Genetic Algorithm Based Approach for Power Generation Dispatch with Emission Constraints

Po-Hung Chen, Hung-Cheng Chen*, and Chun-Liang Hsu

Department of Electrical Engineering,
Saint John's University, Tamsui, Taipei, 25135, TAIWAN.
phchen@mail.sju.edu.tw, liang@mail.sju.edu.tw
* Department of Electrical Engineering,
National Chin-Yi University of Technology, Taichung, 411, TAIWAN.
hcchen@chinyi.ncit.edu.tw

Abstract: - This paper presents a genetic algorithm based approach for solving the thermal generation dispatch with emission constraints. New encoding/decoding techniques are developed in the work. The chromosome contains only an encoding of the normalized system incremental cost. Therefore, the total number of bits of chromosome is entirely independent of the number of units. Moreover, the approach can take emission constraints into account to make the solution results satisfying environmental protection requirements. The salient feature makes the proposed genetic approach attractive in large and complex systems which other methodologies may fail to achieve. Numerical results show the proposed approach has potential in practical applications.

Key-Words: - Genetic Algorithm, Economic Dispatch, Chromosome, Emission Constraints.

1 Introduction

The generation of electricity from fossil fuel power plants emits several pollutants into the atmosphere such as oxides of carbon (COx), oxides of nitrogen (NOx) and oxides of sulfur (SOx). The Clean Air Act Amendments of 1990 mandates that the electricity industry reduce its SO_2 emission by 8.9 million tons per year from the 1980 level. The NOx emission is required to be reduced by 2 million tons per year from the 1980 level [1]. Economic dispatch (ED) plays an important role in power system operation [2-4]. However, traditionally economic dispatch strategies are designed in such a way that the power generation cost is minimized neglecting environmental constraints. The economic dispatch will become more complex and difficult when the emission constraints must be taken into account.

Previous efforts at economic dispatch have applied various mathematical programming methods and optimization techniques. These include the lambda-iteration method [2], the base point and participation factors method [2], the gradient method [2], the recursive method [5], the Newton-Raphson method [6], and a unit-based genetic algorithm (GA) method [7] has also been reported recently. Among these methods, the lambda-iteration method is a well-known method and has been widely used by power utilities for economic dispatch. However, the characteristics and feasibility of the lambda-iteration method have not yet been extensively investigated. Since the lambda-iteration method requires a continuous problem formulation, it cannot be directly applied to the economic dispatch problem with discontinuous valve point zones. The base point and participation factors method assumes that the economic dispatch problem has to be solved repeatedly by moving the unit's MW output linearly from a given schedule (the base point) to another by "participation" in the load change. Since the units' generation cost functions are not in linear form, this method yields a fast but approximate dispatch. The gradient method is a direct search algorithm which starts from a feasible solution and searches for the optimum solution along a MW output trajectory that always maintains a feasible solution in which all the constraint conditions are met. The disadvantage of this method is that there is no clear stopping rule. Therefore, establishing the optimum point is difficult.

GA is a stochastic searching algorithm. GA combines an artificial survival of the fittest principle with genetic operators abstracted from nature to form a surprisingly robust mechanism that is very effective at finding optimal solutions to complex real-world problems [8,9]. In the previous work [10], a GA technique has been adopted to solve the conventional ED problem and applied to the existing Taipower system in Taiwan. This paper develops a lambda-based GA approach for solving the ED problem taking emission constraints into account. A salient feature of the proposed approach is that the solution time grows approximately linearly with problem size other than geometrically. This feature is attractive in large-scale problems. Numerical results show that the proposed approach is robust and efficient.

2 Problem Description and Formulation

2.1 Economic dispatch formulation

The objective of economic dispatch is to minimize the total generation cost of a power system over some appropriate period (one hour typically) while satisfying various constraints. In equation form, this becomes a constrained optimization problem:

$$Minimize\ \ F = \sum_{i=1}^{n} f_i(P_i) \tag{1}$$

Subject to:

$$\sum_{i=1}^{n} P_i = P_D + P_{loss} \tag{2}$$

$$\underline{P_i} \le P_i \le \overline{P_i} \tag{3}$$

where
F: total generation cost of the system
P_i: power generation of unit i
n : total number of units
$f_i(P_i)$: generation cost for P_i
P_D: system load demand
P_{loss}: system transmission network losses
$\underline{P_i}$: minimum generation of unit i
$\overline{P_i}$: maximum generation of unit i

In (1), the generation cost function $f_i(P_i)$ is usually expressed as a quadratic polynomial:

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{4}$$

where a_i, b_i, and c_i are constants.

