Electrical Power and Energy Systems 49 (2013) 399–407

Contents lists available at SciVerse ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Dynamic environmental economic dispatch using multiobjective differential evolution algorithm with expanded double selection and adaptive random restart

Xingwen Jiang [a,b], Jianzhong Zhou [a,b,*], Hao Wang [c], Yongchuan Zhang [a,b]

[a] School of Hydropower & Information Engineering, Huazhong University of Science and Technology, Wuhan 430074, PR China
[b] Hubei Key Laboratory of Digital Valley Science and Technology, Huazhong University of Science & Technology, Wuhan 430074, PR China
[c] China Institute of Water Resources and Hydropower Research, Beijing 100044, PR China

A R T I C L E I N F O

Article history:
Received 26 August 2012
Received in revised form 29 November 2012
Accepted 24 January 2013
Available online 15 March 2013

Keywords:
Dynamic economic emission dispatch
Multiobjective differential evolution
Expanded double selection
Adaptive random restart
Dynamic heuristic constraint handling

A B S T R A C T

The dynamic environmental economic dispatch (DEED) model is presented in this paper, in which the fuel cost and emission effect over a certain period of time are optimized as conflicting objectives. It is a high dimensional, nonlinear constrained multiobjective optimization problem when generators' valve point effect, ramp rate limits and power load variation are considered. This paper proposes a modified adaptive multiobjective differential evolution (MAMODE) algorithm to solve the problem. In MAMODE, expanded double selection and adaptive random restart operators are proposed to modify the evolutionary processes for avoiding premature and a dynamic heuristic constraint handling (DHCH) approach is introduced to deal with the complicated constraints. The DHCH can lessen infeasible solutions gradually. To illustrate the effectiveness of the method, four cases based on three test power systems are studied. The simulation result indicates that the DEED can be solved quickly. Comparison of numerical results demonstrates the proposed method has higher performance.

1. Introduction

Power system optimal operation needs accurate load forecasting, suitable unit commitment and scientific power load allocation. Generally, power load allocation is operated based on the previously determined unit commitment and predicted load curve; it is usually classified as economic dispatch (ED) [1–5] and dynamic economic dispatch (DED) [6–11] according to the division of schedule period. In the past decades, environmental pollution has received more and more attention. The Clean Air Act Amendments of 1990 [12] have forced the electric power industry to reduce pollution emissions. In addition to installing emission reduction equipment, emission dispatch is an effective alternative choice. Therefore, the economic emission dispatch (EED) model optimizing the fuel cost and emission simultaneously have been intensively studied in the past years [13–19]. However, the EED is a static model which does not consider the generators' ramp rate limits and cannot ensure the global optimization from the whole schedule horizon. In view of the importance of DED and EED as well as their respective shortcomings, the coupling model called dynamic economic emission dispatch (DEED) should be studied. However, there are little literatures for this problem. DEED serves to schedule the generators' outputs over the whole dispatch period with the consideration of multiple objectives, generators' ramp rate limits and power load variation. So it is closer to the practical but it is more difficult to be solved because of the high-dimensional and multiple objectives. If considering the nonlinear factors of power losses, valve point effect and prohibited operating zones further, the problem would be more complicated.

The DEED can be simplified by treating the emission as a constraint and minimizing the fuel cost. However, the emission constraint scope is unclear before. If the trade-off curve between emission and fuel cost is convex, the solution with the minimum fuel cost must locate at the boundary of the emission constraint scope. In this situation, the model equals to the DED and the result is not conducive to scientific decision making. In the recent years, to simplify the problem, weight method [20,21], fuzzy satisfying method [22] and price penalty factor [23] are employed respectively to convert the model into a single objective optimization problem. All of these methods have achieved good results, but only one solution can be obtained after the program run once and the true non-inferior solutions are hard to get. The problem can also be simplified by converting into a series of static EED according to the dispatch period dividing [24]. However, there are many non-dominated solutions for each EED. How to combine these solutions at each interval into complete solutions of the whole dispatch period is a complicated problem. Furthermore, the combined solution may not be global optimization from the perspective of the whole dispatch horizon. In addition to these literatures, the DEED model

* Corresponding author at: Hubei Key Laboratory of Digital Valley Science and Technology, Huazhong University of Science & Technology, Wuhan 430074, PR China. Tel.: +86 27 8754 3127.

E-mail address: jz.zhou@hust.edu.cn (J. Zhou).

0142-0615/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ijepes.2013.01.009

is solved as a true multiobjective problem by using NSGA-II and good results are obtained in [25]. However, due to lack of efficient constraint handling and global search ability, the Pareto front obtained is not distributed widely enough. To date, no other methods can solve the problem efficiently.

Differential evolution (DE) is a powerful algorithm developed by Storn and Price [26] which could achieve good results in both single objective optimization and multiobjective optimization [27–33]. However, it shows premature convergence in solving some complicated problems. In this paper, a modified adaptive multiobjective differential evolution algorithm (MAMODE) is proposed to solve the DEED problem. For avoiding the premature, the evolutionary operators of DE are modified and expanded to strengthen the global search ability. According to the feature of constraints, an effective dynamic heuristic constraint handling (DHCH) approach is presented and embedded into MAMODE to deal with the infeasible solutions. Fast nondominated sorting and external archive strategies are used to select and preserve elite solutions along the evolution, respectively. To verify the effectiveness of the proposed method in solving DEED, four simulation examples are studied based on three power systems. The numerical result shows that the DEED can be well solved quickly.

