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Economic dispatch optimization algorithm based on particle diffusion

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ABSTRACT

Due to the widespread installation of emissions control equipment in fossil fuel-fired power plants, the cost of emissions control needs to be considered, together with the plant fuel cost, in providing economic power dispatch of those units to the grid. On the other hand, while using wind power decreases the overall power generation cost for the power grid, it poses a risk to a traditional grid, because of its inherent stochastic characteristics. Therefore, an economic dispatch optimization model needs to consider all of the fuel cost, emissions control cost and wind power cost for each of the generating unit conforming the fleet that meets the required grid power demand. In this study, an optimization algorithm referred as diffusion particle optimization (DPO) is proposed to solve such complex optimization problem. In this algorithm, Brownian motion theory is used to guide the movement of particles so that the particles can search for an optimal solution over the entire definition region. Several benchmark functions and power grid system data were used to test the performance of DPO, and compared to traditional algorithms used for economic dispatch optimization, such as, particle swarm optimization and artificial bee colony algorithm. It was found that DPO has less probability to be trapped in local optimums. According to results of different power systems DPO was able to find economic dispatch solutions with lower costs. DPO was also used to analyze the impact of wind power risk and fossil unit emissions coefficients on power dispatch. The result are encouraging for the use of DPO as a dynamic tool for economic dispatch of the power grid.

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1. Introduction

Economic dispatch provides an avenue to power generators to provide electricity at a minimum cost. Initially, fuel cost was the main variable considered in economic dispatch [1]. With the advent of environmental regulations, power generating unit emissions were introduced and used as part of the cost function for economic dispatch. Economic dispatch became then a multi-objective problem to minimize cost and emissions [2-8]. In addition, grid security and power transmission line losses have been considered as a constraint in the economic dispatch optimization problem [9– 11]. Most recently, due to the introduction and now widely use of renewable energy, wind power has also begun to be taken into account [12] in economic dispatch. The cost of wind power includes the direct cost of wind power purchasing from wind farm operators, the penalty cost for wind power underestimation, and the reserve cost for overestimation of available wind power. In [13], the impact of overestimation and underestimation of available wind power were considered in terms of economic and environmental aspects. Estimation of wind power has been typically obtained using probability distribution functions (PDFs) [14,15]. Additionally, the risk caused by the uncertain characteristic of wind power has also been also taken into consideration in economic dispatch [16]. In Ref. [17], a mean–variance that simultaneously considers the profit and risk in economic dispatch was built. Additionally, chance-constrained stochastic programming [18], Monte Carlo techniques [19,20], and Latin hypercube sampling with Cholesky decomposition [17,21] have been used to deal with the uncertain nature of wind power. What is evident, throughout all of this body of work, is that the economic dispatch problem has become a complex optimization problem, which is difficult to solve by mathematical methods directly.

In the past decades, many heuristic search-based methods were applied to solve the complex power dispatch problem, example of those are simulated annealing (SA) [22], genetic algorithms (GA) [23], differential evolution algorithms (DE) [24,25], evolutionary programming (EP) [26,27], tabu search (TS) [28], artificial immune systems (AIS) [29], artificial bee colony algorithms (ABC) [30,31], bacterial foraging algorithms (BFA) [32], biogeography-based optimization (BBO) [33], particle swarm optimization (PSO) [34], firefly algorithms (FA) [35], honey-bee mating optimization (HBMO) [36],







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ant colony optimization (ACO) [37], and harmony search (HS) [38]. To improve the searching performance of these methods, some modified algorithms derived from their original version have also been proposed, including improved genetic algorithms [39], improved differential evolution algorithms [40], differential real-coded quantum-inspired evolutionary algorithms [41], adaptive chaotic artificial bee colony algorithms [42], modified artificial bee colony algorithms [42], modified artificial bee colony algorithms [45], bare bones particle swarms [46], chaotic particle swarm optimization [47], and quantum-inspired particle swarm optimization [48].

Recent studies specifically focus on hybrid algorithms. One of these hybrid algorithms is the Gbest guided artificial bee colony algorithm, which is a hybrid of ABC and PSO. Gbest was applied to optimize the emissions and cost of wind-thermal power system [49] and to solve optimal power flow problems [50]. Another example of a hybrid approach, aiming at enhancing the local and global search capabilities of the basic GA, is a modified genetic algorithm based on extreme learning machine, which was proposed and applied in the power system economic dispatch problem of Ref. [51]. Hybrid fuzzy adaptive PSO with variable DE (FAPSO-VDE) [52], Hybrid bare-bones particle swarm optimization (BBPSO) with directionally chaotic search (DCS) [53], Hybrid PSO with fuzzy theory [54,55], and Hybrid PSO with bacterial foraging [56] and DE [57] have been also proposed to solve the economic dispatch problem.

