Research on distributed cooperative optimisation control strategy for active distribution network based on combine-then-adapt diffusion algorithm

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Abstract: Considering the problem of cooperative operation of highly intermittent renewable generations (photovoltaic and wind power) and flexible load in active distribution network, a distributed cooperative optimisation operation strategy based on combine-then-adapt diffusion algorithm is proposed in this study. Distributed agents of distributed generation are connected by the distributed sparse network through distributed hierarchical control method. As an agent node of networked system, it exchanges information with its neighbours. In order to make the distribution generator meet the equal incremental cost principle, the adaptive adjacency matrix and fusion matrix with the weighted factor are introduced to update the state value of nodes to obtain the same convergence value. In this strategy, the coordinated source and load is applied by the active power optimisation dispatching for active distribution network. Stimulate analysis and experimental results show that the proposed combine-then-adapt diffusion algorithm can effectively solve the problem of real-time detection signal, can quickly learn and adapt to environmental changes. Finally, the simulation analysis and experimental results of IEEE14-bus distribution test system is carried out to verify the effectiveness and feasibility of the proposed method.

1 Introduction

Active distribution network (ADN) is not only an important component of the smart grid, but also the trend of the development of the future grid. It has been to stimulate renewable energy penetration in existing power systems by improving reliability and resiliency. In both wired and wireless communication infrastructures, during an outage, ADN can be also isolated from the host grid and should be able to continue operation in standalone mode with indeterminate broken communication links and scarce generation resources [1–3]. However, the future ADN also brings new challenges to the study of some basic problems in power systems, one of which is the problem of the coordinated source and load.

Due to the uncertainty and stochasticity of intermittent distributed generators output power and the low inertia characteristics of ADN, sophisticated control systems and optimisation methods are required to coordinate non-dispatchable distributed generator (such as wind power (WP) and photovoltaic), flexible load and dispatchable distributed generator (such as synchronisation motor and energy storage) [4]. Recently, two network types are applied to manage complex ADN structure, namely, centralised control method and decentralised control method. A number of centralised control approaches have been proposed for optimal microgrid control, which include such as Lagrange multipliers [5], gradient search methods, the linear programming [6], Newton’s approach and heuristic methods such as the genetic algorithm [7] and particle swarm algorithm [8] etc. Note that centralised approach not only requires more communicational bandwidth and computational burden, but also they are more susceptible to single-point failures, which can easily jeopardise in case of partial power outages and broken communication links. Decentralised control has been used in a number of studies for microgrid systems [9–11]. In [9, 10], maximising the economic and environmental benefits of microgrid were realised under safe voltage. Cost curves were used for economic dispatch of distributed energy resources and storage systems in microgrid [11]. The proposed method can adjust output power wherein all controllers were connected to each other, while decentralised control lacks collaboration and information communication for among individuals, and difficulty unify and control information flow.

The emerging smart grid concept compels ADN to adopt distributed cooperative methods as a result of the highly dynamic behaviour of ADN. In contrast to the centralised control method, distributed control does not require a central station for control, and controllers work autonomously in a cooperative fashion to reach a global objective. Cooperative operation control requires a tight communication among controllers in a network. Most of the distributed approach refers to a network, where each controller can only communicate with neighbour controllers [12, 13]. So, a large number of microgrid distributed methods have been proposed in the literature. In [14], a replicator dynamic theory-based multi-agent system was introduced with the ability to reach the economic operating point of the microgrid. However, in this framework, a dominant agent was used to aggregate the cost functions of the distributed energy source agent, which still makes the system vulnerable to single-point failures. A comprehensive distributed multi-agent-based microgrid management without any optimisation or communication method was proposed in [15], but this study does not consider hierarchical control. In [16], distributed subgradient-based solution was proposed to study coordinate the operations of different types of distributed renewable generators in a microgrid with high renewable energy penetration. There were some deficiencies in the method: regulating cost was not considered and the system was unable to cope with measurement errors. In [17], coordinated control method based on consensus algorithm was applied to realise the minimisation of the charge and...
 discharge loss for microgrid energy storage system. Although, this study proposed a coordinated control method based on consensus algorithm, information interaction has not been exploited yet the specific communication process and communication protocol for ADN. Resource management based on the consensus algorithm have been proposed for optimisation operation of source and load in [18–21]. But the consensus algorithm has the problems of slow convergence speed and poor adaptability to environment, combine-then-adapt (CTA) diffusion algorithm has fast convergence speed and quickly learns and adapts to environmental changes.

