Hybrid GA/SA Algorithms for Evaluating Trade-off Between Economic Cost and Environmental Impact in Generation Dispatch

Effie Tsoi, Kit Po Wong
Artificial Intelligence & Power Systems Research Group
Department of Electrical and Electronic Engineering
The University of Western Australia
Nedlands 6009, Western Australia.
email : {etsoi, kitpo}@ee.uwa.edu.au

Chun Che Fung
School of Electrical & Computer Engineering
Curtin University of Technology
Bentley, Western Australia.
email : fung_cc@cc.curtin.edu.au

Abstract

Two hybrid algorithms, GAA and GAA2, are proposed in this paper for evaluating trade-off between fuel cost and environmental impact in power dispatch with multiple fuels and multiple pollutants. The two algorithms are developed based on genetic algorithm and simulated annealing. The problem is first formulated as a bi-criterion optimisation problem. This is achieved by combining the total emission of individual pollutants into a single criterion via the use of relative weights in the objective function. Trade-off curves between total fuel cost and emission of each pollutants are then obtained by solving the bi-criterion function at different values of P.E.C. assigned to the total emission. The developed algorithm is demonstrated through an application example in which emission of three pollutants - $S0_2$, NO_x and CO_2 are considered. The trade-off curves obtained are useful in assisting operation engineers to determine the appropriate dispatch when both economic and environmental aspects are considered.

1. Introduction

The primary objective of power dispatch in the past has been concentrated on the minimisation of generation cost in meeting the demand on power system - economic dispatch. The cost incurred however has ignored the environmental impact of power generation due to the emission of various harmful pollutants such as sulfur oxides (SO_2), nitrogen oxides (NO_x) and carbon oxides (CO_2). With the increasing concern for the environment and the introduction of environmental regulations, the effect of emission have to be taken into account in generation dispatch. This can be achieved by incorporating the emission considerations into the economic dispatch algorithm, thus expanding the existing problem to an economic-environmental power dispatch (EEPD) problem [1].

Environmentally oriented dispatch procedures have been reported in the past two decades [1-6]. They differ in terms of their dispatch objectives and the adopted methods for solving the problems. In the reported work, the emission characteristics of the generators have been assumed to be directly proportional to the generator heat-rate characteristics, modelled by quadratic or third order polynomial functions. Minimum emission problems have been tackled by using conventional Lagrange multiplier based methods. For more realistic modelling of the generator heat-rate characteristics, higher-order polynomial functions may also be used. If the turbine-valving effects are to be reflected, the incremental heat-rate characteristics of the generators will become non-monotonic. Furthermore, fuel switching is involved when generators can be operated on more than one type of fuels. Their heat-rate characteristics have to be modelled by piecewise quadratic functions [7]. Under these situations, minimisation algorithms that are based on conventional methods will have difficulties in finding the global or near-global optimum solution. Hence, there is a need to develop an advanced algorithm for the EEPD problem.

Two hybrid algorithms, GAA and GAA2 [8, 9], are employed in this paper for evaluating the trade-off between fuel cost and environmental impact in the EEPD problem. Both algorithms are developed based on the combination of genetic algorithm (GA) and simulated annealing (SA) and differ primarily in their population size requirement. The two hybrid algorithms have been previously applied to economic dispatch problem [9], however, they have not been employed to solve EEPD problem.

The EEPD problem is first formulated as a bi-criterion optimisation problem. This is achieved by combining the total emission of individual pollutants into a single criterion via the use of relative weights in the objective function. Trade-off curves between total fuel cost and emission of each pollutants are then obtained by solving the bi-criterion function at different values of *pseudo environmental cost* assigned to the total emission. The

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developed algorithm is demonstrated through an application example in which emission of three pollutants - $S0_2$, NO_x and CO_2 are considered. The trade-off curves are useful in assisting operation engineers to determine the appropriate dispatch when both economic and environmental aspects are considered.

