

Multiobjective Particle Swarm Optimization for Environmental/Economic Power Dispatch Problem

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Abstract

By the use of fossil based fuels in power generation units requires the consideration of the environmental pollution. A multiobjective particle swarm optimization technique for the solution of environmental economic power dispatch problem is proposed in this paper. Here EED problem is formulated a nonlinear multiobjective function as objective function by considering both equality and inequality constraints. The multi-objective optimization in power systems treats economic and emission as conflicting objectives, to get an optimal solution some reasonable trade off among these objectives are required. So in this paper, the power dispatch is formulated into a two-objective optimization problem, which is to minimize the fuel cost as well as emission simultaneously.

Keywords- Environmental/Economic (EED) dispatch, multiobjective optimization, particle swarm optimization, Pareto optimal solution, compromise factor

I. INTRODUCTION

In order to meet the required load demand at minimum operating cost of electric power generating units is to schedule the committed units, which is the basic objective of economic dispatch(ED), while satisfying all generating units with equality and inequality constraints. Usually while considering economic dispatch, we are not considering the pollution produced by the thermal generating stations. For effective scheduling of all power generating system for planning and operation in order to meet required power demand with minimum operating cost. Emission dispatch (ED) is similar to ECD, that is emission is considered as the objective to be minimized with another objective as cost. Nowadays most countries have focused on the reduction of the pollutions created by fossil fueled thermal power generating plants. Normally power plant emissions are sulphur oxides (SO₂) and nitrogen oxides (NO_x). We know economic cost dispatch (ECD) and emission dispatch(ED) are entirely different. The economic dispatch reduces the total fuel cost (operating cost) of the system at an increased rate of NO_x. As we know that emission dispatch reduces the total emission produced by the thermal power plants. So it is necessary to find an optimum point having minimum operating cost and minimum emission. This optimum point is achieved by the combination of economic dispatch and emission dispatch and getting the environmental/emission dispatch (EED).

The combination of environmental economic dispatch (EED) problem is not a single objective function but having a two conflicting objective functions: operating fuel costs and emission produced by particular thermal plants. The conventional approaches normally used are not sufficient to get the required goals of minimum fuel cost and less emission. Therefore, normally conventional optimization methods are not suitable for this nonlinear optimization problem in order to obtain optimal solution. So many methods are nowadays available to reduce the atmospheric pollutions have been proposed and analyzed [1]–[3]. To reduce these kinds of emissions, so many strategies are proposed here such as the installation of pollutant cleaning equipment, usage of low emission fuels, to change the existing aged fuel burners with new one and efficient emission dispatching techniques. The above mentioned first three methods requires the replacement of new equipment or modification of the existing equipment which causes more capital cost, hence, those methods can be treated for long term solutions. The last option above mentioned which is the emission dispatch, can consider as short term method and both operating fuel cost and emission is minimized with proper dispatch.

Different methodologies have been proposed to solve these types of multiobjective environmental/economic dispatch problem. In [4] the problem is reduced to a single objective problem by considering the emission as a constraint with a permissible limit condition. This multiobjective formulation of environmental/economic dispatch problem having different

difficulties during dispatch solution to get correct relation between the cost and emission. So fuel cost and emissions are to be treated as objective functions. In paper [5], the linear programming based optimization technique in which both emission and fuel cost functions as objective function. But by considering both these functions as objective functions, the environmental/economic (EED) problem becomes a complicated nonlinear optimization problem. So many conventional methodologies are available in order to obtain global optimal solution but all those methods can't attain the global solution. Many techniques based on analytic methods having differential objective functions having the advantage to simplify the above formulated. On the other hand, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the above mentioned environmental/economic (EED) problem. There are so many methods are now available to consider these two cost function and emission function together into a single objective function using the linear combination of two objectives as a weighted sum which is explained [6] and [7]. A Pareto optimal solution is obtained by above mentioned weighted sum method by varying the weights. But much iteration is required to obtain this Pareto optimal global solution. Although all these methods can't use to obtain the global solution due to non convex Pareto optimal front. So in [8] and [9], a method is explained to overcome the above difficulty which is the ϵ -constraint method for the solution of multiobjective optimization. This method is based on getting most optimized solution of multiobjective objective function with some constraints having permissible limits. Recently some modern techniques such as genetic algorithm, evolutionary programming, artificial bee colony, tabu search algorithm, ant colony, bacterial foraging, flower pollination technique, efficient particle swarm optimization technique, genetic algorithm with simulated annealing process have been emerged to solve the complex non linear problem. During the dispatch we can face some problems of handling non smooth fuel cost function and emission function. So an effective and efficient optimization technique is required to solve multiobjective function. Here this paper proposes the use of Particle Swarm Optimization (PSO) to solve the bi-objective function which is a global searching technique.