Therefore, in this paper, a distributed cooperative optimisation control strategy based on CTA diffusion algorithm for ADN is proposed. Distributed agents of distributed generators are connected by the distributed sparse network through distributed hierarchical control method. As an agent node of networked system, it interchanges information with its neighbours. CTA diffusion algorithm is used to obtain power equal incremental cost for ADN, and realise the distributed cooperative operation among the agent. Distributed hierarchical cooperative optimisation method is proposed to realise cooperative optimisation operation of source-loads and maximisation of economic benefits.

This paper is organised as follows: optimal mathematical model for ADN is presented in Section 2. Cooperative optimisation control strategy for ADN based on combine-then-adapt diffusion algorithm is discussed in Section 3. In Section 4, the effectiveness and feasibility performance of the proposed method are examined on the IEEE14-bus distribution test system. Section 5 is the conclusions.

2 Optimisation mathematical model for ADN

2.1 Optimisation objective function

In distributed hierarchical cooperative optimisation control, two types are defined in the ADN, namely, non-dispatchable wind generator and solar generator, as well as dispatchable energy storage, flexible load and synchronous generators (SGs).

The economic optimal operation of ADN is the optimisation problem that the power generation unit and flexible load maximise economic benefits of the whole ADN under the condition of satisfying a series of operation constraints. Maximise the economic benefits given by

\[
\text{max } C = - \sum C_d(P_{L,d}) - \sum C_s(P_{SG,e}) - \sum C_f(P_{B,f}) - \sum C_r(P_{R,g})
\]  

(1)

where \(C_d(P_{L,d})\), \(C_s(P_{SG,e})\), \(C_f(P_{B,f})\), and \(C_r(P_{R,g})\) are the cost function for the flexible load demand, the conventional fuel SG, the battery storage [22], and the renewable energy [23] at the \(d\)th, \(f\)th, and \(g\)th bus systems, respectively. The above cost functions are usually approximated by the following quadratic convex function \(C(P_i)\):

\[
C(P_i) = \frac{1}{2} a_i P_i^2 + b_i P_i + c_i \quad i = 1, 2, \ldots, n
\]  

(2)

where \(a_i, b_i, c_i\) are non-negative quadratic coefficient. \(P_{L,d}\) \(P_{SG,e}\), \(P_{B,f}\), \(P_{R,g}\) are flexible load, the SG, battery storage, and renewable energy power output at the \(d\)th, \(f\)th, \(g\)th bus systems, respectively. \(P_i\) is active power sets of the SG, battery storage, renewable energy and flexible loads. In this paper, the power generation is positive, and the demand power is negative.

Next, the transmission loss is considered in this paper. The transmission loss \(P_{\text{loss,}d}\) is given by

\[
P_{\text{loss,}d} = j_d \cdot P_{L,d}
\]  

(3)

where \(j_d\) is the transmission loss coefficient corresponding to \(P_{L,d}\). Generally, the transmission loss is about 3–7% of the total flexible load [24]. In this paper, assuming the transmission loss is 5% of the total flexible load.

The actual power required by \(r\)th unit becomes

\[
P_{L,d} = P_{L,d} + P_{\text{loss,}d}
\]  

(4)

2.2 Constraint

\[
\begin{align*}
\sum P_{R,g} + \sum P_{B,f} + \sum P_{SG,e} + \sum P_{L,d} &= 0 \\
-P_{B,f} &\leq P_{B,f} \leq P_{B,f}^{\max} \\
P_{SG,e} &\leq P_{SG,e} \leq P_{SG,e}^{\max} \\
P_{L,d} &\leq P_{L,d} \leq P_{L,d}^{\max}
\end{align*}
\]  

(5)

where \(P_{SG,e}^{\max}\) and \(P_{SG,e}^{\min}\) are the SG maximum and minimum power for bus \(e\), respectively. \(P_{B,f}^{\max}\) is the battery storage maximum power for bus \(f\). \(P_{L,d}^{\max}\), \(P_{L,d}^{\min}\) are the flexible loads maximum and minimum power for bus \(d\), respectively. \(P_{SG,e}^{\max}\), \(P_{SG,e}^{\min}\) are the renewable energy maximum and minimum power for bus \(g\), respectively. It is worth noting that \(P_{L,d}^{\min}\) is the value of the maximum power point tracking point for distributed renewable generator \(g\).

