Environmental Economical Power Dispatch problem using Particle Swarm Optimization Technique

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Abstract—This paper presents an approach to Economic Emission Dispatch (EED) with consideration of six thermal generating units using Particle Swarm Optimization (PSO). The traditional way of economic dispatch cannot meet the environmental safety needs, since it focus only on minimizing the total operating and fuel cost of the system. 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 - Economic Dispatch, Emission Dispatch, multiobjectiveoptimization problem.

I. INTRODUCTION

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 (SO_2) 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 havebeen proposed and discussed [1]–[3]. These include installationof pollutant cleaning equipment, switching to lowemission fuels, replacement of the aged fuel-burners with cleaner ones, andemission dispatching. The first three options require installationof new equipment and/or modification of the existing onesthat involve considerable capital outlay and, hence, they canbe considered as long-term options. The emission dispatchingoption is an attractive short-term alternative in which both emission and fuel cost is to be minimized. In recent years, thisoption has received much attention [4]–[8] since it requiresonly 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 problemby treating the emission as a constraint with a permissible limit.This formulation, however, has a severe difficulty in gettingthe trade-off relations between cost and emission. Alternatively, minimizing the emission has been handled as another objectivein addition to usual cost objective. A linear programming basedoptimization procedures in which the objectives are consideredone at a time was presented in [5]. Unfortunately, the EEDproblem is a highly nonlinear optimization problem. Therefore,conventional optimization methods that make use of derivativesand gradients, in general, are not able to locate or identify theglobal optimum. On the other hand, many mathematical assumptionssuch as analytic and differential objective functionshave to be given to simplify the problem. Furthermore, this approachdoes 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 differentobjectives as a weighted sum [6], [7]. The important aspectof this weighted sum method is that a set of non inferior (or Pareto-optimal) solutions can be obtained by varying theweights. Unfortunately, this requires multiple runs as manytimes as the number of desired Pareto-optimal solutions.Furthermore, this method cannot be used to find Pareto-optimalsolutions in problems having a non-convex Pareto-optimalfront. To avoid this difficulty, the -constraint method formultiobjective optimization was presented in [8], [9]. Thismethod is based on optimizing the most preferred objectiveand considering the other objectives as constraints boundedby some allowable levels. These levels are then alteredto generate the entire Pareto-optimal set.

Various optimization techniques had been developed to solve the multi-objective problem. The major disadvantage in solving the EED problem is that they are incapable of handing 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 arerepresented by quadratic functions.

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

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 byfossil-fuelled thermal units can be modelled separately. However, for comparison purposes, the total *ton/h* emission ofthese pollutants can be expressed as,

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

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 plantsis to minimize two competing objective functions: fuel cost and emission.

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

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

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

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

2) Objective Constraints: The EED problem is subject to twoconstraints:

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

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{5}$$

Where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximumpower outputs of the units

Power balance constraint: The total power generation must cover the total demand P_D and the real power loss in transmissionlines P_L. Hence,

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{6}$$

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 thetwo constraints (5), (6), the EED problem can be mathematicallyformulated as follows:

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

Subject to: g(P) = 0

h(P) ≤ 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 intoa 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 : $\sum_{i=1}^{N} P_i = P_D + P_L$

$$P_i^{\min} \le P_i \le P_i^{\max} \ , \ \forall i = 1,2.......N \qquad (7)$$

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 Swam 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 *gbest*. At last, the modified velocity and position of each particle can be calculated as using the following formulas

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

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

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.

The constants c_1 and c_2 pull each particle towards *pbest* and *gbest* 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 $Vi^{\max}$. The parameter $Vi^{\max}$ 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 $Vi^{\max}$ is too high, particles might fly past good solutions. If $Vi^{\max}$ is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, $Vi^{\max}$ was often set at 10-20% of the dynamic range of the variable on each dimension.

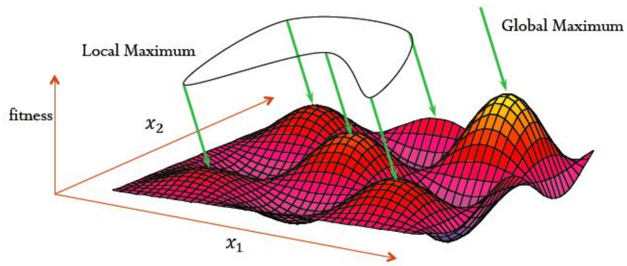

Fig. 1 Local and Global maximum in PSO

Fig 2 Flow chart of PSO

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.

Table I :FUEL COSTCOEFFICIENTS,EMISSIONCOEFFICIENTS, LOSSCOEFFICIENTS AND GENERATINGCAPACITY CONSTRAINTS

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

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

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

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 II 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 COS $/HR		62920.000 $/hr
TOTAL EMISSIO KG/HR		1373.500 Kg/hr
TOTAL GENERATION		1237.920 MW
TOTAL TRANSMIS LOSS		67.9247 MW

Table III 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 COS $/HR		47326.100 $/hr
TOTAL EMISSIO KG/HR		862.876 Kg/hr
TOTAL GENERATION		938.378 MW
TOTAL TRANSMIS LOSS		38.2782 MW

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 abovemethods, 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. CONCLUSIONS

Economic and emission dispatch problems arecombined and converted into a single objectivefunction.This review is undertaken to explore and analyze the existing Economic and emission Dispatchtechniques present in the literature which is very muchrequired to minimize the operating cost whilemaintaining system stability and consistency andprovide better performance.It is observed that PSO can provides better performance than other conventional techniques

REFERENCES

[1] S. F. Brodesky and R. W. Hahn, "Assessing the influence of powerpools on emission constrained economic dispatch," *IEEE Trans. PowerSyst.*, vol. 1, no. 1, pp. 57–62, Feb. 1986.

[2] G. P. Granelli, M. Montagna, G. L. Pasini, and P. Marannino, "Emissionconstrained 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 multiobjectiveoptimization procedures using linear programming techniques,"*IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 731–738, May1995.

[4] R. Yokoyama, S. H. Bae, T. Morita, and H. Sasaki, "Multi-objectivegeneration 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 computerpackage for optimal multiobjective VAR planning in large scale powersystems," *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 668–676, May1994.

[6] C. M. Fonseca and P. J. Flemming, "An overview of evolutionary algorithmsin multi-objective optimization," *Evol. Comput.*, vol. 1, no. 3,pp. 1–16, 1995.

[7] M. A. Abido, "A niched Pareto genetic algorithm for multi-objectiveenvironmental/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 multiobjectiveevolutionary algorithms," *IEEE Trans. Power Syst.*, vol. 18,no. 4, pp. 1529–1537, Nov. 2003.

[10] M. A. Abido, "Multiobjective evolutionary algorithms for electricpower dispatch problem," *IEEE Trans. Evol. Comput.*, vol. 10, no. 3,pp. 315–329, 2006.