II. PROBLEM FORMULATION

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

A. Formulation of Multi-objective Problem Mathematical Models

The generators cost can be written quadratic equation as

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad \dots\dots\dots (1)$$

Where $C_i(P_i)$ is the fuel cost (\$/h), is the power generated (MW), and a_i, b_i, c_i are the fuel cost coefficients of the i^{th} unit, and we suppose $c_i > 0$.

The atmospheric pollutants produced by thermal power plants such as sulphur oxides and nitrogen oxides can be modelled. The total emission can be written in kg/h as

$$E_i(P_i) = d_i + e_i P_i + f_i P_i^2 \quad \dots\dots\dots (2)$$

Where $E_i(P_i)$ is the emission (kg/h), P_i is the power generated (MW), and d_i, e_i, f_i are the emission coefficients of the i^{th} unit, and we suppose $f_i > 0$

B. Environmental/Economic Dispatch

1) Problem Objectives

The EED problem, with N plants is to minimize two objective functions: fuel cost function and emission function.

Minimization of Fuel Cost: The total (\$/h) fuel cost $C(P)$ can be expressed as

$$C(P) = \sum_{i=1}^N C_i(P_i) \quad \dots\dots\dots (3)$$

Minimization of NOx Emission: The total (kg/h) emission can be expressed as

$$E(P) = \sum_{i=1}^N E_i(P_i) \quad \dots\dots\dots (4)$$

2) Objective Constraints

The EED problem is subject to two constraints:

Generation capacity constraint: For stable operation, real power output of each generator is restricted by lower and upper limits as follows

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad \dots\dots\dots (5)$$

Where P_i^{\min} and P_i^{\max} are the minimum and maximum power outputs of the units

Power balance constraint: The total power generation must meet the required total demand P_D and the real power loss in transmission lines P_L . Hence,

$$\sum_{i=1}^N P_i = P_D + P_L \quad \dots\dots\dots (6)$$

Where P_D the total load is demand (MW) and P_L is the total transmission losses (MW).

Aggregating the two conflicting objectives (3), (4) and the two constraints (5), (6), the EED problem can be mathematically formulated as follows:

Minimisation : [C(P), E(P)]

Subject to : $g(P) = 0$

$h(P) \leq 0$

Where g is the equality constraint representing the power balance and h is the inequality constraint representing the unit generation capacity. In general, the EED can be formulated either as an emissions constrained economic dispatch (ECED) or as a multi-objective optimization problem (MOP). Here the two objective functions are combined together to get multiobjective optimization problem using the weighting method. Thus this approach converts it into a single objective optimization problem using the weighted sum of C_i and E_i

$$\text{Minimise : } \delta \sum_{i=1}^N C_i(P_i) + (1 - \delta) \sum_{i=1}^N E_i(P_i)$$

$$\text{Subject to: } \sum_{i=1}^N P_i = P_D + P_L$$

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \forall i = 1, 2, \dots, N \quad \dots\dots\dots (7)$$

Where δ is a constant in the range of [0, 1]

III. COMBINED ECONOMIC AND EMISSION DISPATCH USING PARTICLE SWARM OPTIMIZATION

PSO is based on the social behaviour of nature and this contains population of particles corresponding to each individuals. Each particle has its own position and velocity. In a multi-dimensional search space these particles are flying and thus attaining the new values of position and velocity at different points. In Particle Swarm Optimization, a particle can be defined as a moving point in N dimensional space. For each particle, at each current time step, we can record corresponding position and velocity and the best solution for position and velocity is noted. Let x and v denote a particle position and its corresponding flight velocity in a search space, respectively. The best previous recordings of position and velocity can be treated as the personal best coordinates and represent as *pbest*. The personal best in all the particles is represented as global best that is *gbest*. So each particle have its best value which is personal best (*pbest*) and best value among all the groups is global best (*gbest*). The particles try to improve their own personal bests by modifying its position using the particle velocity. Thus modified values of *pbest* and *gbest* is attained from the coordinates (position and velocity) and those values can be found out following

$$v_i^{k+1} = w * v_i^k + c_1 * \text{rand}_1 * (\text{pbest}_i - x_i) + c_2 * \text{rand}_2 * (\text{gbest}_i - x_i) \quad \dots\dots\dots (8)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad \dots\dots\dots (9)$$