It is to have the logarithmic function of (5), that is

\[
L(P_r, \lambda) = (-C) + \lambda \Delta P + \sum \mu_i^{\min}(P_i - P_i^{\min}) + \sum \mu_i^{\max}(P_i - P_i^{\max})
\]  

(6)

where \(\Delta P = \sum P_{R,g} + \sum P_{B,f} + \sum P_{SG,e} + \sum P_{L,d}\), \(\mu_i^{\max}\) and \(\mu_i^{\min}\) are the logarithmic multipliers associated with constraint in (5). \(P_i^{\min}\), \(P_i^{\max}\) are the elements lower and upper bounds for the active power set, respectively.

A key concept of distributed solutions for maximise the economic benefits is the incremental cost \(r\). Therefore, the incremental cost function is the derivative of the cost function with respect to the power. When constraints are neglected, the optimal conditions of (6) are given by

\[
\frac{L(P_r, \lambda)}{P_i} = -(a_i P_i + b_i) + \lambda = 0
\]  

(7)

Therefore, the necessary condition for the existence of a minimum-cost operating point is that incremental costs of the whole network must be equal to \(\lambda = r^*\). In this case, the optimal the power \(P_i^*\) is given by

\[
P_i^* = (r^* - b_i)/a_i
\]  

(8)

where \(r^*\) is the optimal incremental cost.

When the constraints are considered, we only need the optimal conditions for \(P_i\) in the following form:

\[
\begin{align*}
(a_i P_i + b_i) &= r_i^* \quad (a_i P_i + b_i < P_i^{\min} < P_i^{\max}) \\
(a_i P_i + b_i) &= r_i^* \quad (a_i P_i + b_i > r_i^* \quad (a_i P_i + b_i > P_i^{\min})
\end{align*}
\]  

(9)

The above analysis shows that to achieve the optimal solutions of problem (1), all units in ADN should hold the same incremental cost. Therefore, the proposed approach updates the node state value by using the CTA diffusion algorithm based on communications between neighbours on the communication graph supporting the power system. Then equal incremental cost control and cooperative optimisation control of source-loads for ADN is realised.
The objective of the network is to estimate $J(T)$ in the term of (3) can be approximated via a second-order Taylor series expansion. The term does not depend on the unknown $\hat{T}$. Therefore, we can ignore it so that optimising $J^{\text{glob}}(T)$ is approximately equivalent to optimising the following alternative cost:

$$J^{\text{glob}}(T) \triangleq \sum_{j \in N_i} c_{j} J_j(T) + \sum_{j \in N_{\setminus \{i\}}} \| T - \hat{T} \|_{F}$$

(14)

where $\Gamma_j = \frac{1}{2} \sum_{j} \nabla^2_{T} J^{loc}(\hat{T})$ is the (scaled) Hessian matrix relative to $T$ and evaluated at $T = \hat{T}$, and the notation $\| a \|_2$ denotes $a^T \Sigma a$ for any weighting matrix $\Sigma$. We have to replace the global cost $J^{\text{glob}}(T)$ by a reasonable localised approximation for every node $k$. Thus, initially we limit the summation on the right-hand side of (14) to the neighbours of node $i$ and introduce the cost function as

$$J^{\text{glob}}(T) \triangleq \sum_{j \in N_i} c_{j} J_j(T) + \sum_{j \in N_{\setminus \{i\}}} \| T - \hat{T} \|_{F}$$

(15)

