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Multiobjective Electricity Power Dispatch Using Multiobjective Particle Swarm Optimization[1]

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Abstract: - This paper presents a new approach for Environmental/Economic transaction planning problem in the electricity market. The Environmental/Economic transaction planning problem is formulated as a multi-objective optimal power flow (MOPF) problem. A novel algorithm using multiobjective Particle Swarm Optimization (MOPSO) and non-stationary multi-stage assignment penalty function is proposed to solve this problem. PSO is modified by using dynamic neighborhood strategy, new particle memory updating, and one-dimension optimization to deal with multiple objectives. Incorporating of non-stationary multi-stage assignment penalty function in solving OPF problem can improve the convergence. The proposed method is demonstrated on the IEEE 30-bus system. The results show that the proposed approach can efficiently gain multiple pareto optimal transaction planning that match with the sustainable development strategy.

Key-Words: - Electricity market, Environmental and Economic transaction planning, PSO,Optimal Power Flow,Dynamic neighborhood strategy

1 Introduction

In recent years, the electricity industry has undergone drastic changes due to a world wide deregulation or privation process that has significantly affected energy market. Bidding mechanism is one of the most challenge issues in the power market. In conventional transaction planning, minimal of pool purchase cost or maximal of social profit is market clearing objective function. however, with the increasing public awareness of the environment protection and the passage of the Clear Air Act Amendments of 1990 have forced the utilities to modify their design or operations strategies to reduce pollution and atmospheric emissions of the thermal power plants. Several strategies to reduce the atmospheric emission have discussed [1-5]. These include installation of pollutant clearing equipment, switching to low emission fuels, replacement of the aged fuel-burners with clearer ones, and the Environmental/Economic power dispatching. Multi-objective transaction planning considering environment protection and economic profit in the deregulated power system is discussed in [3-5]. However, This model is formulated as the Environmental and Economic Dispatch problem and the approach that combined fuzzy sets theory and nonlinear programming is adopted to solve it

Optimal Power Flow (OPF) is a useful tool in a modern Energy Management System. The main purpose of an OPF is the optimal allocation of system controls to satisfy the power demand under specific constraints. The equality constraints are the conventional power flow equations; the inequality constraints are the limits on the control variables, operating and security limits. in recent years, the literature on MOPF is vast, and presents the major contributions in this area. Mathematical programming approaches, such as nonlinear programming (NLP), quadratic programming (QP), and linear programming (LP), have been used for the solution of the OPF problem. Multiobjective Optimal Power Flow (MOPF) is a multoobjective optimization problem, for multiobjective optimization problem , objective functions may be optimized separately form each onther and the best solution can be found for each dimension. However, this is because in most cases the objective functions are in conflict each other. The multiobjective only has a parto solutions, that is, if no feasible solutions that decrease some objective values without causing a simultaneous increase in at least one other objective value. Traditional optimization techniques, such as gradient-based method are difficult to extend to the true multiobjective case, because they were not designed to deal with multiple optimal solutions. In most case, multibjective problems have to be scaled to a single objective problem before the optimization.

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Thus the results produces a single pareto optimum for each run of the optimization process and the results is highly sensitive to the weight vector used in the scaling process[3,4]. Because evolution evolutionary algorithm deal with a group of candidate solutions, it seems natural to use it to find a group of pareto optimal solutions simultaneously. There are many papers that have reviewed the evolutionary algorithms based optimizations techniques [2,7,8]. Most of them based on genetic algorithms. Recently, PSO algorithm is successfully used to solve ED and OPF problem [9]. However, this method based on single-objective problem. MOPS is discussed in [10] However, these paper not discussed Multi-objective Optimal Power Flow problem.

In this paper, a new multiobjective approach for Environmental/Economic transaction planning problem in the electricity market is proposed. The Environmental and Economic transaction planning problem is formulated as a multi-objective optimal power flow problem. A new multiobjective algorithm using multiobjective Particle Swarm Optimization and non-stationary multi-stage assignment penalty function is proposed to solve this problem. PSO is modified by using dynamic neighborhood strategy, new particle memory updating, and one- dimension optimization to deal with multiple objectives. Incorporating of non-stationary multi-stage assignment penalty function in solving OPF problem can improve the convergence and gain more accurate values. The proposed method is demonstrated on the IEEE 30-bus system. The results show that the proposed approach can efficiently gain multiple pareto optimal transaction planning that match with the sustainable development strategy.

