

Economic and Environmental Optimal Dispatch Problem in Power Systems Using Particle Swarm Optimization

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Abstract - This study proposes a quantum-behaved particle swarm optimization (QPSO) with a multiplier updating (QPSO-MU) for the economic environmental dispatch (EED) problem of power systems. The QPSO, which is equipped with a migration operation, can efficiently search and actively explore solutions. Multiplier updating (MU) is introduced to avoid deforming the augmented Lagrange function, which results in difficulty in solution searching. The ε -constraint technique is employed to handle the trade-off solutions of the EED problem. The proposed method integrates the QPSO, MU, and ε -constraint technique, which has the advantages of automatically adjusting the randomly given penalty to a proper value and requiring only a small-size population for the EED problem. To evaluate the optimization ability of the proposed QPSO-MU, it was compared with several representative algorithms on the standard IEEE 30-bus test system. The numerical results indicate that the proposed algorithm is more suitable than previous approaches in terms of both the best fuel cost and best emission cost solutions for the EED problem of power systems.

Key Words: economic environmental dispatch, particle swarm optimization, ε -constraint technique.

1. INTRODUCTION

Energy conservation and emissions reduction are beneficial for improving the operational efficiency and market competitiveness of thermal power plants. To achieve this goal, a combined economic emission dispatch is considered an attractive short-term alternative that aims to minimize both fuel and emission costs. Over the past few years, this approach has attracted considerable attention owing to its ability to integrate emissions with only minor adjustments to the fundamental economic dispatch framework [1–3]. With the advent of environmental regulations, power-generating emissions were introduced and used as part of the cost function for economic dispatch. The economic environmental dispatch (EED) problem of power systems has become a constrained optimal problem for minimizing the cost of generation while satisfying the equality and inequality constraints of the power system and keeping pollution within limits [4–7].

In this line, power system planners and operators seek to minimize both EED objectives simultaneously using any developed optimizer. Many optimizers have been developed for this target. Several search-based

optimization algorithms have been introduced to solve the EED problem, such as an artificial bee colony optimization algorithm and a non-dominated sorting genetic algorithm-II (ABC-NSGA-II) [3], an artificial cooperative search algorithm incorporated with the quadratic approximation operator (ACS-QA, ACS) [8], strength pareto evolutionary algorithm (SPEA) [9], niched Pareto genetic algorithm (NPGA) [10], non-dominated sorting genetic algorithm (NSGA) [11], tribe-modified differential evolution (Tribe-MDE) [12], cultural evolution mechanism introduced into quantum-behaved particle swarm optimization (CMOQPSO) [13], backtracking search algorithm (BSA) [14], a new glowworm swarm optimization with weighted sum method (WGSO, GSO-T) [15], an improved scatter search (ISS) [16], a multi-objective directed bee colony optimization algorithm (MODBC) [17], and a modified bacterial foraging algorithm (MBFA) [18], which were used for power optimal EED problems.

Particle swarm optimization (PSO) [19–21] has been widely used to address many real-world problems because of its simplicity and facile realization. However, owing to the restricted velocity, the search area of a particle is limited and diminishes in PSO. This implies that in a PSO system, the search space cannot cover the entire feasible region, and global convergence cannot be guaranteed [22]. This is also the main cause of premature convergence in PSO. To address the disadvantages of PSO, quantum-behaved particle swarm optimization (QPSO) [13] and [23] were proposed for solving the EED problem of power systems.

2. SYSTEM FORMULATION

The EED problem formulation considers both economic and environmental impacts.

2.1 Economic objective F_1

The economic objective F_1 of the generator power output P_i is represented as [9]:

$$F_1 = \sum_{i=1}^{N_g} a_i P_i^2 + b_i P_i + c_i \quad \$/h \quad (1)$$

where F_1 is the total cost of generation, P_i is the generation of the i th generator, a_i , b_i , and c_i are coefficients of the cost

curve of the i th generator, and N_g is the total number of generators.

