Quantum-behaved Particle Swarm Optimization for Multiple-fuel-constrained Generation Scheduling of Power System

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Abstract—This research proposes a quantum-behaved particle swarm optimization with a multiplier updating technique (QPSO-MU) for the multiple-fuel-constrained generation scheduling of power system. The quantum-behaved particle swarm optimization (QPSO) equips with a migration can efficiently search and actively explore solutions. The multiplier updating (MU) is introduced to avoid deforming the augmented Lagrange function and resulting explore solutions. The proposed algorithm integrates the QPSO and the MU that has merits of automatically adjusting the randomly given penalty to a proper value and requiring only a small-size population for the power economic dispatch problem of the multiple-fuel-constrained generation scheduling. Numerical results of two test systems indicate that the proposed algorithm is more suitable than previous approaches in the practical economic dispatch for the multiple-fuel-constrained generation scheduling of power system.

Keywords—quantum-behaved particle swarm optimization; generation scheduling; multiple-fuel-constrained; power system

I. INTRODUCTION

The power economic dispatch (PED) problem involves allocation of generations to different thermal units to minimize the cost of generation, while satisfying the equality and inequality constraints of the power system [1]. In general, the economic dispatch problem aims to increase utilization at the lowest cost of fuel [2], [3]. Generally, the fuel cost function of a generator has been approximately represented by a single quadratic function. However, many generating units, particularly those which are supplied with multi-fuel sources (coal, nature gas, or oil), lead to the problem of determining the most economic fuel to burn. Some studies of the PED problems, such as an efficient crisscross optimization (CSO) [4], double weighted particle swarm optimization (DWPSO) [5], lightning flash algorithm (LFA) [6], numerical method (NM) [7], shuffled frog leap algorithm and global-best harmony search (SFLA-GHS) [8], adaptive Hopfield neural network (AHNN) [9], evolutionary programming technique (EP) [10], augmented Lagrange Hopfield network initialized quadratic programming (QP-ALHN) [11], and an improved particle swarm optimization with a dynamic search space squeezing strategy [12] have considered the multiple-fuel-constrained generation scheduling of power systems.

Particle swarm optimization (PSO) [13]–[16] has been widely used in dealing with many real-world problems because of its simplicity and facile realization. However, owing to the restricted velocity, the searching area of a particle is limited and diminishing in PSO. Which means, in a PSO system, the searching space cannot cover the whole feasible region and global convergence cannot be guaranteed [17]. This is also the main cause of the premature in PSO. In order to dispose of the disadvantages of PSO, quantum-behaved particle swarm optimization (QPSO) [17]–[23] is proposed for solving the PED problems.

II. PROBLEM FORMULATION

The PED problem can be described as an optimization (minimization) process with objective [1]:

$$\text{Minimize } \sum_{i=1}^{n_p} F_i(P_i)$$

(1)

Where $F_i(P_i)$ is the fuel cost function of the $i^{th}$ unit, $P_i$ is the power generated by the $i^{th}$ unit, and $n_p$ is the number of dispatchable units. Subject to the equality constraint of the power balance as:

$$\sum_{i=1}^{n_p} P_i = P_d + P_L$$

(2)

Where $P_d$ is the system load demand and $P_L$ is the transmission loss, and generating capacity constraints as:

$$P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}}, \quad i = 1, \ldots, n_p$$

(3)

Where $P_i^{\text{min}}$ and $P_i^{\text{max}}$ are the minimum and maximum power outputs of the $i^{th}$ unit. The cost function addressing valve-point loadings of generating units is accurately represented as [24]:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + e_i \times \sin\left(f_i \times (P_i^{\text{min}} - P_i)\right)$$

(4)

Where $a_i$, $b_i$, and $c_i$ are the fuel cost coefficients of the $i^{th}$ unit, and $e_i$ and $f_i$ are fuel cost coefficients of the $i^{th}$ unit with valve-point loadings.
points effects. For considering the multiple fuel option, the fuel cost function should be practically expressed as [7]:

\[
F(P) = \begin{cases}
a_{i1} + b_{i1} P_i + c_{i1} P_i^2, & \text{fuel } 1, \ P_i^{\min} \leq P_i \leq P_i^{\max} \\
a_{i2} + b_{i2} P_i + c_{i2} P_i^2, & \text{fuel } 2, \ P_i^{\min} < P_i \leq P_i^{\max} \\
& \vdots \\
a_{ik} + b_{ik} P_i + c_{ik} P_i^2, & \text{fuel } k, \ P_{i-1}^{\min} < P_i \leq P_i^{\max}
\end{cases}
\]

