Solved Environmental/Economic Dispatch Based on Multi-objective PSO

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***Abstract*—A new multi-objective evolutionary algorithm for Environmental/Economic power Dispatch (EED) problem based on Particle Swarm Optimization (PSO) is proposed in this paper. The new algorithm has adopted the maintenance method of Pareto candidate solution set based on the max-min distance density. The algorithm effectively guarantees the convergence of the algorithm and the diversity solutions. The performance of algorithm has been examined over the standard IEEE 30-bus six-generator test system, and other multi-objective evolutionary algorithm are compared. Testing and comparing results showed this paper algorithm is feasible and efficient.**

Keywords-environmental/economic dispatch; multiobjective evolutionary; Particle Swarm Optimization

I. INTRODUCTION

The EED problems of electrical power systems is study that the minimization of cost of power generation and the minimization of emission of harmful gases under meet a certain total power demand of system. It is great significance to the national economy, and has become a research hot topic in recent years [1, 2, 3]. The EED problems is a multi-objective Optimization problem having conflicting objectives, as the minimization of emission is contrary to the maintenance of cost economy. At present, there has been much research techniques to handle the EED problem have been reported. Generally speaking, there are three approaches to solve EED problem. The first approach is that the problem has been reduced to a single objective problem by treating the emission as a constraint with a permissible limit [4]. This formulation, however, has a severe difficulty in getting the tradeoff relations between cost and emission. The second approach is that the emission and the fuel cost are treating as the optimization objective. However, the EED problem was converted to a single objective problem either by linear combination of both objectives or by considering one objective at a time for optimization. A linear programming technique has been proposed in a reference [5] which considers one objective at a time. References [6, 7] linearly combined different objectives through the weighted sum method to convert the multi-objective EED problem in single-objective optimization problem. This type of approach requires a strong prior knowledge. These methods generate the non-dominated solution by varying the weights, thus requiring multiple runs to generate the desired Pareto set of solutions. Moreover, these methods are not efficient in solving problems having non-convex Pareto optimal fronts. The third approach handles both fuel cost and emission simultaneously as competing objectives, and recent studies have also concentrated on these.

PSO is an optimization algorithm proposed by Kennedy and Eberhart in 1995 [8, 9]. It is easy to be understood and realized and has been applied in many optimization problems [2, 3]. The application of PSO in the multi-objective optimization problems could be very promising. A new multi-objective evolutionary algorithm for EED problem based on PSO is proposed in this paper. The new algorithm has adopted the maintenance method of Pareto candidate solution set based on the max-min distance density [10]. To this paper algorithm, it effectively guarantees the convergence of the algorithm and the diversity solutions.

II. ENVIRONMENTAL/ECONOMIC DISPATCH PROBLEM

The EED problem is to minimize two competing objective functions, fuel cost and emission, while satisfying several equality and inequality constraints. Generally the problem is formulated as follows.

A. Fuel Cost Objective

The objective of fuel cost is the minimization of total generation cost, while satisfying several constraints. The total fuel cost can be expressed as the following second-order polynomial

$$C = \sum_{i=1}^{n}\left(a_i + b_i \times P_{Gi} + c_i \times P_{Gi}^2\right)$$

Where C is the total fuel cost, a_i, b_i and c_i are the cost coefficients of the $i-th$ generator, and P_{Gi} is the real power output of the $i-th$ generator, n is the number of generators in the power system.

B. Emission Objective

For the minimal pollution emissions, the main consideration is nitrogen oxides NO_x, the total emission of NO_x can be expressed as

$$E = \sum_{i=1}^{n} 10^{-2}\left(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \xi_i \exp\left(\lambda_i P_{Gi}\right)\right)$$

Where α_i, β_i, γ_i, ξ_i, and λ_i are coefficients of the $i-th$ generator emission characteristics.

C. Constraints

Power balance constraint: The total power generated must cover total demand and total transmission losses.