2.2 Environmental objective F_2

The emission of sulfur dioxide, nitrogen oxides, carbon monoxide, and other gases that cause atmospheric hazards can be mathematically modeled as [18]:

$$F_2 = 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \xi_i e^{(\zeta_i P_i)} \quad (2)$$

where α , β , γ , ξ , and ζ are coefficients of generator emission characteristics.

2.3 System constraints

To ensure a real power balance, an equality constraint was imposed as follows:

$$\sum_{i=1}^{N_g} P_i - P_D - P_{loss} \quad (3)$$

Where P_D is the total demand, and P_{loss} is the real power loss in the transmission lines. The inequality constraint imposed on generator output is

$$P_{i \min} \leq P_i \leq P_{i \max} \quad (4)$$

Where $P_{\min}$ and $P_{\max}$ are the minimum and maximum limits of the loadings of the i th generator, respectively. By aggregating Equations (1) to (4), the multi-objective optimization problem is formulated as follows:

$$\begin{aligned} & \underset{P_i}{\text{minimize}} \quad [F_1(P_i), F_2(P_i)] \\ & \text{subject to} \quad \sum_{i=1}^{N_g} P_i - P_{loss} = P_D \\ & \quad P_{i \min} \leq P_i \leq P_{i \max}; \quad i = 1, 2, \dots, N_g \end{aligned} \quad (5)$$

Where $F_1(P_i)$, $F_2(P_i)$ are the objective functions to be minimized over the set of admissible decision vector P_i .

3. THE PROPOSED ALGORITHM

This section describes the proposed approach for the EED problem. The ϵ -constraint technique is first provided, a brief overview of the QPSO is then discussed, the MU is presented, and the solution procedure of the proposed approach is stated last.

3.1 The ϵ -Constraint Technique

The ϵ -constraint technique is used to generate Pareto-optimal solutions to the multi-objective problem. To proceed, one of the objective functions constitutes the primary objective function, and all other objectives act as

constraints. Specifically, this procedure is implemented by replacing one objective in the problem defined by (5) with one constraint. The problem is reformulated as follows:

$$\begin{aligned} & \min F_j(P_i), \quad j = 1 \text{ or } 2, \quad i = 1, 2, \dots, N_g \\ & \text{subject to } F_k(P_i) \leq \epsilon_k; \quad k = 1 \text{ or } 2, \text{ and } k \neq j \\ & \quad \sum_{i=1}^{N_g} P_i - P_{loss} = P_D \\ & \quad P_{i \min} \leq P_i \leq P_{i \max}; \quad i = 1, 2, \dots, N_g \end{aligned} \quad (6)$$

3.2 The QPSO

In QPSO, the position of a particle is depicted by its local attractor and probability density function. In this case, the particles in the QPSO were not limited by the trajectory. The analysis in [22] shows that QPSO is globally convergent. Another advantage is that there is only one parameter in the QPSO. Hence, QPSO is easy to implement. More details on the QPSO used in the field of power systems have been presented in [13], [22–25].

3.3 The MU

The nonlinear problem with general constraints is as follows: where $h_k(x)$ and $g_k(x)$ represent the equality and inequality constraints, respectively.

$$\begin{aligned} & \underset{x}{\text{minimize}} \quad f(x) \\ & \text{subject to} \quad h_k(x) = 0, \quad k = 1, \dots, m_e \\ & \quad g_k(x) \leq 0, \quad k = 1, \dots, m_i \end{aligned} \quad (7)$$

where x represents an n_c -dimensional variable, and $h_k(x)$ and $g_k(x)$ represent equality and inequality constraints, respectively. The penalty function method is frequently applied to manage the constraints of evolutionary algorithms. This technique converts the primal constrained problem into an unconstrained problem by penalizing constraint violations. The penalty function method is simple in terms of concept and implementation. However, its primary limitation is the degree to which each constraint is penalized. These penalty terms have certain weaknesses that become fatal when the 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.

