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An Optimal Active Power Scheduling Strategy with Renewable Energy Based on Distributed Consensus Algorithms

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Abstract: Aiming at the influence of the uncertainty of renewable energy generation on the power distribution of smart grid, a distributed optimal scheduling strategy for smart grid energy storage units based on consensus algorithm was proposed. This method does not rely on the central controller, but through the local communication between the energy storage units, according to their own information and acquired neighbor information to adjust the deviation between the actual and planed power in real time. In addition, in order to verify that the algorithm can optimize the network loss, MATPOWER is used to calculate the network loss before and after optimization. The system simulation results show that the proposed distributed scheduling strategy can ensure that all storage units converge to the same optimal value, and make the power grid run more economically.

Keywords: Power systems stability, control of renewable energy resources, control of distributed systems.

1. INTRODUCTION

As an environmentally friendly and pollution-free energy, wind energy stands out among new energy generation technologies. However, due to wind power fluctuations caused by random wind in wind farms, large-scale utilization and integration of wind power into the main power grid face great challenges(Zhu *et al.*, 2013). The uncertainty of wind energy leads to a certain deviation between the planned power and the actual power, so it is necessary to adjust the grid output power in real time to make up for this deviation(Cong *et al.*, 2017).

With the rapid development of industrial technology, energy storage technology has attracted more and more attention in solving the problem of wind power access(Wu *et al.*, 2017; Lei *et al.*, 2017). But the energy storage unit of a large number of installation for the traditional centralized control brought a lot of restrictions, by contrast, a distributed control scheme has more advantages: the distributed scheme distributes the calculated load to the controller, the communication failure is more stable and allows flexibility to reconfigure, therefore, a distributed scheduling method gets more and more application.

The distributed scheduling strategy generally realizes the power distribution of energy storage units by applying the consensus algorithm. For example, Yang *et al.* (2019) proposed a distributed consensus algorithm, which only relies on the communication between neighboring nodes and does not need the global information of the system. Ruan *et al.* (2018) based on the multi-agent consensus theory to solve the problem of high communication pressure of centralized control mode that cannot meet plug and play requirements. Zhou *et al.* (2017) proposed a distributed hierarchical control strategy based on the consensus algorithm of multiple agents to maintain the stability of frequency and voltage of the micro-grid system and realize the flexible distribution of active and reactive power loads among distributed power sources. However, the consensus algorithm only ensures the fair distribution of power in the energy storage unit, that is, it ensures that the output value of each energy storage unit is proportional to the planned output power while the charging and discharging state of the energy storage unit remains unchanged, but due to the existence of internal resistance of energy storage battery, loss is bound to occur. So, based on the distributed algorithm, this paper considers the internal resistance of the battery to maximize the charging and discharging efficiency

This paper realizes the real-time scheduling of energy storage units through the distributed consensus algorithm(Yang, 2017) and makes the power distribution reasonable. MATPOWER is used to calculate the network loss before and after optimization to verify that the scheme can optimize the network loss and make the power network run more economically.

2. DISTRIBUTED SCHEDULING MODEL OF ENERGY STORAGE UNIT

Suppose there are n energy storage units distributed in the distribution network to form a distributed energy storage network. Each energy storage unit has a planned output power, which is determined by the scheduling strategy.

The imbalance between the power demand of the power grid and the actual output power of the wind farm is given by the following equation:

$$\Delta P = P^* - P_W \quad (1)$$

Where P_W is the active power generated by the wind farm. P^* is the total reference output power, set and adjusted by the relevant departments according to the operating conditions. In equation (1), $\Delta P > 0$ indicates that the energy storage unit needs to discharge and release additional power to compensate for the power generated by the wind farm. Also, $\Delta P < 0$ indicates that the energy storage unit needs to be charged to smooth the peak power generated by the wind farm.

However, due to the existence of internal resistance of the battery, the energy storage unit will have power loss during charging and discharging:

$$P_{B,i}^{cha} = P_{B,i}\eta_{C,i} \quad (2)$$

$$P_{B,i}^{dis} = P_{B,i}/\eta_{D,i} \quad (3)$$

Where, $P_{B,i}^{cha}, P_{B,i}^{dis}$ represent the actual charging and discharging power of the energy storage unit, and $\eta_{C,i}, \eta_{D,i}$ are the charging and discharging loss coefficient, $0 < \eta_{C,i} < 1 < \eta_{D,i}$.

