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# A modified differential evolution approach for dynamic economic dispatch with valve-point effects

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ABSTRACT

Dynamic economic dispatch (DED) plays an important role in power system operation, which is a complicated non-linear constrained optimization problem. It has nonsmooth and nonconvex characteristic when generation unit valve-point effects are taken into account. This paper proposes a modified differential evolution approach (MDE) to solve DED problem with valve-point effects. In the proposed MDE method, feasibility-based selection comparison techniques and heuristic search rules are devised to handle constraints effectively. In contrast to the penalty function method, the constraints-handling method does not require penalty factors or any extra parameters and can guide the population to the feasible region quickly. Especially, it can be satisfied equality constraints of DED problem precisely. Moreover, the effects of two crucial parameters on the performance of the MDE for DED problem are studied as well. The feasibility and effectiveness of the proposed method is demonstrated for application example and the test results are compared with those of other methods reported in literature. It is shown that the proposed method is capable of yielding higher quality solutions.



## 1. Introduction

Dynamic economic dispatch (DED) is one of the important optimization problems in power system operation, which is used to determine the optimal combination of power outputs of all generating units to minimize the total fuel cost while satisfying various constraints over the entire dispatch periods. Traditionally, the cost function for each generator has been approximately represented by a single quadratic function and the valve-point effects were ignored in the DED problem. This would often lead inaccuracy to the resulting dispatch. The DED problem with valve-point effects is represented as a nonsmooth optimization problem having complex and nonconvex characteristics with many constraints, which makes the challenge of finding the global optimum hard.

Many methods have been developed to solve the DED problem in the past decades. The major methods include linear programming (LP) [1], non-linear programming algorithm (NLP) [2,3], quadratic programming algorithm (QP) [4,5] and Lagrangian relaxation algorithm (LR) [6,7]. These methods were facing problems to give optimal solution due to the non-linear and nonconvex characteristics of generating units. It would generate large errors to use LP to linearize the DED model; For QP and NLP, the objective function should be continuous and differentiable. LR algorithm would lead to the phenomenon of solution oscillation. Dynamic programming is a method that can solve the DED problem without imposing any restrictions on the nature of the cost curves [8]. However, this method suffers from the "curse of dimensionality" leading to high computational cost.

Modern heuristics stochastic optimization techniques such as tabu search (TS) [9], particle swarm optimization (PSO) [10,11], Hopfield neural networks (HNN) [12,13], simulated annealing (SA) [14], genetic algorithm (GA) [15–17] and evolutionary program (EP) [18–20] appear to be efficient in solving DED problem without any restriction on the shape of cost curves due to their ability to seek the optimal solution. Although these heuristic methods do not always guarantee the globally optimal solution, they generally provide a reasonable solution, which is suboptimal nearly the global optimal. But these methods have some drawbacks: An unsuitable transfer function adopted in the HNN model may suffer from excessive numerical iterations, resulting in huge calculations; SA algorithm is difficult to tune the related control parameters of the annealing schedule and may be too slow when applied to solve DED problem; The premature convergence of GA degrades its performance and reduces its search capability that leads to a higher probability toward obtaining a local optimum for DED problem; At the same time, the encoding and decoding schemes essential in the GA approach makes it to take longer time for convergence. The DED results obtained from EP are occasionally just near the global optimum; One main disadvantage of the EP for

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solving DED problems is its slow convergence to a good near optimal.

More precisely, hybrid methods combining stochastic optimization and deterministic methods are found to be effective in solving complex optimization problems. In these methods, initially stochastic optimization methods are used for search purpose to find near optimal solution then deterministic methods are used for fine tune that region to get the final solution. Hybrid evolutionary program and particle swarm optimization (PSO) combined with sequential quadratic programming (SQP) [21,22] have been used to solve DED problem because they can achieve global optimal solution and overcome the nonconvexity problems of the DED. Major problem associated with these algorithms is appropriate control parameters are required. Thus, improving current optimization techniques and exploring new method to solve the DED problem has great significance.

In recent years, a new optimization method known as differential evolution (DE) has gradually become more popular and has been successfully applied to solve optimization problem mainly because it has demonstrated good properties and is principally easy to understand [23]. Coelho and Mariani [24] applied DE to solve economic dispatch optimization problem. Here the constraints were handled by penalty function method. But the performance of DE to dynamic economic dispatch with valve-point effects has not been tested yet. Furthermore, canonical version of DE lacks a mechanism to deal with constraints for optimization problem. Therefore, this paper proposes a modified DE (MDE) method to solve DED problem, which focuses on preventing premature convergence and treatment of constraints when it finds optimal solution during evolutionary search process. The proposed constraint-handling method for DE relies on three simple selection criteria based on feasibility to bias the search towards the feasible region to handle inequality constraints effectively. Especially for handling equality constraints of DED problem, heuristic search rules are proposed for DE method. These modifications are incorporated in DE as the classical DE exhibits difficulties in handling constraints. Finally, the proposed method is applied to solve DED problem with 10-units test system. Simulation results demonstrate the feasibility and effectiveness of the proposed MDE method in terms of solution quality compared with those of other optimization methods.