2.2 Ramp rate limits

In ED research, a number of studies have focused upon the economical aspects of the problem under the assumption that unit generation output can be adjusted instantaneously. Even though this assumption simplifies the problem, it does not reflect the actual operating processes of the generating unit.

The operating range of all on-line units is restricted by their ramp rate limits [2,11]. Fig. 1 shows three possible situations when a unit is on-line from hour t-1 to hour t. Fig. 1(a) shows that the unit is in a steady operating status. Fig. 1(b) shows that the unit is in an increasing power generation status. Fig. 1(c) shows that the unit is in a decreasing power generation status.

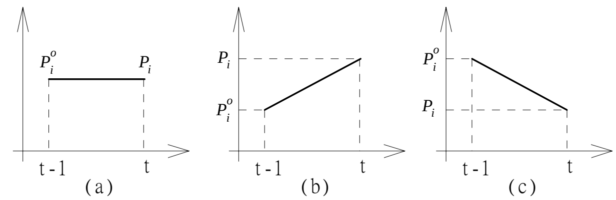

Fig. 1. Three possible situations of an on-line unit.

The operating range of all on-line units is restricted by their ramp rate limits:

1) if generation increases

$$P_i - P_i^o \le UR_i \tag{5}$$

2) if generation decreases

$$P_i^o - P_i \le DR_i \tag{6}$$

where
P_i^o : power generation of unit i at previous hour
UR_i: ramp rate limit of unit i as generation increases
DR_i: ramp rate limit of unit i as generation decreases

Combining (3), (5), and (6), the ramp rate limits are modified as:

$$Max(\underline{P_i}, P_i^o - DR_i) \le P_i \le Min(\overline{P_i}, P_i^o + UR_i) \tag{7}$$

2.3 Prohibited operating zone

Fig. 2 shows an input-output performance curve for a typical thermal unit where P_{pz}^+ and P_{pz}^- are respectively the upper and lower bound of a valve point zone. The prohibited operating zones in the curve are due to steam valve operating or vibration in a shaft bearing. Several studies in the literature [2,7,12,13] discuss the effects of the prohibited zone in the ED problem. For example, Walters & Sheble model the effects of the prohibited zone as a recurring rectified sinusoid function [7]. However, in practice, the shape of the input-output curve in the neighborhood of the prohibited zone is difficult to determine by actual performance testing or operating records. In actual operation, the best economy is achieved by avoiding operation in these areas. As such, a heuristic algorithm is developed in this paper to adjust the generation output of a unit in order to avoid unit operation in the prohibited zones.

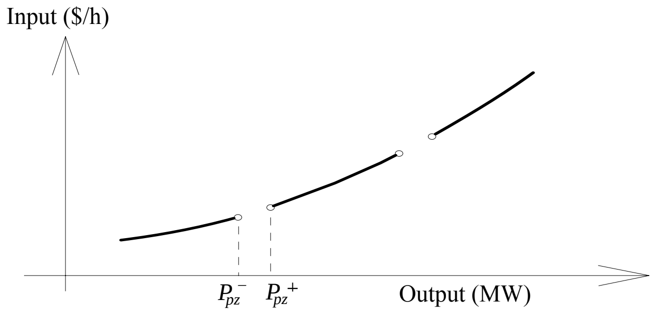

Fig. 2. Input-output curve of a thermal unit.

2.4 Emission constraints

To meet the increased requirements for environmental protection, alternative ED strategies are required for power utility. The environmental constrained ED algorithms reported in the literature can be divided into two categories: (a) methods for minimizing emissions, and (b) methods for minimizing fuel cost subject to emission constraints. The algorithm proposed in this paper belongs to the latter. Considering an emission constrained ED problem, the individual pollutant limit and total emission limit are expressed as

$$E_{ik}^t(P_i^t) \le \overline{E_k} \tag{8}$$

$$\sum_{i=1}^{N} E_{ik}^t(P_i^t) \le E_k^{total} \tag{9}$$

where

$E_{ik}^t(P_i^t)$: emission of k pollutant for P_i^t

$\overline{E_k}$: individual emission limit of k pollutant

E_k^{total} : total emission limit of k pollutant.