In order to facilitate analysis, this paper only considers the operating conditions under charging state. The actual input power of the energy storage unit is:

$$\sum P_{B,i}\eta_{C,i} \quad (4)$$

For the purpose of making the smart grid run more economically, it is necessary to minimize the network loss, that is, to maximize the charging and discharging power by adjusting the charging and discharging parameters of the energy storage unit in equation (4).

$$\begin{aligned} &\arg Max \sum P_{B,i}\eta_{C,i} \\ &s.t. \sum P_{B,i} = \Delta P, P_{B,i}^{\min} \le P_{B,i} \le P_{B,i}^{\max} \end{aligned} \quad (5)$$

Where, $P_{B,i}^{\min}, P_{B,i}^{\max}$ are the minimum and maximum charging power of the energy storage unit.

According to Wang *et al.* (2017), the linear expression of the charging rate α_i and $P_{B,i}$ of energy storage unit are:

$$\alpha_i = a_i - b_i P_{B,i} \quad (6)$$

Where, and a_i and b_i are constant coefficients.

Substitute equation (6) into equation (5) to obtain the objective function:

$$\arg \quad Max \sum a_i P_{B,i} - b_i P_{B,i}^2 \quad (7)$$

The marginal cost of energy storage unit with respect to the partial derivatives of $P_{B,i}$ in equation (8) is defined as :

$$\gamma_i = a_i - 2b_i P_{B,i} \quad (8)$$

In order to make smart power grid operate more economically and minimize network losses, the optimal power flow (Serhat, 2019) is adopted to solve. MATPOWER is an open source power system simulation package based on Matlab developed by Zimmerman *et al.* (2011). MATPOWER is used to determine the power system model analytically and minimize the objective function, as shown in equation (9).

$$Min \sum_{i=1}^{n} f^i(p_g^i) \quad (9)$$

3. DISTRIBUTED CONSENSUS ALGORITHMS

3.1 Graph Theory

Graph G is an ordered binary group $G = (V, E)$,where $V = \{v_1, v_2, ..., v_n\}$ and $E = \{e_1, e_2, ..., e_n\} \subseteq V \times V$, where V is called point set, E is called edge set. In general, undirected graph is denoted by $G =< V, E >$ and directed graph is denoted by $D = \{V, E\}$. If there is a path between any different nodes (v_i, v_j) , it is a directed graph. $A = [a_{ij}] \in R^{n\times n}$ is the associated adjacency matrix.

$$A = (a_{ij})_{n\times n}, a_{ij} = \begin{cases} 0 & (v_i, v_j) \notin E \\ 1 & (v_i, v_j) \in E \end{cases} \quad (10)$$

The set of neighbors of unit i is denoted as $N_i = \{v_j \mid (v_i, v_j) \in E\}$. In a undirected graph, the set of agents which can receive information from unit i is denoted as $N_i^+ = \{v_j \mid (v_i, v_j) \in E\}$. Likewise, the set of agents which can send information to unit i is denoted as $N_i^- = \{v_j \mid (v_i, v_j) \in E\}$. The degree matrix $D \in R^{N\times N}$ is a diagonal matrix, where the i th element is $\deg(v_i)$. The Laplace matrix is defined as $L = D - A \in R^{N\times N}$. The matrix P is defined as $P = [p_{ij}] = E - \varepsilon L \in R^{N\times N}$, ε is a adjustment coefficient, and $0 < \varepsilon < 1/\deg(v_i)$. Matrix P also called the weight matrix, used to update the data and is very important for the calculation in the algorithm below.

3.2 Distributed Scheduling Strategy

The communication topology between distributed energy storage systems is a strongly connected graph G. Suppose that a virtual command node allocates power deviations to a subset of the vertex set V .This "virtual command node" is different from "Leader" in the consistent algorithm of "leader-follower" : "Leader" is the center (scheduling center) used to collect global information of all energy storage units in the system. While "virtual command node" is just to allocate the total power deviation in the system, "virtual command node" is essentially a virtual node that does not participate in the information interaction between energy storage units and does not actually exist in the system operation, but is assumed to exist for the convenience of algorithm design. The virtual command vertex is represented by vertex 0, and N_0^- is the set of vertices that can receive information from vertex 0. The virtual command vertex evenly distributes the total output power ΔP_Σ that needs to be adjusted within the set N_0^-, $1 \le |N_0^-| \le N$.

