Economic/Emission Dispatch of Power System Using Cuckoo Search Algorithm

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Abstract—**This paper presents an integrated algorithm of economic/emission dispatch problem (EEDP) of power systems. Cuckoo search algorithm (CSA) can efficiently search and actively explore solutions. The multiplier updating (MU) is introduced to avoid deforming the augmented Lagrange function and resulting in difficulty to solution searching. To handle the EEDP of power system, the ε-constraint technique is employed. The proposed approach integrates the ε-constraint technique, the CSA, and the MU. The proposed approach (CSA-MU) has the merit of automatically adjusting the randomly given penalty to a proper value and requiring only a small-size population. Numerical results indicate that the proposed algorithm is superior to previous methods in solution quality.**

Keywords- Cuckoo search algorithm; Economic dispatch; Multiplier updating.

I. INTRODUCTION

Due to the continuous increase in demand, research interest is focused towards the efficient operation and planning of power systems. Increased utilization and depletion of natural and fossil fuels means the research focus must include economic as well as environmental concerns. In general, the economic dispatch problem aims to increase utilization at the lowest cost of fuel [1~ 3]. ED provides an avenue to power generators to provide electricity at a minimum cost. Initially, cost was the main variable considered in economic dispatch problem [4]. With the advent of environmental regulations, power generating unit emissions were introduced and used as part of the cost function for economic dispatch. Economic dispatch became then an EEDP to minimize the cost of generation, while satisfying the equality and inequality constraints of the power system and keeping pollution within limits [5~ 7].

Many research efforts were made for the EEDP. Niknam et al. [8] proposed an innovative tribe-modified differential evolution (Tribe-MDE) for the EEDP. Rao and Vaisakh [9] provided a multi objective optimization approach based on adaptive clonal selection algorithm (ACSA) to solve the complex EEDP of thermal generators in power system. Zhang et al. [10] presented a multi-objective optimization algorithm, called the bare-bones multi-objective particle swarm optimization (BB-MOPSO) for solving the EEDP. Niknam and Mojarrad [11] developed a modified adaptive Θ-particle swarm optimization (MAΘ-PSO) algorithm to investigate the EEDP. Gong et al. [12] described a hybrid multi-objective optimization algorithm based on PSO and DE (MO-DE/PSO) for solving the EEDP. Agrawal et al. [13] used a fuzzy clustering-based particle swarm (FCPSO) method to solve the EEDP. A strength pareto evolutionary algorithm (SPEA) based approach was employed to handle system constraints of the EEDP [14].

The cuckoo search algorithm (CSA) is a new meta-heuristic optimization method [15, 16] inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other birds of other species. When the host birds discover an alien egg in their nest, they can throw it away or simply abandon their nest and build a new one elsewhere. The CSA idealized such breeding behavior in combination with Levy flights behavior of some birds and fruit flies for applying to various constrained optimization problems.

II. SYSTEM FORMULATION

In the EEDP formulation, these are economy and environmental impacts.

A. Economy Objective F_1

The economy objective F_1 of generator power output P_i is represented as [14];

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

where F_1 is the total cost of generation, P_i is the generation of the ith generator, a_i, b_i and c_i are coefficients of the cost curve of the ith generator, and N_g is the total number of the generators.

B. Environmental Objective F_2

The emission of sulfur dioxide, nitrogen oxides, carbon monoxide gases etc., which cause atmospheric hazards, can be mathematically modeled as [14];

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

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

C. System Constraints

To ensure a real power balance, an equality constraint is imposed:

$$\sum_{i=1}^{N_g} P_i - P_D - P_{loss} = 0 \tag{3}$$

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

$$P_{i\,\min} \le P_i \le P_{i\,\max} \tag{4}$$

where P_{imin} and P_{imax} are the minimum and maximum limits on the loadings of the ith generator. Aggregating equations (1) to (4), the multi-objective optimization problem is formulated as;

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

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.