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_{Loss} = 0$$

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Where, P_{Gi} is the real power output of the $i-th$ generator, P_D is total load demand and P_{Loss} is transmission losses.

Maximum and minimum limits of power generation: The power generated P_{Gi} by each generator is constrained between its minimum and maximum limits stated as

$$P_{Gi\min} < P_{Gi} < P_{Gi\max} \quad i = 1,\dots,n$$

Where $P_{Gi\min}$ and $P_{Gi\max}$ are maximum and minimum limits of power generation.

Line flow constraints: The transmission line loading is restricted by its upper limit as

$$S_l < S_{l\max} \quad i = 1,\dots,n_l$$

Where, n_l is the number of transmission line.

Obviously, The EED problem is formulated as a constrained multi-objective optimization problem and is given as

$$Min\left(C\left(P_G\right), E\left(P_G\right)\right)$$

$$s.t.$$

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{Loss} = 0$$

$$P_{Gi\min} < P_{Gi} < P_{Gi\max} \quad i = 1,\dots,n$$

$$S_l < S_{l\max} \quad i = 1,\dots,n_l$$

III. Particle Swarm Optimization

The best position in the course of flight of each swarm of PSO is the best solution that is found by the swarm. The best position of the whole flock is the best solution, which is found by the flock. The former is called *pBest*, and the latter is called *gBest*. Every swarm continuously updates itself through the above mentioned best solution. Thus a new generation of community comes into being. In the practical operation, the fitness function, which is determined by the optimization problem, assesses the extent to which the swarm is good or bad.

Obviously, each swarm of PSO can be considered as a point in the solution space. If the scale of swarm is N, then the position of the $i-th$ $(i = 1, 2, \cdots N)$ particle is expressed as X_i. The "best" position passed by the particle is expressed as $pBest[i]$. The speed is expressed with V_i. The index of the position of the "best" particle of the swarm is expressed with g. Therefore, swarm i will update its own speed and position according to the following equations [8, 9,]:

$$\begin{aligned} V_i &= w * V_i + c_1 * rand(\ ) * \left(pBest[i] - X_i\right) \\ &\quad + c_2 * Rand(\ ) * \left(pBest[g] - X_i\right) \qquad (1) \\ X_i &= X_i + V_i \end{aligned}$$

Where c_1 and c_2 are two positive constants, $rand()$ and $Rand()$ are two random numbers within the range $[0,1]$, and w is the inertia weight. The equations consist of three parts. The first part is the former speed of the swarm, which shows the present state of the swarm; the second part is the cognition modal, which expresses the thought of the swarm itself; the third part is the social modal. The three parts together determine the space searching ability. The first part has the ability to balance the whole and search a local part. The second part causes the swarm to have a strong ability to search the whole and avoid local minimum. The third part reflects the information sharing among the swarms. Under the influence of the three parts, the swarm can reach an effective and best position.

In addition, the swarm is limited by $V_{\max}$ when it is adjusting its own position according to the speed. The speed V_i is set to be $V_{\max}$ when V_i exceeds $V_{\max}$.

IV. Proposed Algorithm

A. Max-Min Distance Density

Simplex the algorithm based on Pareto sorting only considers the dominant relation among individuals, but not considers the density distribution of the individual space, therefore, a lot of similar solutions are generated easily, and the diversity of the solutions is hard to be guaranteed. The accepted method of guaranteeing the diversity of solutions is defining the space distribution density of the individual. In SPEA2, the density value of an individual is defined by the distance between the individual and the $k-th$ nearest individual to it. The definition of crowding distance in NSGA2 pointed out the average side of the smallest rectangular solid which contains the individual itself but doesn't contain other individuals. The References [10] proposed the idea of max-min distance density, and definition as follows:

