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A hybrid MILP and IPM approach for dynamic economic dispatch with valve-point effects

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ABSTRACT

Dynamic economic dispatch with valve-point effects (DED-VPE) is a non-convex and non-differentiable optimization problem that is difficult to solve efficiently. In this paper, a hybrid approach combining mixed-integer linear programming (MILP) and the interior point method (IPM), abbreviated as MILP-IPM, is proposed to solve a DED-VPE problem in which complicated transmission loss is also included. Due to the non-differentiable nature of the DED-VPE problem, the classical derivative-based optimization methods can no longer be used. With the help of model reformulation, a differentiable non-linear programming (NLP) formulation that can be directly solved using the IPM is derived. However, if the DED-VPE problem is solved using the IPM in a single step, the optimization can easily become trapped in a poor local optimum due to its non-convex nature and multiple local minima. To obtain a better solution, an MILP method is required to solve the DED-VPE problem without transmission loss, yielding a good initial point for the IPM to improve the quality of the solution. Simulation results demonstrate the validity and effectiveness of the proposed MILP-IPM approach for solving the DED-VPE problem.

1. Introduction

Dynamic economic dispatch (DED) is one of the fundamental issues related to optimal economic operation in power systems. It refers to the attempt to allocate customers' load demands among the available thermal power-generating units in an economic, secure and reliable manner at a given time of interest [1]. Traditionally, the generation cost function for DED is approximated as a convex and differentiable quadratic polynomial. However, in actual operation, wire drawing effects, which occur as each steam admission valve in a turbine starts to open, produce a rippling effect on the generation cost curve [2]; these effects are known as valve-point effects (VPE). To model these effects, a recurring rectified sinusoid contribution is added to the traditional input-output equation [2], which makes the generation cost function non-convex, non-differentiable and multiple local minima in nature. When VPE are ignored, the traditional rough approximation of the generation cost function will introduce some inaccuracies into the dispatch results. To improve the optimality of the solution, a more accurate DED model, dynamic economic dispatch with valve-point effects (DED-VPE), should be considered. However, when VPE are considered, some non-convex, non-differentiable and multiple local minima characteristics are introduced, which make solving the DED-VPE problem more challenging.

Over the past decades, a number of optimization methods have been proposed for solving the DED-VPE problem. Due to the intractability of the problem, most of the currently available approaches are heuristic optimization techniques [2–26], such as genetic algorithm (GA) [2], evolutionary programming (EP) [3], simulated annealing (SA) [5], particle swarm optimization (PSO) [6], differential evolution (DE) algorithm [7], artificial bee colony (ABC) algorithm [12], artificial immune system (AIS) algorithm [13], enhanced cross-entropy (ECE) method [14], harmony search (HS) [15], the imperialist competitive algorithm (ICA) [20], bee swarm optimization (BSO) algorithm [21], and teaching–learning algorithm (TLA) [24]. These heuristic optimization techniques are population-based search methods that do not depend on gradient and Hessian operations on the objective function. Thus, they can be applied to solve the DED-VPE problem effectively. However, they are quite sensitive to various parameter settings, and a different solution may be obtained in each trial. Hence, hybrid methods that combine several heuristic techniques or deterministic approaches

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[3,27–31], such as hybrid evolutionary programming and sequential quadratic programming (EP-SQP) [3], a hybridization of artificial immune systems and sequential quadratic programming (AIS-SQP) [28], a hybrid of a seeker optimization algorithm with sequential quadratic programming (SOA-SQP) [29], and a hybrid immune-genetic algorithm (HIGA) [30], have emerged in the search for better characteristics. Since stochastic search techniques are incorporated, these methods still have some of the intrinsic drawbacks of the heuristic methods mentioned above.

Unlike heuristics, deterministic mathematical programming-based optimization techniques can obtain robust solutions due to their solid mathematical foundations and the availability of powerful software tools. Therefore, a strategy that has recently emerged for DED-VPE is to reformulate the generation cost function to obtain a suitable optimization model that can be solved using a deterministic method. In [32], the VPE cost, which is non-convex and non-differentiable, is linearized in a piecewise manner, and then a mixed-integer quadratic programming (MIQP) formulation is constructed for DED-VPE without considering transmission loss. However, when the MIQP formulation is directly solved using a mixed-integer programming (MIP) solver, the optimization process will suffer from convergence stagnancy and run out of memory. As a result, a multi-step method, a warm start technique and a range restriction scheme are incorporated into the MIQP solution procedure. When the additional complication of transmission loss is considered, based on the above process, more tedious adjustment techniques are needed in the solution procedure.

