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Short Communication

Distributed auction optimization algorithm for the nonconvex economic dispatch problem based on the gossip communication mechanism

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ABSTRACT

This paper presents an efficient distributed auction optimization algorithm (DAOA) based on the gossip communication mechanism for the nonconvex economic dispatch problem. The problem contains several constraints such as generation output limits, valve-point loading effects, multiple fuels, and the supply-demand balance. The gossip communication mechanism runs as two layers. The first layer triggers the leaders to conduct the local auction optimization, and the second layer is the auction protocol that selects the optimal neighbors to cooperate with the leaders to implement the auction decision. Auction optimization is a local optimization method, in which the units evaluate the bids of a certain amount of output power and the paired bid winners update their output power to reduce the generation cost. Better solutions can be obtained through gossip communication and local optimizations. Numerous simulations are conducted to demonstrate the effectiveness of the proposed strategy.

1. Introduction

The economic dispatch problem is a fundamental optimization problem in power systems. The goal of the problem is to optimize the combination of the units output power to reduce the total generation cost while meeting the constraints total load demand and generator constraints [1]. Considerable methods for solving the economic dispatch problem, such as the lambda-iteration method [2], the gradient search method [3], the quadratic programming [4] have been proposed. These mathematical programming techniques require the derivable cost function as the quadratic form. Nevertheless, the cost characteristics of generating units are nonconvex because of the valve-point loading effects [5], and multiple fuels [6]. Thus, the essentially nonconvex optimization problem cannot be directly solved by the above mentioned algorithms. The dynamic programming [7] could handle the problem, but the curse of dimensionality limits the feasibility of the method. Intelligent algorithms are the most efficient techniques to solve nonconvex optimization problems. They mainly include the genetic algorithm (GA) [8,9], the particle swarm optimization (PSO) [10], the simulated annealing algorithm (SA) [11], and several other algorithms [12,13]. The nonconvex optimization problem can be resolved by providing a center node to collect the global information of all generators and to control the optimization. However, several main drawbacks make these algorithms unsuitable for application in the future power grid (smart grid). First, the centralized controller requires high bandwidth communication infrastructures and a high level of connectivity, and it is sensitive to the single point of the failure and modeling error [14–16]. Second, the future power grid and the communication network tend to have a variable topology, which significantly reduces the efficiency of the algorithms. Furthermore, the plug-and-play requirement of the smart grid [17,18] is difficult to satisfy in a central fashion.

In a smart grid, the economic dispatch problem must be solved in distributed ways [19]. On the one hand, the distributed algorithms can fully utilize the sparse communication topology and limited communication infrastructures, because every unit only requires communicating with its neighbors. On the other hand, distributed algorithms can cope with the problems of a variable topology network. The distributed incremental cost consensus algorithm [20,21] which needs the units to control their incremental cost to a common value in a distributed manner. Similarly, the distributed gradient methods [22] also have been studied thoroughly. Nonetheless, these iterative algorithms require convex quadratic cost functions. The projected gradient and finite-time

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Nomenclature

$\alpha_i, \beta_i, \gamma_i, \varepsilon_i, \varphi_i$	the coefficients of cost function for generation unit i
ΔP	power mismatch between the load and total output power
ε	error limit of the power mismatch
dec_k	reference cost of power decreasing
$f(p)$	the total cost function of all the generation units
$f_i(p_i)$	the cost function of generation unit i with output power p_i
inc_k	reference cost of power increasing
$l = [l_1, l_2, \ldots, l_n]^T$	lower limits for output power of generation units 1,2,…,n
$ldec_k$	total cost reduction when leader' power output decreasing while followers' power output increasing
$linc_k$	total cost reduction when leader' power output increasing while followers' power output decreasing
N_i	the neighbors set of the unit i
$p = [p_1, p_2, \ldots, p_n]^T$	output power of generation units 1,2,…,n
P_D	the system load
s	a random amount of power designed by the leaders
scale	a parameter to control s
$u = [u_1, u_2, \ldots, u_n]^T$	upper limits for output power of generation units 1,2,…,n

average consensus algorithms [23] can be applied to a heterogeneous system with thermal generators and wind turbines, but the convex characteristic modeling is still necessary.