2. EEPD Problem Formulation

The best dispatch solution to the EEPD problem is essentially a set of generator loading that results in the total fuel cost and the total pollutant emission being minimised. In the economic dispatch problem, the total fuel cost for a system of n generators at system load demand D with transmission loss P_L, is given by

$$F_t = f_{c1}(P_1) + f_{c2}(P_2)+\ldots+f_{ci}(P_i)+\ldots+f_{cn}(P_n) \tag{1}$$

subject to the system demand constraint :

$$D = \sum_{i=1}^{n} P_i - P_L \tag{2}$$

and the operating constraint of each generator

$$P_{i,\min} \leq P_i \leq P_{i,\max} \quad \text{for } i = 1,\ldots,n \tag{3}$$

F_t is the total fuel cost which can be expressed in terms of heat-rate as H_R (MBtu/hr) or in monetary unit as F_C (\$/hr). The function $f_{ci}(P_i)$ represents the fuel cost of the i^{th} generator operating at power level P_i MW. In the case where a single type of fuel is used by all the generators, optimisation of H_R or F_C will yield identical dispatch solution. However, when multiple fuels are used among the generators, dispatch solutions based on the two objective costs, H_R or F_C, will be different.

In the process of electric power generation, more than one pollutant are emitted depending on the type of fuels being used. The total emission of a single pollutant from generation, E_p, is given by,

$$E_p = f_{p1}(P_1) + f_{p2}(P_2)+\ldots+f_{pi}(P_i)+\ldots+f_{pn}(P_n) \tag{4}$$

where E_p is the total pollutant emission in kg/hr or Ton/hr and $f_{pi}(P_i)$ is the amount of emission from the i^{th} generator at power level P_i MW. Considering m types of pollutants, the EEPD problem becomes a multi-objective function with total fuel cost and emission of m pollutants being minimised simultaneously. In order to reduce the dimension of the problem while reflecting the relative degree of damage caused by individual pollutant, the minimisation of multiple pollutants can be combined into a single criterion by assigning weight to each of the pollutants. Thus, the total weighted emission of m types of pollutant, E_M, is given by

$$E_M = \alpha_1 * E_{p1} + \alpha_2 * E_{p2}+\ldots+\alpha_j * E_{pj}+\ldots+\alpha_m * E_{pm} \tag{5}$$

where E_{pj} is the total emission of the j^{th} pollutant and α_j is the relative weight of j^{th} pollutant representing its relative degree of harmfulness. The weights of all pollutants must have the following relation [10]:

$$\sum_{j=1}^{M} \alpha_j = 1 \tag{6}$$

With the simplified expression of the total emission, the EEPD problem is reduced to a bi-criterion optimisation problem with two conflicting objectives. Although the environmental impact of emission cannot be described in monetary terms, the trade-off between the fuel cost and the total weighted emission can be evaluated by minimising the following expression :

$$F = W * F_T + (1-W) * E_M \qquad 0 \leq W \leq 1 \tag{7}$$

where W represents the relative weight assigned to the fuel cost and consequently, (1-W) is the relative weight assigned to the emission. Eqn. (7) can be rewritten as

$$F = W * \left(F_T + \left(\frac{1-W}{W}\right) * E_M \right) \tag{8}$$

the minimisation of which is identical to the minimisation of the following expression in the context of optimisation [10]

$$F' = F_T + \left(\frac{1-W}{W}\right) * E_M \tag{9}$$

The term (1-W)/W in eqn. (9) has the unit of \$/kg [10] and is here referred to the *pseudo environmental cost* (P.E.C.) of the total weighted emission. The trade-off curve between the total fuel cost and the total weighted emissions can be traced out by minimising eqn. (9) at successive intervals of P.E.C. from zero to infinity, representing economic and emission dispatch respectively.