$$D(i) = \sum\nolimits_{d_j^i \le d_{\max-\min}} |S|$$

S is a set of some individuals, it's size is n. in the objective function space, the Euclid distance between any one individual i in S and other individual can be denoted using $d_j^i\left(j = 1, 2 \cdots n, j \ne i\right)$, where $d_{\min}^i$ indicated the minimum value of d_j^i is the minimum Euclid distance of the individual i, then there is a minimum distance set $d_{\min} = \left(d_{\min}^1, d_{\min}^2, \cdots d_{\min}^n\right)$ exists for all individual in the set, the maximum value of $d_{\min}$ is denoted using $d_{\max-\min}$, so $d_{\max-\min}$ is called that the max-min distance of the set S.

B. Maintaining Pareto Candidate Solution Set

Constituting Pareto candidate solution set to keep Pareto solutions that have been found and maintaining diversity of solutions in Pareto candidate the solution set are the most effective ways of MOEA to achieve Pareto solutions. In this paper a strategy of constituting and maintaining the Pareto's candidate solution set based on max-min distance density is proposed. The process can be expressed as follows:

(1)If the size of the Pareto candidate solution set doesn't reach the prior prescriptive size, add the achieved Pareto solution to the Pareto candidate solution set;

(2)Otherwise, if the new Pareto solutions dominated the individuals in Pareto candidate solution set, delete the individuals which were dominated from the Pareto candidate solution set, and add the individuals to the Pareto candidate solution set, otherwise, add the new Pareto Solution to the Pareto candidate solution set, and calculate the max-min distance density of each individual in Pareto candidate solution set, and delete the individual which has the maximum max-min distance density in the Pareto' candidate solution set.

C. Algorithm Description

1) Set algorithm parameter;
2) Create initial population N randomly in decision space;
3) Add the Pareto Solution in population N to Pareto candidate solution set;
4) According to equation (1), produce the new generation;
5) According to the method in section IV.B, add the Pareto Solution of new generation to the Pareto candidate solution set;
6) If the terminate condition is satisfied, stop the iteration, otherwise go to 4).

V. IMPLEMENTATION OF THE PROPOSED APPROACH

A. Parameterss Set

The parameters of the PSO are that: set the population size $N = 20$, learning rate $c_1 = c_2 = 0.5$, inertia weight is taken from 0.9 to 0.2 with a linear decreasing rate. The maximum velocity $V_{\max}$ is taken as the dynamic range of the particle in each iteration. The approach presented in this paper is simulated on the standard IEEE 30-bus six -generator test system [2] (Fig. 1). The power system is connected through 41 transmission lines. Fuel cost and emission coefficients are provided in Table I and Table II. For simple, we consider only the capacity constraint of generator in test.

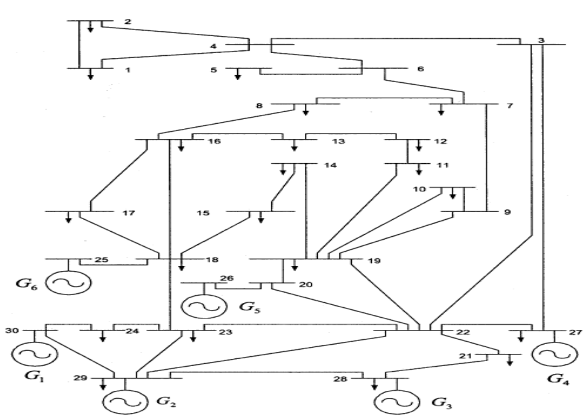

Figure 1. IEEE 30 Bus six-generator system.