Now, observe that Hessian matrices are not known beforehand (especially since they depend on the unknown $\hat{T}$). For this reason, we can approximate each $\Gamma_j$ in (15) by a multiple of the identity matrix, say

$$\Gamma_j \approx b_{ij} J_{M}$$

(16)

where $b_{ij}$ is the non-negative coefficient; observe that we are allowing the coefficients $b_{ij}$ to vary with the node index $i$. The approximation (16) is reasonable since in view of the Rayleigh–Ritz characterisation of eigenvalues. We can bound the weighted squared norm $\| T - \hat{T} \|_{F}^2$ by the unweighted squared norm as follows:

$$\lambda_{\text{min}}(\Gamma_j) \cdot \| T - \hat{T} \|_2^2 \leq \| T - \hat{T} \|_{F}^2 \leq \lambda_{\text{max}}(\Gamma_j) \cdot \| T - \hat{T} \|_2^2$$

(17)

Thus, we replace (16) by

$$J^{\text{glob}}_i(T) \triangleq \sum_{j \in N_i} c_{j} J_j(T) + \sum_{j \in N_{\setminus \{i\}}} b_{ij} \| T - \hat{T} \|_2^2$$

(18)

Each node $k$ can apply the steepest-descent iteration to minimise $J^{\text{glob}}(T)$ by moving along the negative direction of gradient (column) vector of the cost function, namely

$$T_{k}(n+1) = T_{k}(n) - \mu_{k} \sum_{j \in N_{\setminus \{i\}}} c_{j} \nabla_{T} J_{j}[T_{k}(n)]$$

(19)

$$-\mu_{k} \sum_{j \in N_{\setminus \{i\}}} 2b_{ij} [T_{k}(n) - \hat{T}]$$

where $T_{k}(n+1)$ denotes the estimate for $T$ at node $i$ at $n$ iteration, and $\mu_k$ denotes a small constant positive step-size parameter. In this paper, we set step-sizes to $\mu_k = 0.0025$ for the incremental algorithm.

Expression (19) adds two terms to the previous estimate, $T_{k}(n)$, in order to update it to $T_{k}(n+1)$. The correction terms can be added one at time in a succession of two steps, for example, as

$$\psi(n) = T_{k}(n) - \mu_{k} \sum_{j \in N_{\setminus \{i\}}} 2b_{ij} [T_{k}(n) - \hat{T}]$$

(20)

$$T_{k}(n+1) = \psi(n) - \mu_{k} \sum_{j \in N_{\setminus \{i\}}} c_{j} \nabla_{T} J_{j}[\psi(n)]$$

(21)

However, an issue arises while examining (21): iteration (20) requires knowledge of the optimiser $\hat{T}$. However, all nodes are
running similar updates to estimate the \( \hat{T} \). By the time node \( i \) wishes to apply (20), each of its neighbours would have performed its own update similar to (21) and would have available their intermediate estimates, \( \{ T_j(n) \} \). There, we replace \( \hat{T} \) in (20) by \( T_j(n) \). Performing the substitution described in item into (22), we obtain

\[
\psi(n+1) = T_j(n) - \mu_j \sum_{j \in N_i(n)} 2b_{ij}[T_j(n) - \hat{T}]
\]  
(22)

Now introduce the coefficients

\[
a_{ij} \triangleq 2\mu b_{ij}(j \neq i), \quad a_i, \triangleq 1 - \nu_i \sum_{j \in N_i} b_{ij}
\]  
(23)

Note that the \( \{a_{ij}\} \) are non-negative for \( j \neq i \) and \( a_{ii} \geq 0 \) for sufficiently small step-size. Moreover, the coefficient \( \{a_{ij}\} \) satisfies

\[
\sum_{j=1}^{n} a_{ij} = 1, \quad a_{ii} = 0 \quad \text{if} \quad j \notin N_i
\]  
(24)

Using (23) in (22), we arrive at the following CTA diffusion algorithm:

\[
\begin{align*}
\psi(n) &= \sum_{j \in N_i} a_{ij} T_j(n) \\
T_j(n+1) &= \psi(n) - \mu_j \sum_{j \in N_i} c_{ij} \nabla J_j[\psi(n)]
\end{align*}
\]  
(25)