III. The Integrated Algorithm

A. The ε –Constraint Technique

The ε-constraint method 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. To be more specific, this procedure is implemented by replacing one objective in the problem as defined by (5) with one constraint. Re-formulate the problem as follows:

$$\begin{array}{ll} \min & F_j(P_i) \quad , j = 1 \text{ or } 2 \\ \textit{subject to} & F_k(P_i) \le \varepsilon_k; k = 1 \text{ or } 2, \text{ and } k \ne j \\ & \sum_{i=1}^{N_g} P_i - P_{loss} = P_D \\ & P_{i\,\min} \le P_i \le P_{i\,\max}; \quad i = 1,2,\cdots,N_g \end{array} \tag{6}$$

Where ε_k is the maximum tolerable objective level. The value of ε_k is chosen for which the objective constraints in problem (6) are binding at the optimal solution. The level of ε_k is varied parametrically to evaluate the impact on the single objective function $F_j(P_i)$.

B. The CSA

The CSA algorithm is one of the population-based optimization algorithms. CSA is a heuristic search algorithm inspired by the cuckoo bird breeding behavior [15] and [16]. The cuckoo bird lays her eggs in the nest of another host species. The host takes care of the eggs presuming that the eggs are its own. If the host discovers that an egg is not its own, it may either destroy the egg or the nest and then build a new nest at a different location. The cuckoo breeding analogy is used for developing new design optimization algorithm. A generation is represented by a set of host nests. Each nest carries an egg (solution). The quality of solutions is improved by generating a new solution from an existing solution by modifying certain characteristics. The new solution is formed by a random move on the selected solution (i.e. new solution by modifying only one solution with a random move). If the new solution is found to be superior to another randomly chosen existing solution then the old solution is replaced with the new one. Thus, the best solutions in each generation are carried over to the next generation. The number of solutions remains fixed in each generation. Furthermore, during each generation of evolution a new solution is generated from scratch with a certain probability Pa and this solution is inserted in place of the lowest fit solution. This efficiently deals with the problem of convergence on local sub-optimal solutions.

The CSA implements Levy Flight [15] type of search behavior by employing heavy tailed Cauchy distribution. The authur has used Cauchy distribution for generating random moves in CSA. More details of the CSA used in the field of power system have shown in [17~ 25].

C. 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.

$$\begin{array}{lll} & \underset{x}{\min} & f(x) \\ \textit{subject} \quad \textit{to} & h_k(x) = 0, & k = 1,\ldots, m_e \\ & g_k(x) \le 0, & k = 1,\ldots, m_i \end{array} \tag{7}$$

Where x represents a n_C-dimensional variables, and $h_k\,(x)$ and $g_k\,(x)$ stand for equality and inequality constraints, respectively. The augmented Lagrange function [26] is combined with the Lagrange function and penalty terms, yielding

$$\begin{aligned} L_a(x,\nu,\upsilon) = {} & f(x) + \sum_{k=1}^{m_e} \alpha_k \{ [h_k(x) + \nu_k]^2 - \nu_k^2 \} \\ & + \sum_{k=1}^{m_i} \beta_k \{ \langle g_k(x) + \upsilon_k \rangle_+^2 - \upsilon_k^2 \} \end{aligned} \tag{8}$$

Where α_k and β_k are the positive penalty parameters, and the corresponding Lagrange multipliers $\nu = (\nu_1,\ldots,\nu_{m_e})$ and $\upsilon = (\upsilon_1,\ldots,\upsilon_{m_i}) \ge 0$ are associated with equality and inequality constraints, respectively. The contour of the ALF does not change shape between generations while constraints are linear. Therefore, the contour of the ALF is simply shifted or biased in relation to the original objective function, $f(x)$. Consequently, small penalty parameters can be used in the MU. However, the shape of contour of L_a is changed by penalty parameters while the constraints are nonlinear, demonstrating that large penalty parameters still create computational difficulties. Adaptive penalty parameters of the MU are employed to alleviate the above difficulties. More details of the MU have shown in [27, 28].

D. The proposed CSA-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_a. When both inner and outer iterations become sufficiently large, the ALF converges to a saddle-point of the dual problem [27]. Advantages of the proposed CSA-MU are that the CSA efficiently searches the optimal solution in the economic dispatch process and the MU effectively tackles system constraints.

IV. SYSTEM SIMULATIONS

In this section, the proposed CSA-MU is applied to the standard IEEE 30-bus 6-generator test system for solving the EEDP. The detailed data of this system are given in [14]. The proposed approach solves EEDP considering system constraints of power balance (3) and capacity limits (4). The MU algorithm was used in CSA to hand the equality and inequality constraints. 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 used in this test are follows; the population size Np is set as 5. The iteration numbers of outer loop and inner loop are set to (outer, inner) as (10, 3000).