This paper is organized as follows: DED problem formulation is introduced in Section 2. Section 3 briefly describes the basics of differential evolution algorithm. Section 4 proposes modified differential evolution (MDE) algorithm for solving DED problem. Section 5 gives the numerical example. Section 6 outlines the conclusions. Acknowledgements are given in Section 7.

## 2. Formulation of DED problem

### 2.1. Nonsmooth cost functions with valve-point effects

In reality, the objective function of DED problem has non-differentiable property; therefore, the objective function should be composed of a set of nonsmooth cost functions. In this paper, nonsmooth cost functions of generation units with valve-point effects is considered, which the objective function is generally described as the superposition of sinusoidal functions and quadratic functions. The problem has multiple minima, therefore, the task of finding the global solution still remains to be tackled.

The cost function curve of a thermal generator is shown in Fig. 1. Bold line represents the curve approximated by the quadratic function given as follows:

$$f_i(p_i) = a_i + b_i \cdot p_i + c_i \cdot p_i^2 \tag{1}$$

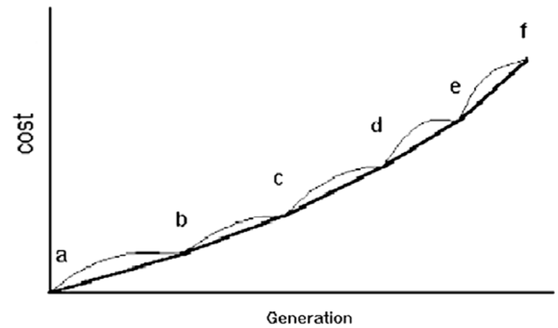


**Fig. 1.** Cost function of generator with valve-points.

where $f_i(p_i)$ is cost function of generator $i$; $a_i$, $b_i$, $c_i$ are cost coefficients of generator $i$; $p_i$ is the power output of generator $i$.

To model the cost function of generators in a more practical manner, the thin line of Fig. 1 should be used instead. The ripples in the input-output curve in the thin line express the result of the sharp increase in losses due to the wire drawing effects, which occur as each steam admission valve starts to open. This phenomenon is called as valve-point effects. A cost function is obtained based on the ripple curve for more accurate modeling. As shown in Fig. 1, this curve contains higher order non-linearity and discontinuity compared with the smooth cost function due to the valve-point effects. To take account for the valve-point effects, sinusoidal functions are added to the quadratic cost functions. Therefore, cost function of a generator can be modified as

$$f_i(p_i) = a_i + b_i \cdot p_i + c_i \cdot p_i^2 + |e_i \times \sin(h_i \times (p_{i\min} - p_i))| \tag{2}$$

where $e_i$ and $h_i$ are the coefficients of generator $i$ reflecting valve-point effects.

The classic DED problem minimizes the total fuel cost function associated to the on-line $N$ units for $T$ intervals in the given time horizon.

$$F = \min \sum_{t=1}^{T} \sum_{i=1}^{N} f_i(P_i^t) \tag{3}$$

where $F$ is total operating cost over the whole dispatch periods, $N$ is the number of generating units, and $T$ is the number of intervals in the scheduled horizon.

### 2.2. Constraints

(1) Real power balance constraint

$$\sum_{i=1}^{N} P_i^t = P_D^t \quad t = 1, 2, \ldots, T \tag{4}$$

where $P_D^t$ is the total load demand during $t$ time interval.

(2) Real power operating limits

$$P_{i\min} \leqslant P_i^t \leqslant P_{i\max} \quad i = 1, 2, \ldots, N \quad t = 1, 2, \ldots, T \tag{5}$$

where $P_{i\min}$ and $P_{i\max}$ are the minimum and the maximum real power outputs of $i$th generator, respectively.

(3) Generating unit ramp rate limits

$$\begin{cases} P_i^t - P_i^{t-1} \leqslant UR_i & \text{if generation increases} \\ P_i^{t-1} - P_i^t \leqslant DR_i & \text{if generation decreases} \end{cases} \tag{6}$$
$$i = 1, 2 \ldots N; \quad t = 1, 2, \ldots, T$$

where $UR_i$ and $DR_i$ are ramp-up and ramp-down rate limits of generator $i$, respectively.