The Lagrange method can markedly overcome the drawbacks of the penalty method. The augmented Lagrange function (ALF) [26] for constrained optimization problems is defined as

$$\begin{aligned} L_0(x, v) = & f(x) + \\ & \sum_{k=1}^{m_e} \alpha_k \{ [h_k(x) + v_k]^2 - v_k^2 \} + \sum_{k=1}^{m_i} \beta_k \{ \langle g_k(x) + v_k \rangle_+^2 - v_k^2 \} \end{aligned} \quad (8)$$

Where α_k and β_k are the positive penalty parameters, and the corresponding Lagrange multipliers $v = (v_1, \dots, v_{m_e})$ and $u = (u_1, \dots, u_{m_i}) > 0$ are associated with equality and inequality constraints, respectively.

The contour of the augmented Lagrange function does not change shape from generation to generation, whereas the constraints are linear. Therefore, the contour of the augmented Lagrange function is simply shifted or biased with respect to that of the original objective function $f(x)$. Consequently, small penalty parameters can be used for MU. However, the shape of the contour of L_a is changed by penalty parameters while the constraints are nonlinear, demonstrating that the computational difficulties of using large penalty parameters for nonlinear constraints remain. Adaptive penalty parameters are employed to alleviate these difficulties. More details on the MU are provided in [27].

3.4 The Proposed Method

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 to produce an upper limit of L_a . When both the inner and outer iterations become sufficiently large, the ALF converges to a saddle point of the dual problem [28].

4. SYSTEM SIMULATIONS

In this section, the proposed QPSO-MU is applied to the standard IEEE 30-bus, 6-generator test system with a load demand (P_D) by example 1 without considering the transmission losses and example 2 with considering the transmission losses. The two examples each contain two cases: case 1 for the best fuel cost (BFC) and case 2 for the best emission cost (BEC). The cost and emission coefficients of this test system are given in [9], and the transmission losses are considered in [14]. The proposed approach solves the EED problem by considering system constraints, such as the power balance (3) and capacity limits (4). The MU algorithm was integrated into the QPSO to handle both equality and inequality constraints. The computation was implemented on a personal computer (Intel(R) Core (TM) i9 CPU @ 3.4 GHz with 16G Ram) using the Matlab software. The parameter settings used in this test were as follows: the population size N_p was set to 5. The iteration numbers of the outer and inner loops were set to (outer, inner) as (10, 3000). The implementation of the proposed algorithm for this test is described as follows:

$$L_a(P_i, v, u) = F_1(P_i) + \alpha_1 \{ [h_1(P_i) + v_1]^2 - v_1^2 \} + \beta_1 \{ \langle g_1(P_i) + u_1 \rangle_+^2 - u_1^2 \} \quad (9)$$

Subject to

$$h_1 : P_D - \sum_{i=1}^{N_g} P_i - P_{loss} = 0$$

$$g_1 : F_1(P_i) - \varepsilon_2 \leq 0$$

where h_1 represents the violation of the power balance constraint (3), and g_1 stands the violation of emission objective for expected ε_2 , ($\varepsilon_2 \in [F_2^{min}, F_2^{max}] = [0.1942, 0.2215]$) [9]. The ALF was solved using the proposed approach. Because cost and emissions are conflicting in nature, the value of objective F_2 is maximized when the value of F_1 objective is the minimum and vice versa. Therefore, the values of the best cost with F_2^{max} and the minimum emission with F_2^{min} are obtained by performing the ALF (9) separately. The best compromise indicates the minimum cost (the optimal power economic dispatch) within expected ε_2 . The expected ε_2 is set as F_2^{max} and F_2^{min} for Examples 1 and 2, respectively.

To verify the feasibility of solutions, the sum of constraint violations defined as $SCV = |h_1| + \max\{g_1, 0.0\}$ is used to elucidate the effect of constraint feasibility on the final solutions. Therefore, SCV represents constraint violation associated with equality constraints only, and is defined in Eq. (3). The ideal value of SCV should be zero or less than some practical "tolerance" value. It was observed that when the tolerance is greater than 0, the algorithm produces better solutions, but such solutions are "infeasible". For comparison, the transmission losses considered in Example 2 were estimated by subtracting the load demand (P_D) 2.834 p.u. from the total generation ($\Sigma P(G)$). All these results were taken at the end of 100 runs, and each run (10, 3000) iterations, the average CPU time (CPU_av) in seconds for the proposed QPSO-MU is provided.