The implementation of the proposed algorithm for this test can be described as follows:

$$L_a(P_i,\nu,\upsilon)= f_1(P_i)+\alpha_1\{\,[h_1(P_i)+\nu_1]^2-\nu_1^2\,\} + \beta_1\{\,\langle g_1(P_i)+\upsilon_1\rangle_+^2-\upsilon_1^2\,\} \tag{9}$$

$$h_1: P_D-\sum_{i=1}^{N_g}P_i-P_{loss}=0 \tag{10}$$

$$g_1: F_2(P_i)-\varepsilon_2\le 0 \tag{11}$$

Where h_1 stands the violation of power balance constraint (3), and g_1 stands the violation of emission objective for expected ε_2, $\left(\varepsilon_2\in\left[F_2^{\min},F_2^{\max}\right]=\left[0.1942,\quad 0.2215\right]\right)$ [14]. The augmented Lagrange function (9) is solved by the proposed approach. Since cost and emission are of conflicting nature, the value of objective F_2 will be the maximum when the value of F_1 objective is the minimum and vice versa. So, 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 within expected ε_2.

For comparison with previous reports, The expected ε_2 is set as $F_2^{\min}$. Table 1 compares eight computational results obtained from the proposed CSA-MU, Tribe-MDE [8], ACSA [9], BB-MOPSO [10], MAΘ-PSO [11], MO-DE/PSO [12], FCPSO [13], and SPEA [14]. As seen from the best solution of CSA-MU listed in Table 1, the emission output is 0.1942 ton/h. It is observed that the best total cost (TC) utilizing CSA-MU is 637.945142 \$/h, which is much less than the best results previously reported in FCPSO [13] and SPEA [14]. The equality constraint (10) of power balance and the expected emission limit (11) are fully satisfied. Therefore, the result obtained from the proposed CSA-MU is an optimal and feasible solution, and Table 1 demonstrates that the proposed approach is superior to previous methods in solution quality.

V. CONCLUSIONS

The CSA-MU for solving the EEDP has been proposed herein. The CSA helps the proposed method efficiently search and refined exploit. 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 CSA and the MU that has the merit of taking a wide range of penalty parameters and a small population. The IEEE 30-bus test system is used to compare the proposed CSA-MU with previous methods. Simulation results show that the proposed algorithm is superior to previous approaches in solution quality for solving the EEDP. The contributions of this study are the MU effectively handles system constraints of EEDP in emission management, the CSA efficiently searches the optimal solutions for EEDP in the economic dispatch process of power systems.

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TABLE I. COMPARES EIGHT COMPUTATIONAL RESULTS OBTAINED FROM THE PROPOSED CSA-MU AND PREVIOUS METHODS

Items / Methods	SPEA [14]	FCPSO [13]	MA Θ-PSO [11]	Tribe-MDE [8]	MO-DE/PSO [12]	BB-MOPSO [10]	ACSA [9]	CSA-MU
$P(G_1)$	0.4116	0.4097	0.406074	0.406074	0.4061	0.4071	0.405160	0.4045
$P(G_1)$	0.4532	0.4550	0.459069	0.459069	0.4581	0.4591	0.458324	0.4582
$P(G_1)$	0.5329	0.5363	0.537939	0.537939	0.5408	0.5374	0.538468	0.5383
$P(G_1)$	0.3832	0.3842	0.382953	0.382953	0.3822	0.3838	0.382954	0.3853
$P(G_5)$	0.5383	0.5348	0.537939	0.537939	0.5376	0.5369	0.538726	0.5383
$P(G_6)$	0.5148	0.5140	0.510027	0.510027	0.5091	0.5098	0.510369	0.5093
ΣP(G)	2.8340	2.8340	2.834001	2.834001	2.8339	2.8341	2.834001	2.8340
Emission (ton/h)	0.1942	0.1942	0.194202938	0.19420294	0.194203	0.194203	0.1942	0.19420
TC ($/h)	638.5100	638.3577	638.2734405	638.273438	638.270	638.262	638.2026	637.9453