2 Formulation of Multiobjective Transaction Planning Problem

2.1 Objective Functions

Minimization of pool purchase cost: the total $ can be expressed as (1)

$$Min \quad F_1 = \sum_{i=1}^{m} (f(P_{gi})P_{gi}) \qquad (1)$$

Where, $f(P_{gi}) = a_i P_{gi} + b_i$ is the bidding function of generating unit i, P_{gi} is the output of generator unit i, m is the number of total generating unit, respectively.

Minimization of emission: the atmospheric pollutants such as sulpher oxides SO_x and nitrogen oxides NO_x caused by fossil-fueled thermal units can be modeled separately. However total ton emission ton can be expressed as (2)

$$Min \quad F_2 = \sum_{i=1}^{m} (\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i) \qquad (2)$$

where $\gamma_i, \beta_i, \alpha_i$ are emission characteristics coefficients of generating unit i.

2.2 Objective Constraints

Real power balance:

$$P_{Gi} - P_{Li} - V_i \sum_{j=1}^{j=n} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \qquad (3)$$

Reactive power balance:

$$Q_{Gi} - Q_{Li} - V_i \sum_{j=1}^{j=n} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \qquad (4)$$

Where P_{Li}, Q_{Li} is the real and reactive power demand of bus i respectively, V_i is the rating voltage of bus i, $\theta_{ij} = \theta_i - \theta_j$ is the difference of voltage angle between bus i and bus j respectively.

Generation constraints: for stable operation, the generator outputs and bus voltage magnitudes are restricted by lower and upper limits as follows:

$$P_{gi\min} \le P_{gi} \le P_{gi\max} \qquad (5)$$

$$Q_{gi\min} \le Q_{gi} \le Q_{gi\max} \qquad (6)$$

$$V_{i\min} \le V_i \le V_{i\max} \qquad (7)$$

Where $P_{gi\min}, P_{gi\max}$ is the lower and upper limits of generating unit i. $Q_{gi}, Q_{gi\min}, Q_{gi\max}$ are stand for reactive output, lower and upper reactive limit of generating unit i respectively. $V_i, V_{i\min}, V_{i\max}$ are stand for voltage magnitude , lower and upper limits of voltage of bus i, respectively.

Security constraints: for secure operation, the transmission line loading is restricted by its upper limits as

$$S_l \le S_{l\max} \qquad (8)$$

Where $S_l, S_{l\max}$ are stand for the power of transmission line l, limits of transfer capacity of transmission lines l. In other words, network congestion are modeled by this constraint.

3 PSO to solve the optimization problem Algorithm for Multiobjective Transaction Planning Problem

3.1 Overview of The Particle Swarm Optimization

Particle Swarm Optimization is a novel optimization method developed by Kennedy and Eberhart [6]. It is based on the behavior of individuals (i.e., particles or agents) of a swarm. Its roots are in zoologist's modeling of the movement of individuals (e.g., fishes, birds, or insects) within a group. It has been noticed that members within a group seem to share information among them, a fact that lead to increased efficiency of the group. The PSO algorithm searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques. An individual in a swarm approaches to the optimum or a quasioptimum through its present velocity, previous experience, and the experience of its neighbors.

Let *x* and *v* denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. The best previous position of particle is recorded and represented as *pbest*. The index of the best particle among all the particle in the group is presented as *gBest.* To ensure convergence of PSO, clerc indicates that use of a constriction function may be necessary. At last, the modified velocity and position of each particle can be calculated as shown in the following formulas:

$$v_{i+1} = K \times [w \times v_i + \varphi_1 \times rand() \times (pBest - x_i) + \varphi_2 \times rand() \times (gBest - x_i)] \quad (9)$$

$$x_{i+1} = x_i + v_{i+1} \quad (10)$$

where i is pointer of iterations, x_i is the current position of particle at iteration i, v_i is the velocity of particle at iteration i, w is the inertia weight factor, φ_1, φ_2 is the acceleration constant, $rand()$ is the uniform value in the range[0,1], K is the constriction factor , is a function of φ_1, φ_2 as reflected in (11)

$$K = \frac{2}{\left|2 - (\varphi_1 + \varphi_2) - \sqrt{(\varphi_1 + \varphi_2)^2 - 4(\varphi_1 + \varphi_2)}\right|} \quad (11)$$

The inertia weight is set according to the following equation

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (12)$$

Where $iter_{\max}, iter$ is the maximum number of iterations, and the current number of iterations, respectively.