3. Features of the Hybrid Algorithms

The two hybrid algorithms, GAA and GAA2, [8, 9] employed in this paper are developed by combining incremental genetic algorithm (IGA) [11] and simulated annealing (SA) [12]. IGA is a variant of genetic algorithm (GA) [13,14] and their difference lies in the processing of newly generated chromosomes. Every new chromosome generated in IGA is evaluated immediately and replaces a selected chromosome to become part of the existing population. GA and SA are both commonly used techniques for solving combinatorial optimisation problems. However, the performance of SA is often hindered by its slow convergence to the optimal or near optimal solution while GA may suffer from premature convergence. The combination IGA and SA enables the introduction of more diversity into the population for preventing premature convergence without the long computation time required by SA. The features outlined in the following sections form the base of the hybrid algorithms.

3.1 Solution Representation and Fitness Measure

Candidate solutions to the problem are represented by fixed length chromosomes. Each chromosome is formed by a string of genes. Every gene in a chromosome contains a floating-number representing the loading of a generator [8]. Thus the length of a chromosome equals the number of generators in the problem. For solving the EEPD problem, the fitness measure is chosen to be

$$f = K * \frac{1}{F} \tag{10}$$

where F' is the value of the objective function defined in eqn. (9). K is a large constant for amplifying the usually small value of 1/F' such that the fitness values of chromosomes are in a wider range for selection process.

3.2 Crossover and Mutation

In the present work, two-point crossover is chosen in preference to the commonly used one-point crossover. The two chromosomes are selected by roulette wheel method [13]. Under the present floating-point coding scheme, the value of a gene of the chromosome selected for mutation is replaced by a value generated from a uniform distribution between $P_{i,min}$ and $P_{i,max}$ in eqn. (3). Probability of crossover and probability of mutation are adopted to determine the rate of performing crossover and mutation respectively.

3.3 Forming Feasible Solutions

Although chromosomes formed after crossover or mutation operations always satisfy the operation limit inequalities, the system demand equality constraint is not necessary met. To transform an infeasible chromosome into a feasible one, the loading of a particular gene in the chromosome is selected to be the *dependent* loading, P_d. Its value is then replaced by P_d' where

$$P_d' = D + P_L - \sum_{i=1, i \neq d}^{n} P_i \tag{11}$$

D is the system demand and P_L is the transmission loss as described in eqn. (2). The chromosome now becomes feasible if P_d' is within its operating limits. Chromosomes remain infeasible after transformation are discarded.

3.4 Replacement Criteria

Replacement criteria [8, 9] is another measure to prevent premature convergence apart from mutation. A newly generated chromosome will replace a selected chromosome in the existing population only when one of the following criterion applies.

(1) if the child chromosome is the fittest among all chromosomes generated so far, otherwise
(2) if the child chromosome is fitter than the selected chromosome, otherwise
(3) if the probability of replacement is greater than a number randomly generated between 0 and 1

The probability of replacement in criterion (3) is the equivalent of the probability of acceptance in SA and is given by [15]

$$\Pr(\Delta) = \left[1/(1 + \exp(\Delta / T))\right] \tag{12}$$

where Δ is the amount of deterioration in fitness value of the new chromosome and the chromosome selected for replacement. T is the temperature level of the current iteration and is reduced at the start of every iteration according to [12, 15]

$$T_k = r^{k-1} T_0 \tag{13}$$

where T_0 and T_k is the initial temperature and the temperature at the k^{th} iteration respectively and r is the temperature reduction factor. Some chromosomes will be replaced by chromosomes with lower fitness value as a result of criterion (3). However, the probability of replacement is gradually reduced as T decreases towards the end of the solution process. Hence, sufficient diversity of chromosomes in the population can be maintained and premature convergence can be eliminated.

4. Hybrid algorithms for EEPD problem

The pseudo code of the hybrid algorithm GAA and the formation of the GAA2 algorithm based on GAA are given in the sections below.

