+1] \\ \mathbf{P_D}[\mathrm{t}+1] \end{bmatrix}_{2n\times 1} = \mathbf{M}\begin{bmatrix} \mathbf{R}[\mathrm{t}] \\ \mathbf{P_D}[\mathrm{t}] \end{bmatrix}_{2n\times 1} \tag{18}$$

$$\mathbf{M} = \begin{bmatrix} \mathbf{D} & \varepsilon\mathbf{I}_n \\ -\mathbf{DH(D - I}_n\mathbf{)} & \mathbf{D(I}_n - \varepsilon\mathbf{H)} \end{bmatrix}_{2n\times 2n} \tag{19}$$

where I_n is a $n \times n$ identity matrix,

Since if ε is very small and can be neglect, there is

$$\left|\lambda\mathbf{I_{2n}} - \mathbf{M}\right| = \left|(\lambda\mathbf{I_n} - \mathbf{D})^2 - \varepsilon\mathbf{I}_n\mathbf{DH(D - I}_n\mathbf{)}\right| \approx \left|\lambda\mathbf{I_n} - \mathbf{D}\right|^2 \tag{20}$$

Therefore, eigenvalue of **M** has repeated eigenvalue same as **D**. As **D** is designed as (9), it can be verified that **M** has $[\mathbf{1_n}, \mathbf{0_n}]^T$ as the eigenvector when $\lambda_1 = 1$ that is

$$\begin{bmatrix} \mathbf{D} & \varepsilon\mathbf{I}_n \\ -\mathbf{DH(D - I}_n\mathbf{)} & \mathbf{D(I}_n - \varepsilon\mathbf{H)} \end{bmatrix}_{2n\times 2n} \begin{bmatrix} \mathbf{1_n} \\ \mathbf{0_n} \end{bmatrix} = \begin{bmatrix} \mathbf{D} \\ -\mathbf{DH(D - I}_n\mathbf{)1_n} \end{bmatrix} = \begin{bmatrix} \mathbf{1_n} \\ \mathbf{0_n} \end{bmatrix} \tag{21}$$

As is proved in [12], this properties of **M** means that the system of (18) will converge to span $[\mathbf{1_n}, \mathbf{0_n}]^T$ with infinity iterations, that is

$$\begin{bmatrix} \mathbf{R}[\infty] \\ \mathbf{P_D}[\infty] \end{bmatrix}_{2n\times 1} = r^* \begin{bmatrix} \mathbf{1_n} \\ \mathbf{0_n} \end{bmatrix} \tag{22}$$

Premultiplying $\mathbf{1}_n^T$ to both sides of (13), it yields,

$$\mathbf{1}_n^T \cdot \mathbf{P_D}[\mathrm{t}+1] = \mathbf{1}_n^T \cdot \mathbf{DP_D}[\mathrm{t}] - \mathbf{1}_n^T \cdot \mathbf{D}(\mathbf{P_G}[\mathrm{t}+1] - \mathbf{P_G}[\mathrm{t}]) = \mathbf{1}_n^T \cdot \mathbf{P_D}[\mathrm{t}] - \mathbf{1}_n^T \cdot (\mathbf{P_G}[\mathrm{t}+1] - \mathbf{P_G}[\mathrm{t}]) \tag{23}$$

$$\mathbf{1}_n^T \cdot \mathbf{P_D}[\mathrm{t}+1] + \mathbf{1}_n^T \cdot \mathbf{P_G}[\mathrm{t}+1] = \mathbf{1}_n^T \cdot \mathbf{P_D}[\mathrm{t}] + \mathbf{1}_n^T \cdot \mathbf{P_G}[\mathrm{t}] \tag{24}$$

Since $\mathbf{P_D}[\infty] = 0$,

$$\mathbf{1}_n^T \cdot \mathbf{P_G}[\infty] = \mathbf{1}_n^T \cdot \mathbf{P_D}[0] - \mathbf{1}_n^T \cdot \mathbf{P_G}[0] = P_D \tag{25}$$

Considering (11), there is

$$\mathbf{1}_n^T \cdot \mathbf{P_G}[\infty] = \mathbf{1}_n^T \cdot \mathbf{HR}[\infty] - \mathbf{1}_n^T \cdot \mathbf{W} = \mathbf{1}_n^T \cdot \mathbf{H} \cdot \mathbf{1}_n^T \cdot r^* - \mathbf{1}_n^T \cdot \mathbf{W} \tag{26}$$

The incremental cost will finally converge to (7).

Multiagent system implementation

The implementation of the multiagent system is a distributed control in which each agent has the identical local control. The local control in a hierarchical structure from bottom to top consists of primary control, frequency regulation for power control and consensus algorithm for optimal dispatch. The structure is shown in Fig. 4.

In the primary level, droop control is adopted to share the power autonomously. To regulate the real power, the nominal frequency is changed according to the mismatch between the actual power generation and the optimal power command. The optimal power command is obtained through distributed incremental consensus algorithm.

