

Emission Constrained Economic Dispatch using Particle Swarm Optimization Technique

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Abstract— Economic Environmental dispatch (EED) is an optimization task on fossil fired thermal power plant operation. A Multiobjective particle swarm optimization technique for the solution of environmental economical 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.

Key words: Economic Dispatch, Emission Dispatch, Multi-Objective Optimization Problem

I. INTRODUCTION

The generation of electricity from fossil fuels releasing Sulphur oxides (SO₂) and nitrogen oxides (NO_x) into atmosphere. Atmospheric pollution affects not only humans but also other life forms such as animals, birds, fish and plants. The basic objective of economic dispatch (ED) of electric power generation is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. Power generation plants have traditionally been dispatched following minimum fuel cost criteria without considering the pollution produced. The most significant crisis in the planning and operation of electric power generation system is the effective scheduling of all generators in a system to meet the required demand. Emission dispatch (ED) is similar to ECD, with emission being the objective to be minimized, instead of cost. However the optimum economic dispatch may not be the best in terms of the environmental criteria. Recently many countries throughout the world have concentrated on the reduction of the amount of pollutants from fossil fuel power generating units. The two primary power plant emissions from a dispatching perspective are Sulphur oxides (SO₂) and nitrogen oxides (NO_x). The economic dispatch and emission dispatch are considerably different. The economic dispatch reduces the total fuel cost (operating cost) of the system at an increased rate of NO_x. On the other hand emission dispatch reduces the total emission from the system by an increase in the system operating cost. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (EED).

The Combined Environmental Economic Dispatch (EED) problem is a bi criteria optimization problem with

two conflicting objective functions: operating costs and environmental impact of emissions. Due to the contrasting/conflicting goals and non-commensurable natures of fuel cost and emission minimization objectives, conventional approach which optimizes the integrated two objective functions seems not appropriate for this class of multi-objective optimization problems. Therefore, conventional optimization methods based on derivatives and gradients are not suitable for this nonlinear and multimodal optimization problem. Several strategies to reduce the atmospheric emissions have been proposed and discussed [1]–[3]. These include installation of pollutant cleaning equipment, switching to low emission fuels, replacement of the aged fuel-burners with cleaner ones, and emission dispatching. The first three options require installation of new equipment and/or modification of the existing ones that involve considerable capital outlay and, hence, they can be considered as long-term options. The emission dispatching option is an attractive short-term alternative in which both emission and fuel cost is to be minimized. In recent years, this option has received much attention [4]–[8] since it requires only small modification of the basic economic dispatch to include emissions.

Different techniques have been reported in the literature pertaining to environmental/economic dispatch (EED) problem. In [4] the problem has been reduced to a single objective problem by treating the emission as a constraint with a permissible limit. This formulation, however, has a severe difficulty in getting the trade-off relations between cost and emission. Alternatively, minimizing the emission has been handled as another objective in addition to usual cost objective. A linear programming based optimization procedures in which the objectives are considered one at a time was presented in [5]. Unfortunately, the EED problem is a highly nonlinear optimization problem. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, are not able to locate or identify the global optimum. On the other hand, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved.

In other research direction, the EED problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [6], [7]. The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having

a non-convex Pareto-optimal front. To avoid this difficulty, the -constraint method for multi-objective optimization was presented in [8], [9]. This method is based on optimizing the most preferred objective and considering the other objectives as constraints bounded by some allowable levels. These levels are then altered to generate the entire Pareto-optimal set.

Various optimization techniques have been developed to solve the multi-objective problem. The major disadvantage in solving the EED problem is that they are incapable of handling non smooth fuel cost and emission functions. An efficient and reliable technique is needed. This paper proposes the use of Particle Swarm Optimization (PSO) to solve the non-smooth functions. PSO searches from a population of points, not a single point. The population can move over hills and across valleys. It can search a complicated and uncertain area to find the solution. Therefore, PSO can discover a globally or near globally optimal point. Since PSO is a global searching technique, it is more capable of getting away from the local minimum to improve the quality of solution.

II. PROBLEM FORMULATION

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. Formulation of Multi-Objective Problem Mathematical Models

The generators cost curves are represented by quadratic functions.