Combining (1), (2), (8), and (9); the emission constrained ED problem can be expressed as a LaGrange function:

$$L = \sum_{i=1}^{N} F_i^t(P_i^t) - \lambda(\sum_{i=1}^{N} P_i^t - P_L^t - P_{loss}^t) - \sum_{k=1}^{N_p} W_k(\sum_{i=1}^{N} E_{ik}^t(P_i^t) - E_k^{total}) \tag{10}$$

where W_k is the weight (LaGrange multiplier) with respect to the type k pollutant.

The two primary thermal unit emissions from a dispatching perspective are SOx and NOx. Modeling of emission function is generally dependent on the amount of fuel burned. That is, the emission function is proportional to the thermal unit's fuel consumption. As a result, the emission function will be a quadratic polynomial form as that of the fuel cost function employed in this research:

$$E_{ik}^t(P_i^t) = \alpha_i(P_i^t)^2 + \beta_i P_i^t + \gamma_i \tag{11}$$

where α_i , β_i , and γ_i are constants.

3 Solution Methodology

3.1 Overview of GA

Recently, a global optimization technique known as genetic algorithm (GA) has become a candidate for many optimization applications due to its flexibility and efficiency. GA is a search algorithm based on the mechanics of natural genetics and natural selection [8]. It combines the adaptive nature of the natural genetics or the evolution procedures of organs with functional optimizations. By simulating “the survival of the fittest” of Darwinian evolution among chromosome structures, the optimal chromosome (solution) is searched by randomized information exchange. In every generation, a new set of artificial chromosomes is created using bits and pieces of the fittest of the old ones. While randomized, GA is not a simple random walk. It efficiently exploits historical information to speculate on new search points with expected improved performance [8,9].

GA is essentially derived from a simple model of population genetics. The three prime operators associated with the GA are reproduction, crossover, and mutation.

Reproduction is simply an operation whereby an old chromosome is copied into a “mating pool” according to its fitness value. More highly fitted chromosomes (i.e., with better values of the objective function) receive a higher number of copies in the next generation. Copying chromosomes according to their fitness values means that chromosomes with a higher value have a higher probability of contributing one or more offspring in the next generation.

Crossover is an extremely important component of the GA. It is a structured recombination operation. This operation is similar to two scientists exchanging information. This study applies a new crossover technique known as “uniform crossover” as shown in

Fig. 3. Syswerda [14] shows that convergence speed of the uniform crossover is faster than the popular one-point crossover and two-point crossover.

Parent A :	1	0	1	0	0	1	0
Parent B :	0	1	1	1	0	0	1
Swapping mask :	0	1	0	1	1	0	0
Offspring A :	1	1	1	1	0	1	0
Offspring B :	0	0	1	0	0	0	1

Fig. 3. The uniform crossover.

Although reproduction and crossover effectively search and recombine existing chromosomes, they do not create any new genetic material in the population. Mutation is capable of overcoming this shortcoming. It is an occasional (with small probability) random alternation of a chromosome position as shown in Fig. 4. This provides background variation and occasionally introduces beneficial materials into the population.

Offspring A :	1	1	1	1	0	1	0
			↓				
New offspring :	1	1	0	1	0	1	0

Fig. 4. The binary mutation.

3.2 GA solution algorithm

The detailed solution methodology includes: the encoding and decoding techniques, constrained generation output calculation, the fitness function, parent selection, and parameter selection. These are described in more detail below.

Implementation of a problem in a GA starts from the parameter encoding (i.e., the representation of the problem). The encoding must be carefully designed to utilize the GA's ability to efficiently transfer information between chromosome strings and objective function of problem. The proposed approach uses the equal system λ (equal system incremental cost) criterion as its basis. The only encoded parameter is the normalized system incremental cost, λ^{nm} , where $0 \le \lambda^{nm} \le 1$. The advantage of using system λ instead of units' output as the encoded parameter is that the number of bits of chromosome will be entirely independent of the number of units. This is particularly attractive in large-scale systems.

The resolution of the solution depends upon how many bits are used to represent λ^{nm}. In other words, the more encoding bits there are, the higher the resolution. However, on the other hand, the more encoding bits there are, the slower the convergence. In this paper, we use 10 bits to represent λ^{nm}.