Among these algorithms, approaches based on PSO and ABC have been more widely studied, due to their high convergence speed and simple implementation procedure. However, even if these algorithms can find optimal solutions on a fast and accurate fashion, they all have a high probability to be trapped into a "local best" solution. These "local best" solutions if applied to a power grid application, would cause great financial losses. Inspired from the Brownian diffusion motion of particles, a global searching algorithm for optimization of economic power dispatch, called diffusion particle optimization (DPO), was developed and reported in this paper. The rest of the paper is organized as follows: Section 2 provides the mathematical formulations used to model economic dispatch, Section 3 provides procedure description of the algorithm of diffusion particle optimization (DPO), Section 4 presents solutions and optimization test results of for several benchmark functions and economic dispatch results applied to several grid system data.

2. Mathematical model for economic dispatch considering unit emissions and wind power

2.1. Cost function

A cost function that represents the contributions from the different elements to be considered in an economic dispatch optimization is given by Eq. (1). Eq. (1) is for the particular case of economic dispatch of a power generation fleet made of fossil fuel-fired units and wind power generators,

$$C = \sum_{i=1}^{n} F_i + \sum_{i=1}^{n} E_i + \sum_{i=1}^{m} R_i$$
(1)

where, *C* is the overall cost, *F* is the fuel cost, which depends on the power output and efficiency of the plant. *E* is the emissions control cost, which depends on the fuel type, different emissions control equipment unit power output, and unit operating conditions. *R* is the cost of wind power, which depends on the type of wind turbine, and the particular weather conditions to the wind farm. Finally, *n* is the number of fossil fuel-fired power plants, while *m* is the number of wind turbines.

2.1.1. Fuel cost

There are three different types of total fuel cost (h) functions which have been defined in the literature [50]. These functions are displayed in Eqs. (2)–(4):

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |d_i \sin(f_i(P_{Gi,min} - P_{Gi}))|$$
(3)

$$F_{i}(P_{i}) = \begin{cases} a_{i1}P_{i}^{2} + b_{i1}P_{i} + c_{i1} & P_{Gi,min} \leqslant P_{Gi} \leqslant P_{Gi1} \\ a_{i2}P_{i}^{2} + b_{i2}P_{i} + c_{i2} & P_{Gi1} \leqslant P_{Gi} \leqslant P_{Gi2} \\ & \dots \\ a_{ih}P_{i}^{2} + b_{ih}P_{i} + c_{ih}, & P_{Gih-1} \leqslant P_{Gi} \leqslant P_{hi,max} \end{cases}$$
(4)

where a_i , b_i , c_i , d_i , f_i are the cost coefficients of unit *i*, and a_{ik} , b_{ik} , c_{ik} are the fuel cost coefficients of *i*th thermal unit for fuel type *h*.

Eqs. (2)–(4) are named quadratic, quadratic with value point loading effects and piecewise quadratic, respectively.

2.1.2. Emissions cost

The total ton/h of emission of atmospheric pollutants, such as sulfur oxides (SO_x) and nitrogen oxides (NO_x) produced by fossil fuel-fired thermal units can be expressed by [4]:

$$e_i(P_i) = \sum_{i=1}^N 10^{-2} (\alpha + \beta_i P_i + \gamma_i P_i^2) + \xi_i \exp(\lambda_i P_i)$$
(5)

where α_i , β_i , γ_i , ξ_i , λ_i are the emission coefficients of unit *i*, which depends on boiler type, operating conditions, and fuel type. $e_i(P_i)$ is the corresponding emissions from *i*th unit.

Using Eq. (5), the overall emissions from the power generating unit can obtained. Minimizing stack emissions is regarded as another optimization objective by many researches [4–8]. Nowadays, most of the fossil fuel-fired power plants, particularly coal-fired boilers install emissions control equipment to reduce pollutant discharge at the stack. The emissions control cost should be considered. A simplistic way to consider this cost is to assume that is proportional to the emissions level, as displayed in Eq. (6):

$$E_i(P_i) = E_{ei}e_i(P_i) \tag{6}$$

where E_{ei} (\$/ton) is the emissions control cost coefficient of the *i*th unit, and it depends on emissions control equipment, control method, and fuel type. This cost also includes equipment acquisition cost, installation cost and operation and maintenance cost.

2.1.3. Wind power cost function

Classical wind power cost functions have been suggested by many researchers [14,15,48,50]. The form of this function is given in Eq. (7):

$$R_{i}(w_{i}) = C_{wi}(w_{i}) + C_{ui}(W_{i,av} - w_{i}) + C_{oi}(w_{i} - W_{i,av})$$
(7)

where $C_{wi}(w_i)$ represents the production cost of *i*th wind generator. Although the wind energy conversion system has a low cost, the operation and maintenance cost of the wind turbine cannot be ignored. $W_{i,av}$ is the available power of the *i*th wind power generator. w_i is the actual output power of the *i*th wind power generator. C_{ui} is the penalty cost coefficient for not using all available power from the *i*th wind power generator. C_{oi} is the required reserve cost coefficient, related to the uncertainty of the potential wind power. The second and third terms in Eq. (7) represent the penalty cost brought from underestimation and overestimation of wind power.

Probability density functions or PDFs have been used by other researchers [14] together with fuzzy theory [12] to estimate available wind power W_{av} . Factors such as weather information and turbine parameters are used to obtain the PDF, including wind speed,

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