Where v_i^k : velocity of particle i at iteration k

w : inertia weight factor

c_1, c_2 : learning factor

$\text{rand}_1, \text{rand}_2$: random number between 0 and 1

x_i^k : position of particle i at iteration k

x_i^{k+1} : position of particle i at iteration $k+1$

v_i^{k+1} : velocity of particle i at iteration $k+1$

From the above formula, the constants c_1 and c_2 are known as acceleration constants and optimises the given problem towards *pbest* and *gbest* positions. Usually the values of acceleration constants are set at 2.0 depending on previous experience. The low values of acceleration constants will make the whole system which wander around the targeted position before comes into stable operation. So for higher values of acceleration constants will make the system fast into converging towards the optimum point. In eqn. (8), ' w ' is the inertia weight which provides sufficient balance between local and global optimum

solution. So requires less number of iterations to find sufficiently optimum solution. At normal iterations the value of w is decreased about 0.9 to 0.4. From eqn. (8), the particle changes its own position depending on the new velocity.

Here iteration process is carried out with maximum particle velocity V_i^{\max} and this parameter V_i^{\max} has the ability to determine the fitness and resolution in the target position with present position in the N dimensional space. The proper selection of V_i^{\max} will determine the efficient optimization with optimum solution. If we choose high value of V_i^{\max} the particles might fly past the required solution. Similarly if we choose low value of V_i^{\max} , the particles may not attain the correct local solution.

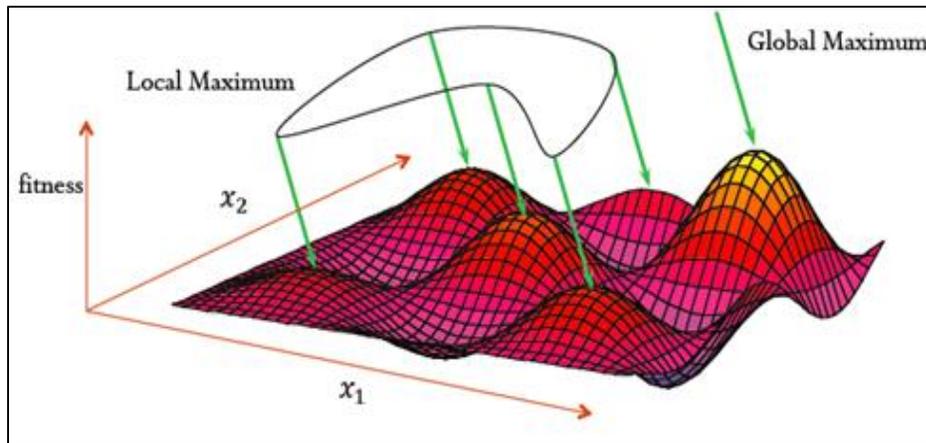


Fig. 1: Local and Global maximum in PSO



Fig 2: Flow chart of PSO

IV. SIMULATION RESULTS

The proposed Particle Swarm optimization is used and verified the effectiveness of the system. Here three thermal power generating units with six generators were tested. Fuel cost coefficients, emission co efficient and generation limits for each generating unit of the test system were given in Table 1.

Table 1: Fuel Cost coefficients, Emission Coefficients, Loss Coefficients and Generating Capacity Constraints

Plant	Unit	a_i	b_i	c_i	d_i	e_i	f_i
1	G1	756.79886	38.53973	0.15247	13.85932	0.32767	0.00419
	G2	451.32513	46.15916	0.10587	13.85932	0.32767	0.00419
	G3	1049.32513	40.39655	0.02803	40.2669	-0.54551	0.00683
2	G4	1243.5311	38.30553	0.03546	40.2669	-0.54551	0.00683
	G5	1658.5696	36.32782	0.02111	42.89553	-0.51116	0.00461
3	G6	1356.6592	38.27041	0.01799	42.89553	-0.51116	0.00461

Plant	Unit	P_i^{\min}	P_i^{\max}	B_{ij}	1	2	3
1	G1	10	125	1	0.000091	0.000031	0.000029
	G2	10	150	2	0.000031	0.000062	0.000028
	G3	40	250	3	0.000029	0.000028	0.000072
2	G4	35	210				
	G5	130	325				
3	G6	125	315				

Table 2: Economic Dispatch (With Transmission Losses)
POWER DEMAND: 1170 MW & compromise factor 1