Evaluation of a chromosome is accomplished by decoding the encoded chromosome string and computing the chromosome's fitness value using the decoded parameter. The decoding of λ^{nm} can be expressed as:

$$\lambda^{nm} = \sum_{i=1}^{10}\left(d_i \times 2^{-i}\right) \qquad d_i \in \{0,1\} \tag{12}$$

The relationship between the actual system incremental cost, λ^{act} , and the normalized system incremental cost, λ^{nm}, is

$$\lambda^{act} = \underline{\lambda_{sys}} + \lambda^{nm}(\overline{\lambda_{sys}} - \underline{\lambda_{sys}}) \tag{13}$$

where $\overline{\lambda_{sys}}$ and $\underline{\lambda_{sys}}$ are the maximum and minimum values of system incremental cost.

Applying the methods of the LaGrange function and Kuhn-Tucker conditions [2] to the constrained optimization problem, the ED problem can be reformulated as

$$2a_i P_1 + b_i = \lambda^{act} \quad for\ \ Max(\underline{P_i}, P_i^o - DR_i) \le P_i \le Min(\overline{P_i}, P_i^o + UR_i) \tag{14}$$

subject to the power balance constraint. For a given λ^{act}, the generation output of each unit can be determined from (14).

As mentioned in Section 2.3, in actual operation, the best economy is achieved by avoiding unit operation in the prohibited zone. If the generation output calculated from (14) is located in a prohibited zone, it needs heuristic adjustment to leave this area. If the dispatching hour in a load increasing period (the forecasted load of the next hour is greater than this hour), the adjusting point is the upper bound, P_{pz}^{+}, to follow the load fluctuation. On the contrary, when in a load falling period, the adjusting point is the lower bound, P_{pz}^{-}.

Implementation of a problem in a genetic algorithm is realized within the fitness function. Since the proposed approach uses the equal incremental cost criterion as its basis, the constraint equation can be rewritten as

$$\varepsilon = \left| \sum_{i=1}^{n} P_i - P_D - P_{loss} \right| \tag{15}$$

Then, the converging rule is when ε decreases to within a specified tolerance.

In order to emphasize the "best" chromosomes and speed up convergence of the iteration procedure, fitness is normalized into the range between 0 and 1. The fitness function adopted is

$$FIT = \frac{1}{1 + k(\frac{\varepsilon}{P_D})} \tag{16}$$

where k is a scaling constant (k=200 in this study).

Fig. 5 shows the general flow chart of the proposed GA approach for economic dispatch.

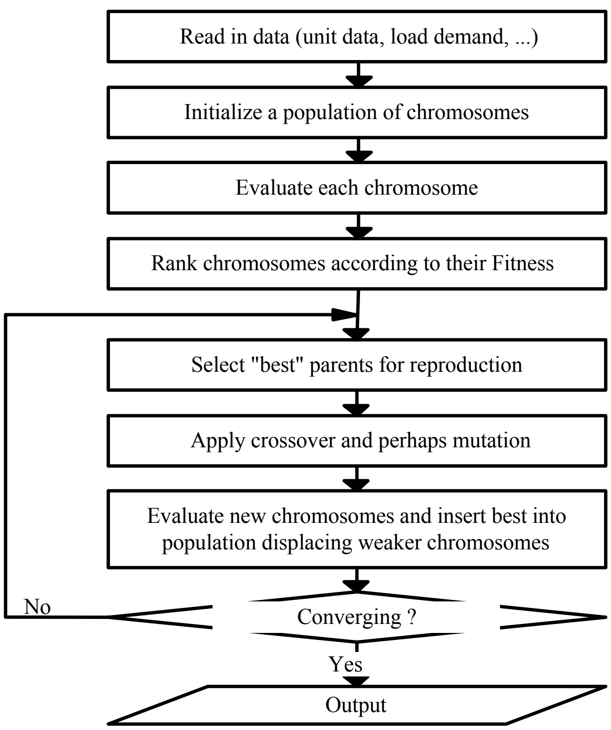

Fig. 5. General flow chart of the proposed approach.

4 Test Results

The proposed solution methodologies and its computer program have been completed and demonstrated through a three-unit test example. Table 1 shows the unit's characteristics including unit's capacity, cost coefficients, emission coefficients, and emission limits. The load demand of the system is 300MW and the converging rule is set as when load mismatch decreases to within one percent of the load demand, that is, 3MW.

Table 1. Unit's characteristics.