A. No Internal Resistance

Initialization:

$$\begin{cases} \lambda_i(0) = 0 \\ \Delta P_i(0) = 0 \\ x_i(0) = \begin{cases} \Delta P_\Sigma / |N_0^+|, i \in N_0^- \\ 0 \end{cases} \end{cases}, i \in V \tag{11}$$

Where, λ_i is the power output increment ratio, and ΔP_i is the deviation between the actual output power of wind farm and the planned output power, x_i is the deviation between the power to be adjusted by wind farm i and the actual adjusted power.

The real-time power distribution strategy of the wind farm is as follows:

$$\lambda_i(k+1) = \sum_{j \in N^+} p_{i,j} \lambda_j(k) + \varepsilon x_i(k) \tag{12}$$

$$\Delta P_i(k+1) = c_i \lambda_i(k+1) \tag{13}$$

$$x_i(k+1) = \sum_{j \in N^+} q_{i,j} x_i(k) - \left(\Delta P_i(k+1) - \Delta P_i(k)\right) \tag{14}$$

Where, ε is a constant with a sufficiently small convergence coefficient, $c_i = u_i P_{i0}$.

Since the communication topology is a strongly connected graph, each energy storage unit in the system can get the information $\left(\Delta P_i(k), x_i(k)\right)$ of other energy storage units through interaction with the information of neighboring units, and integrate it into the global information $x_i(k)$, and then adjust the power output $\Delta P_i(k)$ of each energy storage unit according to this global information.

In order to analyze the nature and convergence of equation (12) - equation (14) of distributed scheduling, equation (12) - equation (14) is written as a matrix:

$$\boldsymbol{\lambda}(k+1) = P\boldsymbol{\lambda}(k) + \varepsilon \boldsymbol{x}(k) \tag{15}$$

$$\Delta P(k+1) = C\boldsymbol{\lambda}(k+1) \tag{16}$$

$$x(k+1) = Qx(k) - \left(\Delta P(k+1) - \Delta P(k)\right) \tag{17}$$

where, $\lambda, \Delta P, x, C$ is the column vector form of $\lambda_i, \Delta P_i, x_i, c_i$.

Multiply the left and right sides of equation (17) by 1^T. Since Q is a column random matrix, it can be obtained

$$\begin{aligned} & 1^T x(k+1) = 1^T Qx(k) - 1^T \left(\Delta P(k) - \Delta P(k)\right) \\ & = 1^T x(k) - 1^T \left(\Delta P(k) - \Delta P(k)\right) \\ & \Rightarrow 1^T \left(x(k) + \Delta P(k)\right) = 1^T \left(x(k) + \Delta P(k)\right) \end{aligned} \tag{18}$$

For all k, $1^T \left(\boldsymbol{x}(k) + \Delta \boldsymbol{P}(k)\right)$ is a constant. Notice that the initial values $x_i(0)$ and $\Delta P_i(0)$, we can get $\sum_{i \in V} x_i(0) + \Delta P_i(0) = \Delta P_\Sigma$. So, $1^T x(k) = \Delta P_\Sigma - 1^T \Delta P(k)$ is the deviation between the power to be adjusted and the actually adjusted power. The first term of the right part of equation (12) is the consistent part, which controls all $\lambda_i(k)$ to reach the same value. The second term $\varepsilon x(k)$ serves as a feedback mechanism to control all $\lambda_i(k)$ to the optimal value λ^*.