To ensure uniform velocity through all dimensions, the maximum velocity is as

$$v^{\max} = (x^{\max} - x^{\min}) / N \quad (13)$$

Where *N* is a chosen number of iterations.

3.2 Overview of The MOPSO Alogrithm

Until recently PSO had only been applied to single objective problems, however, in a large number of design Applications there are a number of competing quantitative measures that define the quality of a solution. For instance, in designing the ubiquitous widget, a firm may wish to minimise its production cost, but also maximise/minimise one or more widget performance properties. These objectives cannot be typically met by a single solution, so, by adjusting the various design parameters, the firm may seek to discover what possible combinations of these objectives are available, given a set of constraints (for instance legal requirements and size limits of the product). The curve (for two objectives) or surface (more than two objectives) that describes the optimal trade-off possibilities between objectives is known as the true Pareto front. A feasible solution lying on the true Pareto front cannot improve any objective without degrading at least one of the others, and, given the constraints of the model, no solutions exist beyond the true Pareto front. The goal, therefore, of multi-objective algorithms (MOAs) is to locate the Pareto front of these non-dominated solutions. Sharing many characteristics with other evolutionary algorithms, PSO could be a potential method for multi-objective optimization. However, basic global and local version PSO algorithm are not suitable for there is no absolute global optimum in multiobjective functions. It is not easy to define a single *gBest* during each generation. Compared with genetic algorithms(GAs), The information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only *gBest* gives out information each other. However, due to the point-centered characteristics, global PSO is unable to locate the pareto front, which includes multiple optimal points. The neighborhood (local) version does not work either, because the neighbors are predefined and they often only refine the search near the optimum.

A number of different studies published on multi-objective PSO (MOPSO) [10-12]. However, although most of these studies were generated in tandem, each of these studies implements MOPSO in a different fashion. Given the wealth of MOEAs in the literature this may not seem particularly surprising, however the PSO heuristic puts a number of constraints on MOPSO that MOEAs are not subject to. In PSO itself the swarm population is fixed in size, and its members cannot be replaced, only adjusted by their pbest and the gbest, which are themselves easy to define. However, in order to facilitate an MO approach to PSO a set of non-dominated solutions (the best individuals found so far using the search process) must replace the single global best individual in the standard uni-objective PSO case, in addition, there may be no single previous best individual for each member of the swarm. Interestingly the conceptual barrier of *gBest* and *lBest* tends to get blurred in the MO application of PSO. A local individual may be selected for each swarm member, however these *lBest* individuals may all also be non-dominated (representing local areas of the estimated Pareto front maintained by the swarm), making them all also *gBest*. Here a dynamic neighborhood PSO is introduced [12]. In each generation, after calculating distances to every other particle, each particle finds its new neighbors. Among the new neighbors, each particle finds the local best particle as the *lBest.* The problem is how to define the distances and how to define the local best particle. Two-objective continuous numeric optimizations are used to demonstrate the dynamic neighborhood PSO as follows: In two-dimensional fitness-value space, the pareto front is the boundary of fitness value region, it includes the combination of continuous or discontinuous lines and/or points. For a minimization problem, the boundary should be located at lower left side of the fitness space. If the first values are fixed, only optimize the second objective function, and the final solution should be "dropped" onto the boundary line, which includes the pareto front.

3.3Mopso Alogrithm for MOPF

Environmental /Economic multiobjective transaction planning problem is can be solved by the dynamically neighborhood PSO and incorporating non-stage multi-stage penalty function. The algorithm is can be described in the following steps.