4.1 Pseudo code of the GAA algorithm

```
GAA( )
{       t = T0
        initialise evaluate population;
        while{termination criteria not reached) {
                while ( p < P) {
                        t = Tk;
                        select chromosomes for crossover;
                        perform crossover and evaluate new chromosomes;
                        check replacement criteria;
                }
                perform mutation and check replacement criteria for each chromosome;
        }
}
```

P and p in the algorithm represent the population size and the number of new chromosomes generated in the current iteration respectively. The algorithm is terminated when the maximum number of iteration is reached. The solution to the EEPD problem is obtained from the fittest chromosome in the final population.

4.2 The GAA2 Algorithm

In the GAA2 algorithm, the population size is restricted to two chromosomes throughout the entire solution process, thus the memory requirement during computation is reduced to minimum. No selection of chromosomes is required for crossover as there are only two chromosomes in the existing population. The diversity in the population is maintained by including the replacement criteria (2) and (3) in Section 3.4. Criterion (1) is omitted due to the small population size. However, elitism is adopted where the fittest chromosome is re-introduced into the population before the next iteration. The temperature level in each iteration is reduced when a pre-defined *pseudo population size* is reached.

5. Application Example

The two proposed hybrid algorithms have been implemented in C programming language on a 486 DX-100 computer. The algorithm are applied to a system of 10 generators with a total generating capacity of 3695 MW [7]. The heat-rate characteristics of these generators consist of 2 to 3 segments of quadratic function due to the utilisation of different types of fuel. The coefficients of the heat rate characteristics and the fuel types in each segment are shown in Table 1. Three pollutants, SO_2, NO_x and CO_2, are considered in the present example. For the purpose of comparison, two sets of relative weight , Pace and Mass, based on US studies are used [10]. The relative weight of the individual pollutant, emission content and cost of each fuel are given in Table 2 [10].

The two hybrid algorithms have been tested at demand level of 3300 MW with transmission loss being discounted. Crossover and mutation probability for GAA algorithm are 0.6 and 0.1 respectively. A constant population of 100 chromosomes is maintained throughout the process and maximum number of iterations is chosen as 2000. The initial temperature is 1,000,000 with a reduction factor of 0.98. The GAA2 algorithm has the same parameters except an unity crossover probability is adopted owing to the population size of two and a pseudo population size of 100. Evaluation of the trade-off curve is carried out at interval of P.E.C. from 0 to 20 with an increment of 0.5. Theoretically, the value of P.E.C. ranges from 0 to infinity, however, the test results show that there is no significant change in fuel cost when P.E.C. exceeds the value of 12.

The results from GAA and GAA2 are very close with the difference in objective cost averaged below 0.05 % in each study. It shows that GAA2 can perform as good as GAA despite having a small population. Fig. 1 shows the variation of the total fuel cost as a function of P.E.C. Fuel switching is evident in the graph where there is a significant increase in fuel cost. For example in the case of Mass study, the change in fuel cost from P.E.C. at 2.5 to P.E.C. at 3.0 is a consequence of the third generator switching from coal to gas. Fuel switching occurs quite frequently as P.E.C. increases from 0 initially. However, there is no significant change in fuel allocation as P.E.C. increases further. Table 3 shows the fuel allocation of all generators in the Mass study determined by GAA algorithm at different values of P.E.C..