B. Considering the Internal Resistance

Initialization:

$$\begin{cases} \lambda_i(0) = a_i - b_i P_i(0) \\ \Delta P_i(0) = \begin{cases} \Delta P / |N_0^-|, i \in N_0^-, i \in V \\ 0 \end{cases} \end{cases} \tag{19}$$

Where, λ_i is the marginal cost, $P_i(0)$ is the initial power of the energy storage unit, and $\Delta P_i(0)$ is the deviation between the power to be adjusted and the actual adjusted power.

$$\lambda_i(k+1) = \sum_{j \in N^+} p_{i,j} \lambda_j(k) + \varepsilon x_i(k) \tag{20}$$

$$P_i(k+1) = \left(a_i - \lambda_i(k+1)\right) / b_i \tag{21}$$

$$\Delta P_i(k+1) = \sum_{j \in N^+} q_{i,j} \Delta P_i(k) - \left(P_i(k+1) - P_i(k)\right) \tag{22}$$

Where, ε is a positive constant with a sufficiently small convergence coefficient.

The proof process is similar to the one in the previous section without internal resistance, so it is not repeated here.

4. EXAMPLES SIMULATION AND ANALYSIS

IEEE30-node system was used to verify the effectiveness and correctness of the distributed consensus algorithms. IEEE30-node system diagram is shown in the Fig. 1. All the simulations were made by MATLAB. And the net loss obtained by each example is calculated by MATPOWER.

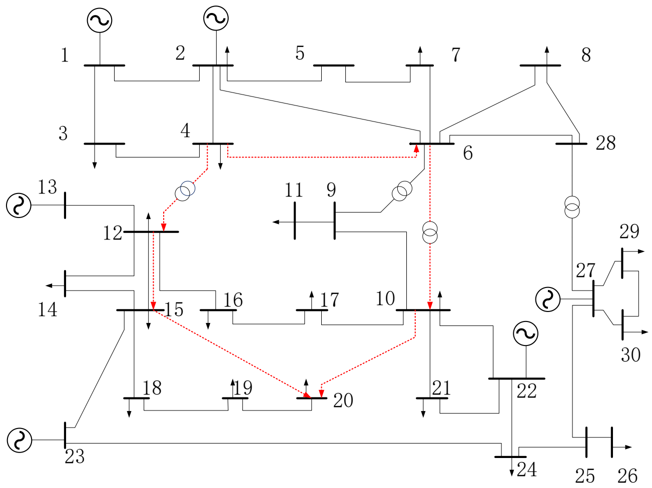


Fig. 1. IEEE30-node system diagram

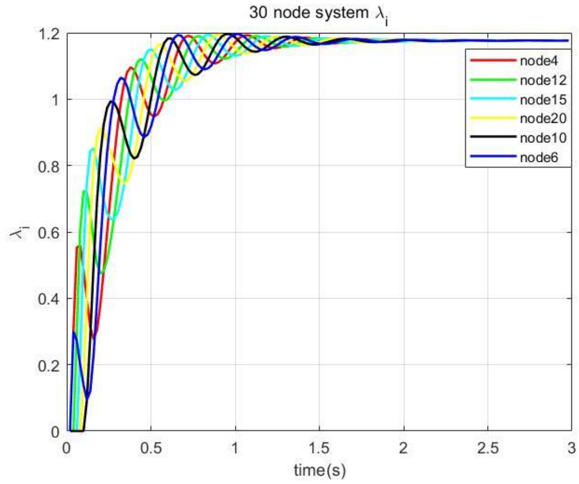
The red dotted line represents communication line and the black solid line represents distribution line. Where, "virtual command node" connects node 4 and node 6. Nodes 1, 2, 13, 22, 23 and 27 are wind power generation system, nodes 4, 12, 15, 20, 10 and 6 are energy storage units, and the directed diagram is formed according to the sequence in the figure. The disturbance constant ε is 0.0003.

4.1 Case 1: No Internal Resistance

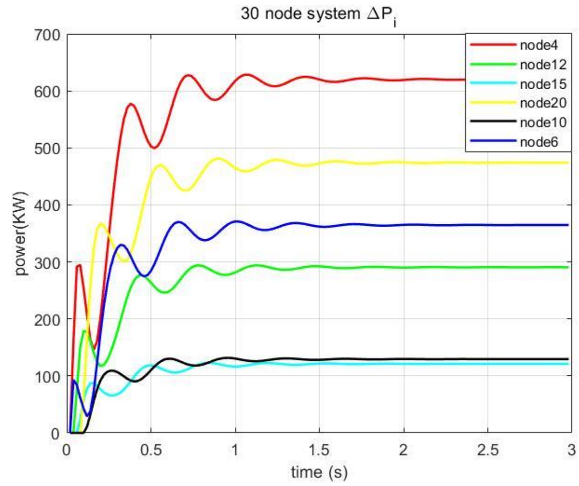
The planned output power of each energy storage unit is shown in Table 1, and the total planned output power is 1700kW.