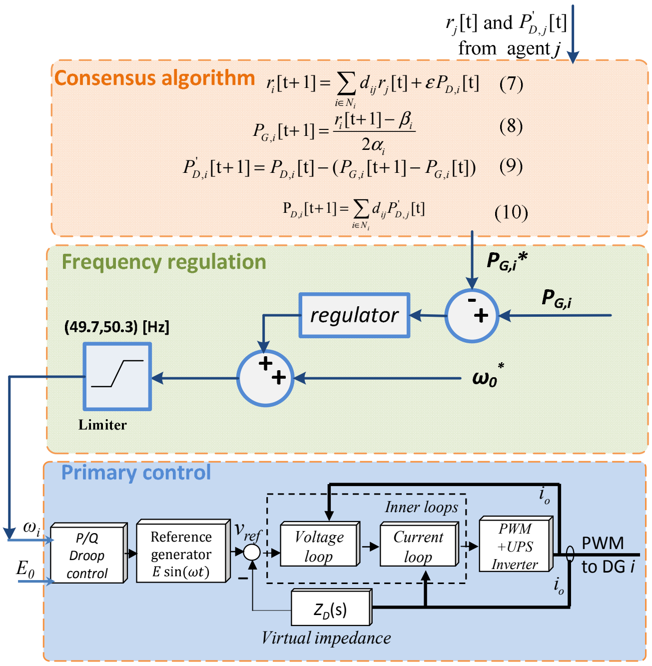

Fig. 4 Control scheme of proposed control strategy

Case study

In order to verify the proposed algorithm, case study is carried out under an example microgrid with three different DG units having different generation cost. The coefficients of the operation cost function of each unit are listed in Table I. The control parameters of the system are listed in Table II.

Table I. Coefficients of the operation cost function

Unit	α_i	β_i	γ_i
1	7.15*10e-5	9.5*1e-3	0.2
2	4.75*10e-5	8.5*1e-3	0.5
3	3.75*10e-5	7.7*1e-3	0.1

Table II. Parameter of the system

Parameters	Symbol	Value	Units
Nominal voltage	E_{0i}	230	V
Nominal frequency	ω_0^*	314	rad/s
Cut-off frequency of low pass filter for each DG unit	ω_f	0.7	rad/s
Proportional frequency droop for each DG unit	K_{Pi}	0.002	rad/Ws
Proportional amplitude droop for each DG unit	K_{Qi}	0.02	V/Var
LC filter inductor for each DG unit	L_f	1.8	mH
LC filter capacitor for each DG unit	C_f	27	µF
Initial load impedance	Z_D	17.2	Ω

At the beginning, cost minimization control is not activated and the 17.2Ω resistive load is shared equally among these three units. At the time of 50 s, cost minimization control activates. At the time of 130 s, an extra paralleled 154 Ω load is added to the system. The power dispatch results of each unit are shown in Fig. 5. The comparison of operation cost between proposed method and the conventional method with equal sharing of the load is shown in Fig. 6. As can be seen, the operation cost is reduced effectively. The consensus process for two consensus circles is shown in Fig. 7.

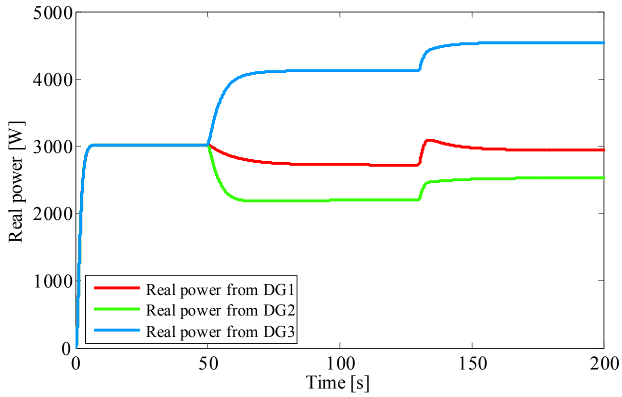

Fig. 5 Operation cost comparison

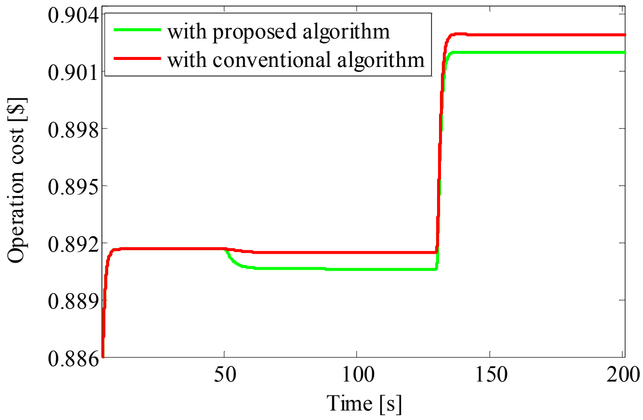

Fig. 6 Power dispatch results

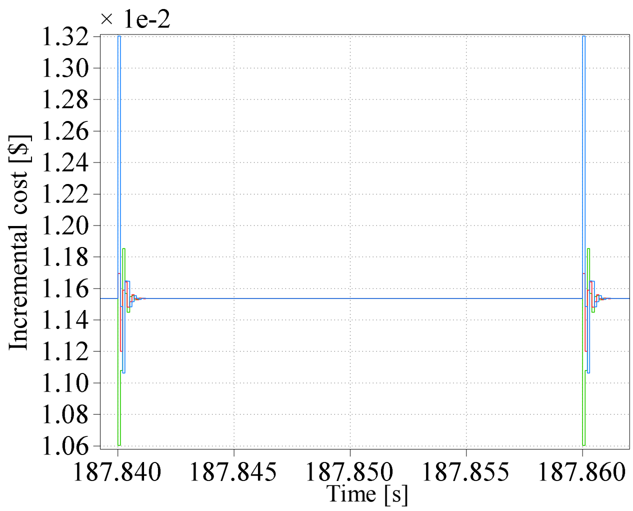

Fig. 7 Incremental cost consensus process

Conclusion

In this work, a multiagent based distributed operation cost minimization method is proposed to dispatch the power economically based on the different generation cost of DG units. Each DG unit is acting as an agent which regulates the power according to the command obtained through consensus algorithm with only light communication with direct neighbours. Detailed power regulation method based on frequency scheduling is proposed and implemented. An incremental cost consensus algorithm is designed to obtain the power dispatch command for each DG unit. The proposed algorithm is verified in an example microgrid with three different DG units. With this strategy the operation cost is reduced effectively with only light communication with direct neighbours.

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