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

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 such as sulphur oxides and nitrogen oxides caused by fossil-fuelled thermal units can be modelled separately. However, for comparison purposes, the total ton/h emission of these pollutants can be expressed as,

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

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 competing objective functions: fuel cost and emission.

a) Minimization of Fuel Cost

The total (\$/h) fuel cost $C(P)$ can be expressed as

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

b) Minimization of NO_x Emission

The total (kg/h) emission can be expressed as

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

2) Objective Constraints

The EED problem is subject to two constraints:

a) Generation Capacity Constraint

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

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

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

b) Power Balance Constraint

The total power generation must cover the total demand P_D and the real power loss in transmission lines P_L . Hence,

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

Where P_D is the total load 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:

– Minimize

$$[C(P), E(P)]$$

– 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 using the weighting method. Thus the approach converts it into a single function optimization problem using the weighted sum of C_i and E_i

– Minimise

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

– Subject to

$$\sum_{i=1}^N P_i = P_D + P_L$$

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

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

III. COMBINED ECONOMIC AND EMISSION DISPATCH USING PARTICLE SWARM OPTIMIZATION

Like evolutionary algorithms, PSO technique conducts search using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO system, particle changes their positions by flying around in a multi-dimensional search space until computational limitations are exceeded. In Particle Swarm Optimization, a particle is defined as a moving point in hyperspace. For each particle, at the current time step, a record is kept of the position, velocity, and the best position found in the search space so far.

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 a particle is recorded and represented as $pbest$. The index of the best particle among all the particles in the group is represented as $gbest$. Each particle knows the best value so far ($pbest$) and best value in the group ($gbest$). The particle tries to modify its position using the current velocity and the distance from $pbest$

and g_{best} . At last, the modified velocity and position of each particle can be calculated as using the following formulas

$$v_i^{k+1} = w * v_i^k + c_1 * rand_1 * (pbest_i - x_i) + c_2 * rand_2 * (gbest - x_i) \quad (8)$$

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

Where

v_i^k : velocity of particle i at iteration k

w : inertia weight factor ; C_1, C_2 : learning factor

$rand_1, rand_2$: random number between 0 and 1

x_i^k : position of particle i at iteration k

It is worth mentioning that the second term in eqn. (8) represents the cognitive part of PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptive of knowledge.