To run algorithm (25), we only need to select combination coefficients \( \{a_{ij}, c_{ij}\} \) satisfy (11) and (24), respectively; there is no need to worry about the intermediate coefficients \( \{b_{ij}\} \) any more, since they have been blended into the \( \{a_{ij}\} \). In this paper, we set \( C' = [c_{ij}] = I \) in the CTA diffusion algorithm, namely,

\[
\begin{align*}
\psi(n) &= \sum_{j \in N_i} a_{ij} T_j(n) \\
T_j(n+1) &= \psi(n) - \mu_j \nabla J_j[\psi(n)]
\end{align*}
\]  
(26)

During the optimisation, not all agents necessarily need to be informed. Only conventional fuel SG agents, flexible load agents and energy storage agents have a gradient for the second term of (26). All other agents are uninformed. However, these uninformed agents still have a purpose in disseminating the information across the network by implementing the first term of (26).

To guarantee stability, good adapt and convergence of the diffusion algorithm, the adjacency matrix of weights \( A = \{a_{ij}\} \) was chosen as the following metropolis matrix [28]:

\[
a_{ij} = \begin{cases} 
\frac{1}{\max(n_i, n_j)} + 1 & \text{if } j \in N_i \\
1 - \sum_{i \in N_j} \frac{1}{\max(n_i, n_j)} + 1 & \text{if } i = j \\
0 & \text{otherwise}
\end{cases}
\]  
(27)

where \( n_i, n_j \) are the number of nodes in the neighbourhood of node \( i \) and \( j \), respectively.

3.3 Cooperative optimisation control strategy for ADN based on CTA diffusion algorithm

Since each agent has unique knowledge of its own resource, the cost function and gradient for dispatchable agent \( i \) are only defined as follows:

\[
J_i(T_i) = C(r_i)
\]  
(28)

The non-dispatchable power must be supplied among the dispatchable agents. The total power is included in the optimisation formulation in the following way:

\[
\sum_{i=0}^{n} P_i = 0
\]  
(29)

To keep the equality in (30), after the gradient update by the dispatchable agents in (26), we have

\[
\Delta P_i(n) = \nabla J_i[\psi(n)]
\]  
(31)

Furthermore, we can obtain as follows:

\[
\sum_{i=0}^{n} (P_i + \Delta P_i(n)) + \sum_{j} P_j = 0
\]  
(32)

Diagram of active power calculation of agent \( i \) is shown in Fig. 2. Each agent employs both top-level control and bottom-level control. Since the proposed algorithm is implemented based on the multi-agents framework, each agent can exchange information with its neighbours to complete the determined objective. The proposed algorithm is implemented in the top level to generate the output reference for bottom-level control based on the information from both the local measurement and its neighbour's measurement. The distributed algorithm can guarantee the output power and incremental cost converge to the optimal solution as long as there exist an optimal point and communication network is connected.

4 Simulation experiments analysis

In this paper, the proposed CTA algorithm is tested in the IEEE 14-bus system, as shown in Fig. 3, which contains three schedulable SGs, two battery storage systems (BESS), one non-schedulable PV generator, one non-schedulable WP generation, and seven loads. The parameters of the SGs, loads, PV, WP, and BESS are summarised in Table 1. For the simulation experiment, the controller signal is the quadrature phase shift keying signal under Gauss white noise channel. The baseband symbol transmission rate is 2 kbp. The carrier signal is 10 kHz. The data sampling rate is 50 kHz.

4.1 Performance analysis of CTA diffusion algorithm

To compare the performance of the distributed CTA diffusion algorithm versus the distributed consensus algorithm for coordinating the operation of the source load, we take a hypothetical scenario using the ADN shown in Fig. 3. The communication among agents of Fig. 3 can be independent from the physical bus connections. In this paper, the agents are assumed to communicate with adjacent agents. Therefore, the communication channel set is
$E = \{(k - 2, k), (k - 1, k), (k, k + 1), (k, k + 2) | 3 \leq k \leq 12\} \\
\cup \{(14, 1), (13, 1), (14, 2), (13, 2)\}

Convergence curve of the CTA diffusion algorithm and consensus algorithm is shown in Fig. 4. As shown in Fig. 4, iteration times of the CTA diffusion algorithm convergence to equal incremental cost value is 17, while the consensus algorithm need to be about 45. It can be seen that the convergence rate of the CTA diffusion algorithm is obviously more quickly than the consensus algorithm. So, the CTA diffusion algorithm is more suitable for information diffusion in distributed network, which can improve the convergence rate of network and the detection efficiency of agent nodes, and achieve faster frequency response for ADN.
verified that the proposed distributed algorithm can obtain the results greater than consensus algorithm and PSO algorithm of centralised control.