Step1)Input parameters of system, and specify the lower and upper boundaries of each variable.

Step2)Initialize randomly the particles of the population. These initial particles must be feasible candidate solutions that satisfy the practical operation constraints.

Step3)To each particles of the population, employ the Newton-Raphson method to calculate power flow and the transmission loss.

Step 4)Calculate the evaluation value of each particle by using the evaluation the first objective function and the non-stationary multi-stage assignment penalty function in the population.

Step5)Compare each particle's evaluation with its *pBest*. The best evaluated value among the *pBest* is *gBest*.

Step6:))Calculate the distances of the current particle from other particles in the fitness value space of first objective function (not variable space).

Step7:)Find the nearest *m* particles as the neighbors of the current particle based on the distances calculated above.

Step8)Find the local optima among the neighbors in terms of the fitness value of the second objective function.

Step9)Update the time counter $t=t+1$.

Step10)Update the inertia weight *w* given by (12).

Step11)Modify the velocity v of each particle according to (9).

Step12)Modify the position of each particle according to (10). If a particle violates its position limits in any dimension, set its position at the proper limits.

Step13)Each particle is evaluated according to its updated position. The *pBest* is the best position history. Only when a new solution dominates the current *pBest,* is the *pBest* is updated.

Step14) If one of the stopping criteria is satisfied then go to Step 15. Otherwise, go to Step 9.

Step15)The particle that generates the latest *gBest* is the pareto optimal value.

4 Numberical Results

The proposed MOPSO-based approach has been tested on the standard IEEE 30-bus test system, Table. 1 is the coefficients of environmental and economic, Other parameters are given in Refc. [16-18].

Table 1 Generator bidding price and emission coefficients

		G1	G2	G3	G4	G5	G6
Cost	a	7.0	8.4	9.2	10	8.4	9.2
$\times 10^{-2}$	b	20	15	18	16	18	17
Emis-sion $\times 10^{-2}$	α	4.091	2.543	4.258	5.246	4.258	6.131
	β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
	γ	6.490	5.638	4.586	3.380	4.586	5.151

To demonstrate the effectiveness of the proposed approach to multiobjective optimization problem, three different cases have been simulated as follows:

Step1)minimization of the pool purchase cost transaction planning based on OPF using PSO.

Step2)minimization of the emission pollution transaction planning based on OPF using PSO.

Case 3) minimization of both the pool purchase cost and emission pollution using proposed approach.

In the simulation results, Table 2 shows the comparison of generators bidding output for each case; Table 3 is the comparison of value of objective function for each case.

Table 2 Comparsion for objective function for each case

	Case 1	Case 2	Case 3
Pool purchase cost /$	2248.25	2256.97	2244.33
Emission /ton	244.478	187.743	221.361

Table 3 Comparsion for real power output of genertors unit:MW

Case	Gen1	Gen2	Gen3	Gen4	Gen5	Gen6
1	35.21	34.34	31.89	29.18	28.32	32.89
2	22.81	26.43	34.65	34.33	25.92	47.25
3	30.87	31.57	32.85	30.98	27.48	37.91

We can know form Table 3, while we take the economic or environmental objective as market clearing objective, we only get a single-objective optimization bidding results individually. If we can know that this proposal model can make environment/economic optimized, the proposed approach can solve multiobjective optimal power flow problem.

5 Conclusion

In this paper, a new multiobjective approach for Environmental/Economic transaction planning problem in the electricity market is proposed. The Environmental and Economic transaction planning problem is formulated as a multi-objective optimal power flow problem. A new multiobjective algorithm using multiobjective Particle Swarm Optimization and non-stationary multi-stage assignment penalty function is proposed to solve this problem. PSO is modified by using dynamic neighborhood strategy, that is, new particle memory updating, and one-dimension optimization to deal with multiple objectives. Incorporating of non-stationary multi-stage assignment penalty function in solving OPF problem can improve the convergence and gain more accurate values. The proposed method is demonstrated on the IEEE 30-bus system. The results show that the proposed approach can efficiently gain multiple pareto, this multiobjective optimal transaction planning with proposed approach more match with the sustainable development strategy than that of with single-objective optimal method.

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