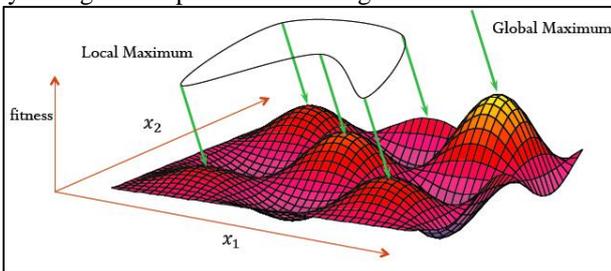


Fig. 1: Local and Global maximum in PSO

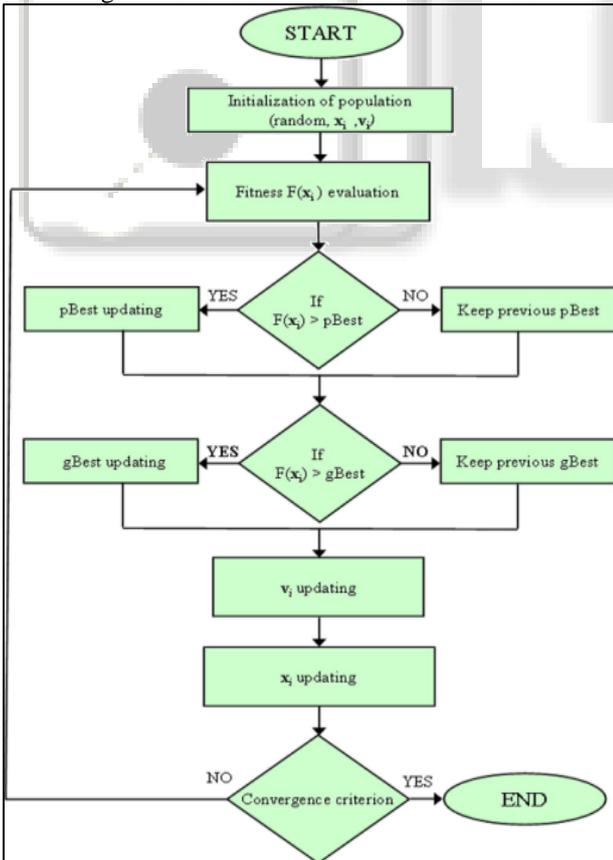


Fig. 2: Flow chart of PSO

The constants C_1 and C_2 pull each particle towards p_{best} and g_{best} positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement

towards, or past, target regions. Hence, the acceleration constants C_1 and C_2 are often set to be 2.0 according to past experiences. Suitable selection of inertia weight ‘ w ’ provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, w often decreases linearly from about 0.9 to 0.4 during a run.

In the iteration process the particle velocity is limited by some maximum value v_i^{max} . The parameter v_i^{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning. If v_i^{max} is too high, particles might fly past good solutions. If v_i^{max} is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, v_i^{max} was often set at 10-20% of the dynamic range of the variable on each dimension.

IV. SIMULATION RESULTS

To verify the effectiveness of the proposed particle swarm optimization method, a three-unit thermal power generating plant with six generators was tested. Fuel cost coefficients, emission co efficient and generation limits for each generating unit of the test system were given in Table 1.

Plant	Unit	ai	bi	ci
1	G1	756.79886	38.53973	0.15247
	G2	451.32513	46.15916	0.10587
	G3	1049.32513	40.39655	0.02803
2	G4	1243.5311	38.30553	0.03546
	G5	1658.5696	36.32782	0.02111
3	G6	1356.65920	38.27041	0.01799

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

Plant	Unit	di	ei	fi
1	G1	13.85932	0.32767	0.00419
	G2	13.85932	0.32767	0.00419
	G3	40.2669	-0.54551	0.00683
2	G4	40.2699	-0.54551	0.00683
	G5	42.89553	-0.51116	0.00461
3	G6	1356.65920	-0.51116	0.00461

Table 2: Simulation Result

Plant	Unit	Pi min	Pi max
1	G1	10	125
	G2	10	150
	G3	40	250
2	G4	35	210
	G5	130	325
3	G6	125	315

Table 3: Simulation Result

Bij	1	2	3
1	0.000091	0.000031	0.000029
2	0.000031	0.000062	0.000028
3	0.000029	0.000028	0.000072

Table 4: Simulation Result

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		1237.920 MW
Total Transmission Loss		67.9247 MW

Table 5: Economic Dispatch (with Transmission Losses)
Power Demand: 1170 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		938.378 MW
Demand		38.2782 MW

Table 6: Economic Dispatch (With Transmission Losses)
Power Demand: 900 MW & Compromise Factor 1

V. FUTURE SCOPE

The solution of the EED problem using the different methods proposed in literature consumes considerable computing time. It should be noted that, in all the above methods, the EED problem was addressed considering only one loading condition for a given system. So, its real-time exploitation is impossible when dealing with a load curve. Moreover, these heuristic methods do not always guarantee discovery of the globally optimal solution; they only provide a reasonable solution (suboptimal, nearly global optimal). To date, only one analytical approach has been developed to find the global solution to EED.

In order to solve a constrained economic and emission dispatch problem, a PSO algorithm was developed to obtain efficiently a high-quality solution within practical power system operation. The PSO algorithm was utilized mainly to determine the optimal lambda and hence power generation of each unit that was submitted to operation at the specific period, thus minimizing the total emission and generation cost. The PSO approach has demonstrated an ability to provide accurate and feasible solutions within reasonable computation time

VI. CONCLUSION

Economic and emission dispatch problems are combined and converted into a single objective function. This review is undertaken to explore and analyze the existing Economic and emission Dispatch techniques present in the literature which is very much required to minimize the operating cost while maintaining system stability and consistency and provide better performance. It is observed that PSO can provides better performance than other conventional techniques

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