In this paper, a deterministic hybrid method that combines mixed-integer linear programming (MILP) with the interior point method (IPM), abbreviated as MILP-IPM, is proposed to solve the DED-VPE problem while considering transmission loss. Due to the non-differentiable nature of the DED-VPE problem, the classical derivative-based optimization methods can no longer be used. With the help of model reformulation, we derive a non-linear programming (NLP) formulation of the DED-VPE problem, which can be immediately solved using the polynomial-time IPM. However, it is well known that the IPM is a local optimization method. If the DED-VPE problem is solved using the IPM in a single step, the optimization can easily become trapped in a poor local optimum due to its non-convex nature and multiple local minima. To overcome this deficiency, an MILP method is incorporated to generate a good initial point for the IPM. Then, by solving the NLP formulation via the IPM, a high-quality optimal solution to the DED-VPE problem can be determined. The main contributions of this paper are summarized as follows: (1) An MILP formulation, which can be solved to a global optimal solution directly and efficiently, is constructed for the DED-VPE problem. (2) When transmission loss is included, a differentiable NLP formulation for the DED-VPE problem is derived, which can be immediately solved using the polynomial-time IPM. (3) To search for a high-quality local optimal solution, a deterministic MILP-IPM approach that is easy to implement is developed to solve the DED-VPE problem considering transmission loss. The validity and effectiveness of the proposed method are successfully demonstrated for 5-, 10-, and 54-unit test systems.

The remainder of this paper is organized as follows. Section 2 describes the mathematical formulation of the DED-VPE problem. Section 3 derives an NLP formulation for the DED-VPE problem. Section 4 introduces the implementation of the MILP-IPM approach. Section 5 presents simulation results and analysis. Section 6 offers conclusions.

2. Mathematical formulation of the DED-VPE problem

For conventional DED, the generation cost of each unit can be modeled as a convex quadratic polynomial:

$$c_i^{quad}(P_{i,t}) = \alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2, \tag{1}$$

where $P_{i,t}$ is the power output of unit i in period t and α_i, β_i and γ_i are positive coefficients for unit i. When VPE are considered, a recurring rectified sinusoidal function

$$c_i^{vpe}(P_{i,t}) = e_i|\sin(f_i(P_{i,t}-P_i^{\min}))| \tag{2}$$

is added to the conventional generation cost, which makes the generation cost function non-convex and non-differentiable in nature [2]. Above, $P_i^{\min}$ is the minimum power output of unit i, and e_i and f_i are positive coefficients of the VPE cost for unit i. Consequently, the unit generation cost for DED-VPE can be expressed as

$$c_i(P_{i,t}) = c_i^{quad}(P_{i,t}) + c_i^{vpe}(P_{i,t}). \tag{3}$$

The objective of DED-VPE is to minimize the total generation cost over a scheduled time horizon, which can be written as

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N} c_i(P_{i,t}), \tag{4}$$

where N and T are the total numbers of units and periods, respectively.

The minimized DED-VPE problem should be subject to the following constraints.

- Power balance equations:

$$\sum_{i=1}^{N} P_{i,t} = D_t + P_t^{Loss},\ \forall\ t, \tag{5}$$

where D_t is the load demand in period t and P_t^{Loss} is the transmission loss in period t, which can be calculated based on the B-coefficient method and expressed as a quadratic function of the power outputs [33]:

$$P_t^{Loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{i,t}B_{i,j}P_{j,t},\ \forall\ t, \tag{6}$$

where $B_{i,j}$ is the (i,j)-th element of the matrix of the transmission loss coefficients, B.

- Power generation limits:

$$P_i^{\min} \leqslant P_{i,t} \leqslant P_i^{\max},\ \forall\ i,t, \tag{7}$$

where $P_i^{\max}$ is the maximum power output of unit i.

- Ramp rate limits:

$$DR_i \leqslant P_{i,t}-P_{i,t-1} \leqslant UR_i,\ \forall\ i,t, \tag{8}$$

where DR_i and UR_i are the ramp-down and ramp-up rates of unit i, respectively.

- Spinning reserve constraints:

$$\begin{cases} SR_{i,t} \leqslant P_i^{\max}-P_{i,t},\ \forall\ i,t,\\ SR_{i,t} \leqslant \tau UR_i,\ \forall\ i,t,\\ \sum_{i=1}^{N} SR_{i,t} \geqslant R_t,\ \forall\ t, \end{cases} \tag{9}$$

where $SR_{i,t}$ is the spinning reserve provided by unit i in period t,R_t is the spinning reserve requirement of the system in period t, and τ is the time for the units to deliver the reserve [22]. When the renewable energy such as wind power is integrated, similar linear up and down spinning reserve constraints [34] can be formulated to suppress the fluctuation.

3. An NLP formulation for DED-VPE

As seen from Section 2, DED-VPE is a non-convex and non-differentiable optimization problem and thus is difficult to tackle. Due to the non-differentiable nature of the DED-VPE problem, classical mathematical programming-based methods, also known as derivative-based optimization methods, are no longer suitable. To overcome this difficulty, we replace $|\sin(f_i(P_{i,t}-P_i^{\min}))|$ with an auxiliary variable $s_{i,t}$; then, the objective function given in (4) can be equivalent to