Characteristics	Unit 1	Unit 2	Unit 3
$\overline{P_i}$ (MW)	250	150	100
$\underline{P_i}$ (MW)	50	5	15
a_i	0.00525	0.00609	0.00592
b_i	8.663	10.04	9.76
c_i	328.13	136.91	59.16
UR_i (MW/h)	55	55	45
DR_i (MW/h)	95	78	64
α_i	0.00427	0.00619	0.00592
β_i	0.5394	0.2521	0.3366
γ_i	15.25	35.69	42.75
$\overline{E_k}$ (kg/Hr)	200	100	150

The emission constraints taken into account in this example are the SO_2 emission limits. Test results are shown in Tables 2 and 3. Table 2 shows the test results ignoring emission constraints. This is similar to the traditionally cost-minimized ED and used as the main benchmark of comparison for the proposed approach. Table 3 shows the test results of the proposed emission constrained ED.

From the study, test results show that the SO_2 emission of unit 1 decreases from 235.65 to 200 (kg/Hr) in order to satisfy individual emission limit. Moreover, total SO_2 emission decreases from 432.46 to 418.21 (kg/Hr). However, on the other hand, the fuel cost increases from 3737.26 to 3750.68 ($/Hr).

Table 2. Test results ignoring emission constraints.

Results	Unit 1	Unit 2	Unit 3
P_i (MW)	194.27	50	79.63
Fuel cost ($/Hr)		3737.26	
E_i (kg/Hr)	235.65	84.01	112.8
Total SO_2 emission (kg/Hr)		432.46	

Table 3. Test results of the proposed approach.

Results	Unit 1	Unit 2	Unit 3
P_i (MW)	154.22	72.04	97.76
Fuel cost ($/Hr)	3750.68		
E_i (kg/Hr)	200	85.98	132.23
Total SO_2 emission (kg/Hr)	418.21		

5 Conclusion

This paper presents a novel approach for solving the emission constrained ED problem. In comparison with other ED methods, using probabilistic rules rather than deterministic rules impart to the proposed approach a robust and global optimization algorithm. A salient feature of the proposed approach is that the solution time in solving ED problem increases approximately linearly with the number of units. This feature is attractive in large-scale problems. This approach can also take emission constrains, network losses, ramp rate limits, and prohibited zone avoidance into account to make the dispatch more practical.

References

[1] Lamont, J.W., and Obessis, E.V., "Emission dispatch models and algorithms for the 1990's," IEEE Transactions on Power Systems, Vol. 10, No. 2, May 1995, pp. 941 - 947.

[2] Wood, A.J., Wollenberg, B.F.: Power Generation, Operation, and Control. 2nd edn. John Wiley & Sons, New York, 1996

[3] Chowdhury, B.H. and Rahman, S., "A review of recent advances in economic dispatch," IEEE Transactions on Power Systems, Vol. 5, No. 4, Nov. 1990, pp. 1248-1259.

[4] Happ, H.H., "Optimal power dispatch - a comprehensive survey," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-96, June, 1971, pp. 841 - 854.

[5] Wong, K.P. and K. Doan, "A recursive economic dispatch algorithm for assessing the costs of thermal generation schedules," IEEE Transactions on Power Systems, Vol. 7, No. 2, May 1992, pp. 577 - 583.

[6] Lin, C.E., et al., "A direct Newton-Raphson economic dispatch," IEEE Transactions on Power Systems, Vol 7, No. 3, August 1992, pp. 1149 - 1154.

[7] Walters, D.C. and G.B. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading," IEEE Transactions on Power Systems, Vol. 8, No. 3, August 1993, pp. 1325 - 1332.

[8] Goldberg, D.E., Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, 1989.

[9] Davis, L., Handbook of Genetic Algorithms, Van Nostrand Reinhold, 1991.

[10] Chen, P.H., and Chang, H.C., "Large-Scale Economic Dispatch by Genetic Algorithm," IEEE Transactions on Power Systems, Vol. 10, No. 4, November 1995, pp. 1919 - 1926.

[11] Wang, C. and Shahidehpour, S.M., "Effects of ramp-rate limits on unit commitment and economic dispatch," IEEE Transactions on Power Systems, Vol. 8, No. 3, August 1993, pp. 1341 - 1350.

[12] Shoults, R.R., et al., "A dynamic programming based method for developing dispatch curves when incremental heat rate curves are non-monotonically increasing," IEEE Transactions on Power Systems, Vol. 1, February 1986, pp. 10-16.

[13] Lee, F.N., and Breipohl, A.M., "Reserve constrained economic dispatch with prohibited operating zones," IEEE Transactions on Power Systems, Vol. 8, February 1993, pp. 246 - 254.

[14] Syswerda, G., "Uniform crossover in genetic algorithms," Proceedings of the 3rd International Conference on Genetic Algorithms, June 1989, pp. 2 - 9.