Several distributed algorithms [24,25] have been proposed to solve the nonconvex economic dispatch problem. An optimization technique in [24] based on market rules and multi-agent systems was applied to the problem, and a relatively flexible solution search space was permitted with the improvement of multiple steps. [25] proposed a composite algorithm combining a meta-heuristic technique and a flooding-based consensus algorithm that could solve the nonconvex problem in a decentralized manner. However, both the optimization approaches required the units to reach the consensus on certain states at each iteration, such as the best bid evaluations [24] and the collected information of units [25]. The process of information spreading, collecting, and updating for the system consensus are usually time consuming and may lead to certain complexity in the applications. The plug-and-play characteristic of the smart grid was not discussed in both works. In our paper, a distributed auction optimization algorithm based on the gossip communication mechanism [26,27] is presented to solve the nonconvex economic dispatch problem. The gossip communication mechanism runs as two layers. The first layer triggers the leaders to conduct the local auction optimization, and the second layer is the auction protocol that selects the optimal neighbors to cooperate with the leaders to implement the auction decision. The auction protocol is a method of optimization, in which units evaluate the bids of a certain amount of output power and the paired bid winners update their output power to reduce the generation cost. The iterative communication and local optimization produce better solutions. The following are the contributions of our work.

1. The nonconvex economic dispatch problem considering the valve-point loading effects and multiple fuels is solved in a fully distributed way. The plug-and-play requirement of smart grid can be well satisfied.
2. The proposed algorithm doesn't require any system consensus process compared with the proposed one in [24,25]. Such an advantage has reduced the consensus computation burden for units.

The rest of this paper is organized as follows. The nonconvex economic dispatch problem is formulated in Section 2. Section 3 illustrates the proposed distributed method. In Section 4, numerical simulation tests are conducted to verify the efficiency of the method and the results are also showed to clarify some key factors affecting the algorithm, and the plug-and-play characteristic is also simulated. Conclusions are given in Section 5.

2. Problem formulation

The economic dispatch problem minimizes the total generation cost $f(p)$ which is the sum of the generation cost $f_i(p_i)$ of unit i given below.

$$\min f(p) = \sum_{i=1}^{n} f_i(p_i), \tag{1}$$

subject to

$$\sum_{i=1}^{n} p_i = P_D, \tag{2}$$

$$l_i \leqslant p_i \leqslant u_i, \quad i = 1, 2, \ldots, n, \tag{3}$$

where P_D denotes the system load demand, and $p_i(p = [p_1, p_2, \ldots, p_n]^T), l_i(l = [l_1, l_2, \ldots, l_n]^T), u_i(u = [u_1, u_2, \ldots, u_n]^T)$ is the actual output power, lower power bound and upper power bound of generator unit i. The generation cost $f_i(p_i)$ is conventionally expressed in the following quadratic form [3].

$$f_i(p_i) = \alpha_i p_i^2 + \beta_i p_i + \gamma_i, \tag{4}$$

where $\alpha_i, \beta_i, \gamma_i$ are the cost coefficients of generator unit i. Eq. (2) represents the supply-demand balance constraint, in which the total output power $\sum_{i=1}^{n} f_i(p_i)$ of all units has to meet the power demand P_D.

However, the actual unit cost function is usually nonconvex. The generator cost function is usually obtained from data points taken during "heat run" tests, when input and output data are measured as the unit is slowly varied through its operating region. Wire drawing effects, occurring as each steam admission valve in a turbine starts to open, produce a rippling effect on the unit curve [6]. The practical cost model of generating units must conclude the valve-point effects for accurate analysing, and the expression (4) should be reformulated as below:

$$f_i(p_i) = \alpha_i p_i^2 + \beta_i p_i + \gamma_i + \mid \varepsilon_i \sin(\varphi_i((l_i - p_i))) \mid, \tag{5}$$

where ε_i and φ_i are the cost coefficients of ith generator with the valve-point loading effects. The generating units are usually supplied with multiple fuel sources, so the cost function of the units should be represented with several piecewise quadratic functions [2]. Once the valve-point loading effects and multiple fuels option are considered, the exact cost model of generating units is formulated as below.

$$f_i(p_i) = \begin{cases} \alpha_i p_i^2 + \beta_i p_i + \gamma_i + \mid \varepsilon_i \sin(\varphi_i((l_i - p_i))) \mid, & \text{for fuel } 1, l_i \leqslant p_i \leqslant p_{i1}, \\ \alpha_i p_i^2 + \beta_i p_i + \gamma_i + \mid \varepsilon_i \sin(\varphi_i((l_i - p_i))) \mid, & \text{for fuel } 2, p_{i1} < p_i \leqslant p_{i2}, \\ \ldots & \\ \alpha_i p_i^2 + \beta_i p_i + \gamma_i + \mid \varepsilon_i \sin(\varphi_i((l_i - p_i))) \mid, & \text{for fuel } k, p_{i(k-1)} < p_i \leqslant u_i. \end{cases} \tag{6}$$