(5)

Where \(a_{ik}, b_{ik}, \) and \(c_{ik}\) are cost coefficients of the \(i^{th}\) generator using the fuel type \(k\). To obtain an accurate and practical economic dispatch solution, the realistic operation of the PED problem should be considered both valve-point effects and multiple fuels. This paper proposed an incorporated cost model, which combines the valve-point loadings and the fuel changes into one frame. Therefore, the cost function should combine (4) with (5), and can be realistically represented as [3]:

\[
F(P) = \begin{cases}
a_{i1} + b_{i1} P_i + c_{i1} P_i^2 + k_i \times \sin(f_i \times (P_{i-1}^{\min} - P_i^{\max})), & \text{for fuel } 1, \ P_i^{\min} \leq P_i \leq P_i^{\max} \\
a_{i2} + b_{i2} P_i + c_{i2} P_i^2 + k_i \times \sin(f_i \times (P_i^{\min} - P_i^{\max})), & \text{for fuel } 2, \ P_i^{\min} < P_i \leq P_i^{\max} \\
& \vdots \\
a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + k_i \times \sin(f_i \times (P_{i-1}^{\min} - P_i^{\max})), & \text{for fuel } k, \ P_{i-1}^{\min} < P_i \leq P_i^{\max}
\end{cases}
\]

(6)

Complication of the actual PED problem is due to the incorporated cost model composed of both valve-point effects and multiple fuels. Hence, an algorithm that overcomes these complexities has to be evolved.

III. THE PROPOSED ALGORITHM

A. The QPSO

In QPSO, the position of a particle is depicted by its local best position, and the velocity of each particle is characteristic of its local search area. The QPSO has been shown to be effective in solving constrained optimization problems, especially those with multiple fuel options. The QPSO is based on the concept of a swarm intelligent algorithm, which is capable of finding the global optimum solution.

B. The MU

Considering the nonlinear problem with general constraints as follows: Where \(h_k(x)\) and \(g_k(x)\) stand for equality and inequality constraints, respectively.

\[
\min f(x) \\
\text{subject to} \quad h_k(x) = 0, \quad k = 1, \ldots, m_e
\]

\[
g_k(x) \leq 0, \quad k = 1, \ldots, m_i
\]

(7)

Where \(x\) represents a \(n_e\)-dimensional variable, and the \(h_k(x)\) and \(g_k(x)\) stand for equality and inequality constraints, respectively. The penalty function method is frequently applied to manage constraints in evolutionary algorithms. Such a technique converts the primal constrained problem into an unconstrained problem by penalizing constraint violations. The penalty function method is simple in concept and implementation. However, its primal limitation is the degree to which each constraint is penalized. These penalty terms have certain weaknesses that become fatal when penalty parameters are large. Such a penalty function tends to be ill conditioned near the boundary of the feasible domain where the optimum point is usually located.

Lagrange method can markedly overcome the drawbacks of the penalty method. The augmented Lagrange function (ALF) [25] for constrained optimization problems is defined as:

\[
L_u(x, \nu, \lambda) = f(x) + \sum_{i=1}^{m} \alpha_i \{ h_i(x) + \nu_i \} - \nu_i^2 \} + \sum_{i=1}^{m} \beta_i \{ g_i(x) + \nu_i \} - \nu_i^2 \}
\]

(8)

Where \(\alpha_i\) and \(\beta_i\) are the positive penalty parameters, and the corresponding Lagrange multipliers \(\nu = (\nu_1, \ldots, \nu_{m_p})\) and \(\nu = (\nu_1, \ldots, \nu_{m_p}) \geq 0\) are associated with equality and inequality constraints, respectively.