The rest of this paper is organized as follows: Section 2 presents the problem formulation. Related works and key points of MAMODE are described in Section 3. In Section 4, the proposed method using MAMODE to solve DEED is given. Four cases based on three power systems are studied and the simulation results are discussed in Section 5. The conclusion is summarized in Section 6 followed by an acknowledgement.

2. Problem formulation

2.1. Objectives

2.1.1. Minimization of fuel cost

For each generating unit, the fuel cost of a generating unit considering valve-point effect can be modeled as the sum of a quadratic and a sinusoidal function. The total fuel cost (FC) over the whole dispatch period is expressed as

$$\min \quad \mathrm{FC} = \sum_{t=1}^{T}\sum_{i=1}^{N}[a_i + b_i P_{i,t} + c_i(P_{i,t})^2 + |d_i \sin(e_i(P_{i,\min} - P_{i,t}))|] \tag{1}$$

where T is the number of intervals in the dispatch period; N is the number of generating units; $P_{i,t}$ is the power output of ith generating unit at interval t; $P_{i,\min}$ is the lower output limit for ith generating unit; a_i, b_i, c_i, d_i, and e_i are the coefficients of fuel cost function for the ith generating unit.

2.1.2. Minimization of emission

The main atmospheric pollutants of power system caused by fossil-fueled generators are SO_x, NO_x and CO_2. The emission of each pollutant can be modeled separately. In this paper, the emission of a generating unit is modeled as the sum of a quadratic and an exponential function. The total emission (EM) over the whole dispatch period is expressed as

$$\min \quad \mathrm{EM} = \sum_{t=1}^{T}\sum_{i=1}^{N}[10^{-2}(\alpha_i + \beta_i P_{i,t} + \gamma_i(P_{i,t})^2) + \eta_i \exp(\delta_i P_{i,t})] \tag{2}$$

where α_i, β_i, γ_i, η_i, and δ_i are the coefficients of emission function of the ith generating unit.

2.2. Constraints

(1) Generator capacity constraints

$$P_{i,\min} \leqslant P_{i,t} \leqslant P_{i,\max}, \quad (i = 1,2,\ldots,N; t = 1,2,\ldots,T) \tag{3}$$

where $P_{i,min}$, $P_{i,max}$ are the lower and up generation output limit of the ith generating unit.

(2) Real power balance constraints

$$\sum_{i=1}^{N} P_{i,t} - P_{L,t} - P_{D,t} = 0, \quad (t = 1,\ldots,T) \tag{4}$$

where $P_{D,t}$ and $P_{L,t}$ are the load demand and power loss at interval t, respectively. The exact value of $P_{L,t}$ can be determined by a power flow solution, but the most popular approach for finding an approximate value is by the way of Kron's loss formula:

$$P_{L,t} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{i,t} B_{ij} P_{j,t} + \sum_{i=1}^{N} P_{i,t} B_{i0} + B_{00}, \quad (t = 1,\ldots,T) \tag{5}$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} and B_{00} are ith element of the loss coefficient vector and the loss coefficient constant, respectively.

(3) Generators' ramp rate limits

$$\begin{cases} P_{i,t} - P_{i,t-1} \leqslant UR_i \cdot \Delta t \\ P_{i,t-1} - P_{i,t} \geqslant DR_i \cdot \Delta t \end{cases}, \quad (i = 1,2,\ldots,N;\ t = 1,2,\ldots,T) \tag{6}$$

where UR_i and DR_i are the ramp up and down rate limits of ith generating unit, respectively, Δt is the length of each time interval.

2.3. Mathematical model

Aggregating the objectives and constraints listed above, the DEED problem can be formulated as a nonlinear constrained multiobjective optimization problem (MOP). Without loss of generality, the MOP can be described mathematically as follows [34]:

$$\begin{aligned} \min \quad & \boldsymbol{y} = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_k(\boldsymbol{x})) \\ \text{s.t.} \quad & g_i(\boldsymbol{x}) = 0, \quad i = 1,2,\ldots,p \\ & h_j(\boldsymbol{x}) \leqslant 0, \quad j = 1,2,\ldots,q \end{aligned} \tag{7}$$

where $\boldsymbol{x}$ is a decision vector which represents a solution of the problem; $\boldsymbol{y}$ is the objective function vector with k objectives; $f_i(\boldsymbol{x})$ is the ith objective function; p and q are the numbers of equality and inequality constraints, respectively.

The purpose of MOP is exploring the relationship among the involved conflicting objectives and providing decision support. A MOP gives rise to a set of Pareto optimal solutions instead of one optimal solution. The concept of Pareto optimal is based on the definition of "dominate". For a minimization MOP, a solution $\boldsymbol{x}_1$ dominates $\boldsymbol{x}_2$ (written as $\boldsymbol{x}_1 \prec \boldsymbol{x}_2$) if and only if the following two conditions satisfied: (1) $\forall i \in \{1, 2, \ldots, k\}$: $f_i(\boldsymbol{x}_1) \leqslant f_i(\boldsymbol{x}_2)$ and (2) $\exists j \in \{1, 2, \ldots, k\}$: $f_i(\boldsymbol{x}_1) < f_i(\boldsymbol{x}_2)$. In general, the solution which is not dominated by any other solution is called nondominated or Pareto optimal solution. The set of all nondominated solutions is called Pareto optimal set, the corresponding set in objective space is called Pareto optimal front (POF).

3. Related works and key points of MAMODE

3.1. Classic differential evolution

DE starts from a random initialized population $\boldsymbol{P}$ which comprises of N_p floating-point encoded individuals. Each individual $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ is a vector containing t decision variables. DE