4.2 The dynamic performance analysis

To demonstrate the dynamic performance of the proposed control strategy in real time, an experimental study has been performed on the reconfigurable power system. The experimental parameters of the system are same as the simulation model. Here, the implement agent simulates the distributed communication infrastructure. Consequently, the power points of the distributed energy sources are adjusted to their economic dispatch points through the CTA diffuse algorithm.

Fig. 5 illustrates the experimental performance of the proposed cooperation control strategy to accommodate time-varying load for ADN. In this study, the load demand has been changed thrice: (i) at time $T=20$ s, node 4 increased a load, and its parameter is the same with the load $L_{10}$; (ii) at time $T=40$ s, node 5 increased a load, and its parameter is the same with the load $L_{14}$; (iii) at time $T=60$ s, the increased load at time 20 and 40 s was removed from the system. During the experiment, the two BESS was the discharge state, and their state of charge was within the maximum and minimum. The system responds automatically to change in the load demand converging to a new solution.

As shown in Fig. 5, after time $T=20$ s, the SG1, SG2 and SG3 output active power increased from 31.568, 41.465, 34.205 kW to 37.171, 51.659, 42.544 kW, respectively; the storage battery BESS13 and BESS7 output active power increased from 8.160, 11.132 kW to 10.527, 15.766 kW, respectively; the incremental cost converges to 6.869 ($/kW\cdot h$). It can be seen that power generation cost of the SG2 is least in all agents, which results in it most power increase. Power generation cost of the SG1, BESS7, and BESS13 are highest in the system, which leads to their least increased active power output. Therefore, the maximisation of economic benefit for ADN is realised. Moreover, after time $T=40$ s, the SG1, SG2 and SG3 output active power increased to 41.325, 53.593, 55.839 kW, power output of storage battery BESS13 and BESS7 increased to 11.633 and 17.645 kW, and the incremental cost converges to 7.036 ($/kW\cdot h$). It can be seen that the SG2 increased output active power is largest in the system. The maximisation of economic benefit for ADN is realised. Moreover, after time $T=60$ s, the increased load at time 20 and 40 s was removed. The SG1, SG2, SG3, BESS7 and BESS13 output active power recovered start value. WP and PV output active power were hardly changed after increased load at 20 and 40 s. Although, the WP and PV output active power decreases when the increased load
was removed at 60 s, they quickly recovered the maximum power point. In the statistical period, the maximum and the minimum frequency of the system is 50.31 and 49.86 Hz, respectively, and the fluctuation range of voltage is 0.90–1.10 (pu). Requirements are satisfied. Therefore, the proposed CTA diffusion algorithm can effectively solve the problem of real-time detection signal and can quickly learn and adapt to environmental changes. Besides, the cooperative operation of source-loads and maximisation of the ADN economic benefits is realised.

5 Conclusion
This paper proposed a distributed cooperative optimisation control strategy based on CTA diffusion algorithm to solve the cooperative operation problem of dispatchable and non-dispatchable distributed energy. Optimal solution is obtained by the multi-agent network via exchanging and processing local information. All of the incremental cost of multi-agent can converge to the common value by using CTA diffusion algorithm. Then cooperative operation of the source loads and maximisation of economic benefits are realised by optimised dispatching the active power of ADN. Better economic benefit is obtained by CTA diffusion algorithm compared with consensus algorithm and PSO algorithm of centralised control. Finally, through the simulation analysis and experimental results of IEEE14-bus distribution test, it can be proved that distributed cooperative control method based on the CTA algorithm can effectively solve the cooperative operation between source load for ADN and the problem of real-time detection signal, and the optimisation of the whole process of the system can be achieved.

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