4.1 Example 1, without considering transmission losses

The generation schedules for the BFC and BEC without considering transmission losses, obtained using the proposed QPSO-MU are presented in Table 1. In Table 1, it is worth noting that the SCV for all the results obtained by the proposed method is zero. In Table 2, the results of BFC reported in previous literature are compared with the results obtained using the proposed method. This table is sorted from smallest to largest based on the SCV. From this table, the proposed algorithm provides the minimum fuel cost with zero constraint violation; therefore, it is present at the top. In Table 3, the best emission cost results reported in the literature are compared with those obtained using the proposed method. The table is sorted according to SCV in ascending order. The proposed algorithm provides the minimum emission with zero SCV;

therefore, the proposed solution is better than the other solutions.

Table -1: BFC and BEC results IEEE 30-bus system for a load of 2.834 p.u. (without transmission losses), using proposed QPSO-MU.

Items Methods	BFC (\$/h)	BEC (\$/h)
P(G1)	0.109730	0.404501
P(G2)	0.299770	0.458192
P(G3)	0.524308	0.538343
P(G4)	1.016194	0.385334
P(G5)	0.524281	0.538343
P(G6)	0.359717	0.509287
$\Sigma P(G)$ (p.u.)	2.834000	2.834000
Emission (ton/h)	0.222144	0.194203
Total Cost (\$/h)	600.111408	637.945142
SCV	0.000000	0.000000
CPU_av (sec)	86.02	99.67

Table -2: BFC results IEEE 30-bus system, reported in literature and by using proposed QPSO-MU for a load of 2.834 p.u. (without transmission losses).

Case1 Algorithms	BFC (\$/h)	Emission (ton/h)	$\Sigma P(G)$ (p.u.)	SCV
Proposed method	600.111408	0.222144	2.834	0.00000
ABC-NSGA-II [3]	600.111408	0.222144	2.834	0.0
BSA [14]	600.1114	0.222144	2.834	0.0
CMOQPSO [13]	600.08973	0.194178*	2.834	0.0
MBFA [18]	600.17	0.22	2.834	0.0
Tribe-MDE [12]	600.111408	0.22214486	2.833999	1.0E-06
NPGA [10]	600.31	0.2238	2.8341	0.0001
NSGA [11]	600.34	0.2241	2.8341	0.0001
SPEA [9]	600.22	0.2206	2.8341	0.0001
MODBC [17]	599.22	0.2221	2.82996	0.00404

Table -3: BEC results IEEE 30-bus system, reported in literature and by using proposed QPSO-MU for a load of 2.834 p.u. (without transmission losses).

Case2 Algorithms	BEC (\$/h)	Emission (ton/h)	$\Sigma P(G)$ (p.u.)	SCV
Proposed method	637.945142	0.194203	2.834000	0.000000
ABC-NSGA-II [3]	638.273441	0.194203	2.834	0.0
CMOQPSO [13]	638.289451	0.194203	2.834	0.0
SPEA [9]	640.42	0.1942	2.834	0.0
NPGA [10]	636.04	0.1943	2.834	0.0
Tribe-MDE [12]	638.273439	0.194203	2.834001	1.0E-06
MBFA [18]	636.73	0.1942	2.8341	0.0001
NSGA [11]	633.83	0.1946	2.8341	0.0001
MODBC [17]	637.4649	0.1942	2.829998	0.004002
BSA [14]	638.2734	0.194203	2.833999	0.034529

Table -4: BFC and BEC results IEEE 30-bus system for a load of 2.834 p.u. (with transmission losses), using proposed QPSO-MU.