ITEM	GEN	WITH TRANSMISSION LOSS
DEMAND		1170 MW
UNIT GENERATION	1	71.269 MW
	2	66.655 MW
	3	250.000 MW
	4	210.000 MW
	5	325.000 MW
	6	315.000 MW
TOTAL FUEL COST (\$/Hr)		62920.000 \$/hr
TOTAL EMISSION (Kg/Hr)		1373.500 Kg/hr
TOTAL GENERATION(MW)		1237.920 MW
TOTAL TRANSMISSION LOSS		67.9247 MW

Table 3: Economic Dispatch (With Transmission Losses)
POWER DEMAND: 900 MW & compromise factor 1

ITEM	GEN	WITH TRANSMISSION LOSS
DEMAND		900 MW
UNIT GENERATION	1	33.870 MW
	2	12.793 MW
	3	151.115 MW
	4	148.936 MW
	5	297.021 MW
	6	294.543 MW
TOTAL FUEL COST (\$/Hr)		47326.100 \$/hr
TOTAL EMISSION (Kg/Hr)		862.876 Kg/hr
TOTAL GENERATION(MW)		938.378 MW
TOTAL TRANSMISSION LOSS		38.2782 MW

V. FUTURE SCOPE

In literature survey so many methods are proposed for the solution of environmental/economic dispatch problem. In all above mentioned papers, we are only considering one loading condition for a given system. All these methods can't find the global optimal solution but gets reasonable solution which is nearly global optimal.

In order to obtain Pareto Optimal solution of environmental/economic dispatch problem, a PSO algorithm was developed solve a constrained economic and emission dispatch problem. The PSO algorithm was mainly used to determine the optimal lambda solution and hence power generation of each unit that was submitted to operation at the specific period, thus minimizing the total emission and total generation cost. The PSO approach has the ability to provide accurate and feasible solutions within reasonable computation period.

VI. CONCLUSIONS

A multiobjective dispatch problem is obtained by combining economic and emission dispatch which is proposed in this paper. The converted objective function is analyzed here using Particle Swarm Optimization technique. The analysis is based on existing methods which is described in literature survey. Particle swarm optimization method is simple, robust and efficient. The performance of PSO is validated with six generating test units. The results show that dispatch is conducted effectively than other conventional methods.

REFERENCES

- [1] S. F. Brodesky and R. W. Hahn, "Assessing the influence of power pools on emission constrained economic dispatch," IEEE Trans. Power Syst., vol. 1, no. 1, pp. 57–62, Feb. 1986.
- [2] G. P. Granelli, M. Montagna, G. L. Pasini, and P. Marannino, "Emission constrained dynamic dispatch," Elect. Power Syst. Res., vol. 24, pp. 56–64, 1992.
- [3] A. Farag, S. Al-Baiyat, and T. C. Cheng, "Economic load dispatch multiobjective optimization procedures using linear programming techniques," IEEE Trans. Power Syst., vol. 10, no. 2, pp. 731–738, May 1995.
- [4] R. Yokoyama, S. H. Bae, T. Morita, and H. Sasaki, "Multi-objective generation dispatch based on probability security criteria," IEEE Trans. Power Syst., vol. 3, no. 1, pp. 317–324, Feb. 1988.
- [5] Y. T. Hsiao, H. D. Chiang, C. C. Liu, and Y. L. Chen, "A computer package for optimal multiobjective VAR planning in large scale power systems," IEEE Trans. Power Syst., vol. 9, no. 2, pp. 668–676, May 1994.
- [6] C. M. Fonseca and P. J. Fleming, "An overview of evolutionary algorithms in multi-objective optimization," Evol. Comput., vol. 1, no. 3, pp. 1–16, 1995.
- [7] M. A. Abido, "A niched Pareto genetic algorithm for multi-objective environmental/economic dispatch," Int. J. Elect. Power Energy Syst., vol. 25, no. 2, pp. 97–105, 2003.
- [8] M. A. Abido, "A novel multiobjective evolutionary algorithm for environmental/economic power dispatching," Elect. Power Syst. Res., vol. 65, no. 1, pp. 71–81, 2003.
- [9] M. A. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," IEEE Trans. Power Syst., vol. 18, no. 4, pp. 1529–1537, Nov. 2003.
- [10] M. A. Abido, "Multiobjective evolutionary algorithms for electric power dispatch problem," IEEE Trans. Evol. Comput., vol. 10, no. 3, pp. 315–329, 2006