The contour of the augmented Lagrange function does not change shape from generation to generation while constraints are linear. Therefore, the contour of the augmented Lagrange function is simply shifted or biased in relation to that of the original objective function, \(f(x)\). Consequently, small penalty parameters can be used in the MU. However, the shape of contour of \(L_u\) is changed by penalty parameters while the constraints are nonlinear, demonstrating that the computational difficulties of using large penalty parameters for nonlinear constraints remain. The adaptive penalty parameters are employed to alleviate the above difficulties. More details of the MU have shown in [26].

C. The Proposed QPSO-MU

The ALF is used to obtain a minimum value in the inner loop with the given penalty parameters and multipliers, which are then updated in the outer loop toward producing an upper limit of \(L_u\). When both inner and outer iterations become sufficiently large, the ALF converges to a saddle-point of the dual problem [27].

IV. SYSTEM SIMULATIONS

This section employs two examples to illustrate the effectiveness of the proposed QPSO-MU with respect to the quality of the solution obtained. The first example considers with multi-fuel effects and without the valve-point loadings. The other example considers both valve-point effects and multiple fuels. The MU algorithm was used in QPSO to handle the equality and inequality constraints for the two tests. The computation was implemented on a personal computer (Intel(R) Core(TM) i7-3770 CPU @ 3.4 GHz with 8G Ram) in FORTRAN-90 language. Setting factors were used identically in the two tests as follows;
the population size is set as 5. The iteration numbers of outer loop and inner loop are set to (outer, inner) as (10, 3000). The proposed approach solves PED problems considering system constraints of power balance (2) and capacity limits (3).

### A. Example 1

The proposed algorithm was employed to solve the multiple-fuel-constrained generation scheduling of power system with the cost model (5). This example system contained ten dispatching units addressing multiple fuels for a load demand of 2500 MW. The system data of this example are given in [5]. The implementation of this example can be described as follows:

\[
L_a(x, v, t) = f(x) + \alpha \left( \sum_{i=1}^{10} h_i(x) + v_i^2 \right) \quad (9)
\]

### B. Example 2

This test system considers both multiple fuel options and valve-point effects with the cost model (6) for a load demand of 2700 MW. The system data of this example are given in [5]. The implementation of the proposed algorithm of this example are identical to the example 1, as (9)–(11). The comparisons between the proposed algorithm with MSFLA [8], CCEDE [28], RCgé [29], SPPo [3], CSO [4], and DPWSO [5] are illustrated in Table II, and the proposed QPSO-MU exhibits not only better solution quality but also acquire an exact TP, TC, and FT stand the total power, total cost, and the fuel types respectively. Not only do the results obtained by the proposed QPSO-MU supply sufficient load demand, but the results obtained by the proposed method have lower costs than that obtained by the previous approaches. This example reveals that the QPSO-MU is more suitable than previous methods in application because the proposed algorithm is easy to implement, and has a satisfactory result of solving the PED problem with multiple-fuel-constrained generation scheduling.

### TABLE I. COMPUTATIONAL RESULTS OF THE PROPOSED QPSO-MU AND FIVE PREVIOUS METHODS FOR EXAMPLE 1.

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### TABLE II. COMPUTATIONAL RESULTS OF THE PROPOSED QPSO-MU AND SIX PREVIOUS METHODS FOR EXAMPLE 2.

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TP (MW) | 2700.00000 | 2700.00000 | 2700.00000 | 2699.00000 | 2699.9995 | 2697.0000 | 2700.0000 |

TC ($) | 624.11569 | 623.8288 | 623.8281 | 623.8279 | 623.8237 | 622.7333 | 623.8093 |

objective : \[
\min_{x \in \{P_1, P_2, \ldots, P_9\}} f(x) = \sum_{i=1}^{10} F_i(P) \quad (10)
\]

subject to \[
\sum_{i=1}^{10} P_i - P_d = 0 \quad (11)
\]
V. CONCLUSIONS

The realistic PED problem is complicated because change fuels must be considered. The QPSO helps the proposed algorithm efficiently search and explore. The MU helps the proposed method avoid deforming the augmented Lagrange function and resulting in difficulty of solution searching. The proposed method integrates the QPSO and MU such that it has merits of automatically adjusting the randomly given penalty to a proper value and requiring only a small-size population. Numerical results of the two examples demonstrate that the proposed method has more advantages for solving the PED problems with multiple-fuel-constrained generation scheduling than previous approaches for power operations.

REFERENCES