Items Methods	BFC (\$/h)	BEC (\$/h)
P(G1)	0.120967	0.401482
P(G2)	0.286309	0.458596
P(G3)	0.583567	0.545415
P(G4)	0.992852	0.407384
P(G5)	0.523963	0.544881
P(G6)	0.351903	0.510784
$\Sigma P(G)$	2.859561	2.868542
Loss (p.u.)	0.025561	0.034542
Emission (ton/h)	0.220729	0.194200
Total Cost (\$/h)	605.998227	643.873700
SCV	0.000000	0.000000
CPU_av (sec)	98.58	123.62

4.2 Example 2, with considering the transmission losses

The same IEEE 30-bus test system for solving the EED problem as in Example 1 was used in Example 2, except that Example 2 considers the transmission losses. The

generation schedules for the BFC and BEC with transmission losses, obtained using the proposed QPSO-MU for this test system, are listed in Table 4. It is important that the SCV for all the results obtained by the proposed method is also zero.

Table -5: BFC results IEEE 30-bus system, reported in literature and by using proposed QPSO-MU for a load of 2.834 p.u. (with transmission losses).

Case1 Algorithms	BFC (\$/h)	Emission (ton/h)	ΣP(G) (p.u.)	SCV
Proposed method	605.998227	0.220729	2.859561	0.000000
ABC-NSGA-II [3]	605.99837	0.220729	2.859562	0.0
Tribe-MDE [12]	605.9984	0.220729	2.859562	8.63E-07
BSA [14]	605.9984	0.220729	2.859562	1.00E-06
MBFA [18]	606.17	0.2174	2.8595	1.89E-05
WGSO [15]	606.0	0.2207	2.8596	3.63E-05
CMOQPSO [13]	605.977	0.22058	2.8595	7.59E-05
GSO-T [15]	606.0	0.2207	2.8595	7.77E-05
ACS [8]	606.002	0.2205	2.859	0.000366
ACS-QA [8]	605.866	0.2207	2.8587	0.000851
SS [16]	603.685	0.2165	2.8475	0.012719
ISS [16]	603.589	0.2159	2.8457	0.012762

Table -6: BEC results IEEE 30-bus system, reported in literature and by using proposed QPSO-MU for a load of 2.834 p.u. (with transmission losses).

Case2 Algorithms	BEC (\$/h)	Emission (ton/h)	ΣP(G) (p.u.)	SCV
Proposed method	643.873700	0.194200	2.868542	0.000000
ABC-NSGA-II [3]	646.207004	0.19418	2.86933	0.0
Tribe-MDE [12]	646.207003	0.19418	2.86933	1.11E-08
BSA [14]	646.2072	0.19418	2.86933	8.82E-08
GSO-T [15]	646.16	0.1942	2.8693	1.86E-05
MBFA [18]	643.84	0.1942	2.8685	2.51E-05
CMOQPSO [13]	646.237913	0.194178	2.8694	6.55E-05
WGSO [15]	646.21	0.1942	2.8694	6.98E-05
ACS-QA [8]	646.205	0.1941	2.8691	0.000210
ACS [8]	646.759	0.1941	2.8695	0.000312
ISS [16]	633.3926	0.19447	2.8438	0.021950

SS [16]	632.4107	0.19456	2.8436	0.022340
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In Table 5, the results of BFC reported in past literature are compared with the results obtained using the proposed method. This table is sorted by SCV from the lowest to the highest. From Table 5, the proposed algorithm gives the minimum BFC and zero SCV, so it is present at the top. In Table 6I, the results of BEC reported in previous literature are compared with the results obtained using the proposed method. This table is also sorted according to SCV. The proposed algorithm provides the minimum BEC with a zero SCV; therefore, the proposed method is more suitable for application in the EED problem than previous approaches.

5. CONCLUSIONS

The proposed QPSO-MU for solving the EED problem of power systems has been presented herein. The QPSO enables the proposed method to perform efficient searches and refined exploitation. The MU helps the proposed method avoid deforming the ALF and resulting in difficulty of solution searching. The proposed algorithm integrates the ϵ -constraint technique, the QPSO, and the MU, which has the advantage of accommodating a wide range of penalty parameters and requiring only a small population. The IEEE 30-bus test system is used to compare the proposed QPSO-MU with earlier methods. Simulation results show that the proposed algorithm is superior to previous approaches in solution quality for solving the EED problem. The contributions of this study are the MU effectively handles system constraints of EED problem in emission management, and the QPSO efficiently searches the optimal solution for EED problem of power systems.

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