Table 1. The planned output power of each energy storage unit

node	4	12	15	20	10	6
power/kW	527	247	103	403	110	310



(a)



(b)

Fig. 2. simulation result diagram of Case 1

The simulation results are shown in Fig. 2. As can be seen in the figure (a) from Fig. 2, λ_i of each energy storage unit finally converges to the same consistent value, and the charging and discharging state of each energy storage unit remains unchanged. And the figure (b) from Fig. 2 shows the ΔP_i of each unit are [619.9, 290.6, 121.2, 474.2, 129.4, 364.7]kW, which are proportional to the planned output power. And the total storage power of 30-node is equal to 2000kW.

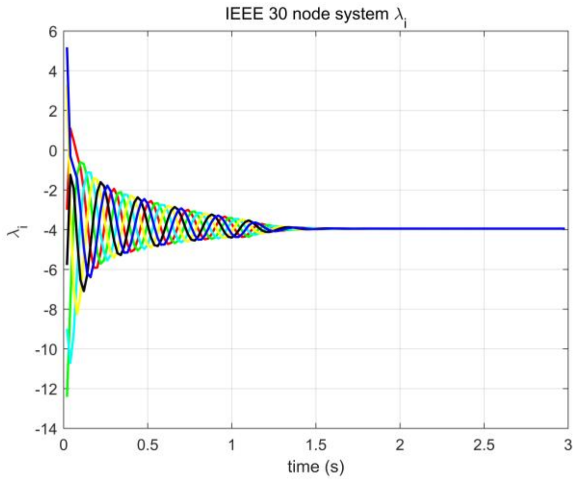
The network loss calculated by MATPOWER is 2.860MW before optimization and 2.403MW after optimization.

4.2 Case 2: Considering the Internal Resistance

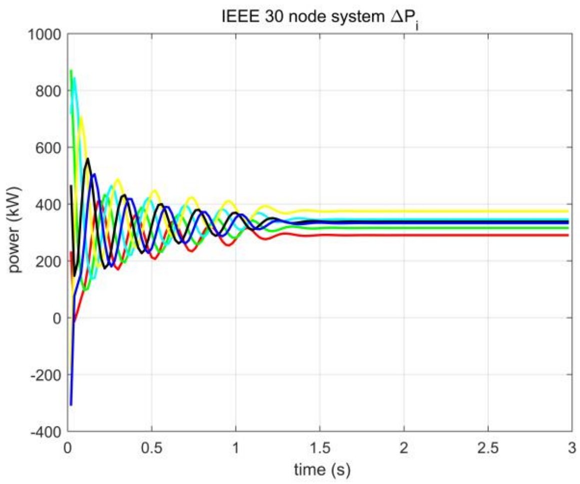
The initial power of each energy storage unit are $P_i(0)$ =[760, 1120, 820, 220, 580, 0]kW, the total input power is 2000kW. Where, the parameters of each energy storage unit are shown in Table 2. The simulation results are shown in Fig. 3.

Table 2. The parameters of each energy storage unit

node	4	12	15	20	10	6
a_i	0.873	0.855	0.760	0.926	0.855	0.780
b_i	0.0083	0.0076	0.0068	0.0065	0.0071	0.0071



(a)



(b)

Fig. 3. simulation result diagram of Case 2

Case 2 adopts the same communication topology diagram in Case 1. And Fig. 3 shows that the marginal cost of 30-node system still converges to the same value.

The network loss calculated by MATPOWER is 2.411MW, by comparing the calculation results before and after optimization, it can be seen that the algorithm can reduce network losses.

5. CONCLUSIONS

This paper is devoted to the study of the scheduling problem of distributed energy storage system: that is, the distributed energy storage can be used to suppress the power fluctuations caused by renewable energy generation, and the scheduling strategy to maximize the power input or output considering the internal resistance of the battery. In this paper, the validity of the distributed algorithm is verified through the simulation analysis of IEEE30-node, and the algorithm can reduce network loss through the calculation of MATPOWER.

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