TABLE I. FUEL COST COEFFICIENTS

Generator	a_i	b_i	c_i	$P_{Gi\min}$	$P_{Gi\max}$
G_1	10	200	100	0.05	0.50
G_2	10	150	120	0.05	0.60
G_3	20	180	40	0.05	1.00
G_4	10	100	60	0.05	1.20
G_5	20	180	40	0.05	1.00
G_6	10	150	100	0.05	0.60

TABLE II. EMISSION COEFFICIENTS

Generator	α_i	β_i	γ_i	ξ_i	λ_i
G_1	4.091	-5.554	6.490	2.0×10^{-4}	2.857
G_2	2.543	-6.047	5.638	5.0×10^{-4}	3.333
G_3	4.258	-5.094	4.586	1.0×10^{-6}	8.000
G_4	5.426	-3.550	3.380	2.0×10^{-3}	2.000
G_5	4.258	-5.094	4.586	1.0×10^{-6}	8.000
G_6	6.131	-5.555	5.151	1.0×10^{-5}	6.667

B. Results Analysis

In this paper, we consider that two the most representative non-inferior solutions: best fuel cost and best emission. As shown in the Table III and Table IV.

We consider only the capacity constraint of generator in test. In this case, Table III show the best fuel cost and a corresponding emission obtained by the this paper algorithm as compared to Linear Programming (LP)[5], Multi-Objective Stochastic Search Technique (MOSST)[11], Non-dominated Sorting Genetic Algorithm (NSGA[12]), Niched Pareto Genetic Algorithm (NPGA)[13], Strength Pareto Evolutionary Algorithm (SPEA)[1] and NSGAII[14]. Table IV show the best emission and a corresponding fuel cost obtained by this paper algorithm as compared to LP MOSST, NSGA, NPGA, SPEA and NSGAII.

From Table III, we can see that the best fuel cost is 600.352 \$/hr by this algorithm with a corresponding emission of 0.22298 ton/hr. In this case, this paper algorithm is better than LP, MOSST and NSGA. From Table IV we also can see that the best emission is 0.19425 ton/hr by this paper algorithm with a corresponding fuel cost is 638.232 \$/hr. In this case, this paper algorithm is better than NSGA, NPGA and SPEA. But, this paper algorithm has adopted the maintenance method of Pareto candidate solution set based on the max-min distance density. In best fuel case, 20 particles of the PSO are used and 20 solutions are obtained. The 20 solutions are more uniform distributed.

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TABLE III. BEST FUEL COST

	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	This Paper
P_{G1}	0.1500	0.1125	0.1567	0.1080	0.1062	0.1059	0.1095
P_{G2}	0.3000	0.3020	0.2870	0.3284	0.2897	0.2177	0.3148
P_{G3}	0.5500	0.5311	0.4671	0.5386	0.5289	0.5216	0.5310
P_{G4}	1.0500	1.0208	1.0467	1.0067	1.0025	1.0146	1.0082
P_{G5}	0.4600	0.5311	0.5037	0.4949	0.5402	0.5159	0.5218
P_{G6}	0.3500	0.3625	0.3729	0.2574	0.3664	0.3583	0.3489
Best cost	606.314	605.889	600.572	600.259	600.15	600.155	600.352
Emission	0.22330	0.22220	0.22282	0.22116	0.2215	0.22188	0.22298

TABLE IV. BEST EMISSION

	LP	MOSST	NSGA	NPGA	SPEA	NSGA-II	This Paper
P_{G1}	0.4000	0.4095	0.4394	0.4002	0.4116	0.4074	0.4205
P_{G2}	0.4500	0.4626	0.4511	0.4474	0.4532	0.4577	0.4507
P_{G3}	0.5500	0.5426	0.5105	0.5166	0.5329	0.5389	0.5287
P_{G4}	0.4000	0.3884	0.3871	0.3688	0.3882	0.3837	0.3901
P_{G5}	0.5500	0.5427	0.5553	0.5751	0.5383	0.5352	0.5372
P_{G6}	0.5000	0.5142	0.4905	0.5259	0.5148	0.5110	0.5112
Best Emission	0.19424	0.19418	0.19436	0.19433	0.1943	0.19420	0.19425
Cost	639.600	644.112	639.231	639.182	638.51	638.269	638.232

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