TABLE 1 : HEAT-RATE CHARACTERISTICS AND FUEL TYPES OF GENERATORS IN TEST SYSTEM

Gen	Seg-ment	Power level from	to	Heat-rate characteristics coeff. a	b	c	Fuel Type
1	i	100	196	2.70E+01	-3.98E-01	2.18E-03	Coal
	ii	196	250	2.11E+01	-3.06E-01	1.86E-03	Oil
2	i	50	114	1.87E+00	-3.99E-02	1.14E-03	Oil
	ii	114	157	1.37E+01	-1.98E-01	1.62E-03	Gas
	iii	157	230	1.18E+02	-1.27E+00	4.19E-03	Coal
3	i	200	332	3.98E+01	-3.12E-01	1.46E-03	Coal
	ii	332	388	2.88E+00	3.39E-02	8.04E-04	Gas
	iii	388	500	5.91E+01	4.86E-01	1.18E-05	Oil
4	i	99	138	1.98E+00	-3.11E-02	1.05E-03	Coal
	ii	138	200	5.29E+01	-6.35E-01	2.76E-03	Oil
	iii	200	265	2.67E+02	-2.34E+00	5.94E-03	Gas
5	i	190	338	1.39E+01	-8.73E-02	1.07E-03	Coal
	ii	338	407	9.98E+01	-5.21E-01	1.60E-03	Oil
	iii	407	490	5.40E+01	4.46E-01	1.50E-04	Gas
6	i	85	138	1.98E+00	-3.11E-02	1.05E-03	Oil
	ii	138	200	5.29E+01	-6.35E-01	2.76E-03	Coal
	iii	200	265	2.67E+02	-2.34E+00	5.94E-03	Gas
7	i	200	331	1.89E+01	-1.33E-01	1.11E-03	Coal
	ii	331	391	4.38E+01	-2.27E-01	1.17E-03	Oil
	iii	391	500	4.34E+01	3.56E-01	2.45E-04	Gas
8	i	99	138	1.98E+00	-3.11E-02	1.05E-03	Coal
	ii	138	200	5.29E+01	-6.35E-01	2.76E-03	Oil
	iii	200	265	2.67E+02	-2.34E+00	5.94E-03	Gas
9	i	130	213	1.53E+01	-4.51E-02	7.03E-03	Oil
	ii	213	370	8.85E+01	-5.68E-01	1.55E-03	Coal
	iii	370	440	1.42E+01	-1.82E-02	6.21E-04	Gas
10	i	200	362	1.40E+01	-9.94E-02	1.10E-03	Coal
	ii	362	407	4.67E+01	-2.02E-01	1.14E-03	Gas
	iii	407	490	6.11E+01	5.08E-01	4.16E-05	Oil
Heat-rate function is $a + b(P) + c(P^2)$ MBtu/hr with P in MW							

TABLE 2 : FUEL COSTS, POLLUTANT CONTENTS AND RELATIVE WEIGHTS

	Fuel cost (\$/MBtu)	SO_2 (kg/MBtu)	NOx (kg/MBtu)	CO_2 (kg/MBtu)
Coal 2.37% S	1.50	1.45	0.18	96.12
Oil 1.5% S	2.70	0.71	0.27	73.84
Gas	2.75	0	0.12	51.12
Relative Weight : Pace		0.7105	0.287	0.0025
: Mass		0.1899	0.8073	0.0028

FIGURE 1 : TOTAL FUEL COST AS A FUNCTION OF P.E.C.

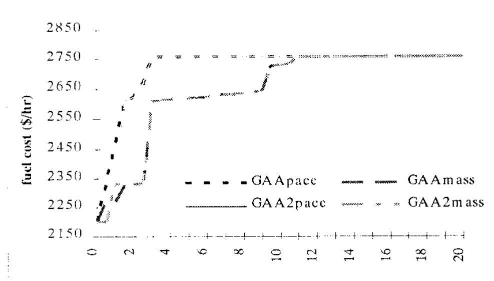


TABLE 3 : FUEL ALLOCATION IN MASS STUDY DETERMINED BY GAA ALGORITHM

P.E.C.	Generator 1	2	3	4	5	6	7	8	9	10
0	oil	coal	oil	gas	coal	gas	gas	gas	coal	coal
0.5	coal	coal	oil	gas	coal	gas	gas	gas	gas	coal
1	coal	coal	oil	gas	coal	gas	gas	gas	gas	coal
1.5	coal	coal	coal	gas	gas	gas	gas	gas	gas	coal
2	coal	coal	coal	gas	gas	gas	gas	gas	gas	coal
2.5	coal	coal	coal	gas	gas	gas	gas	gas	gas	coal
3	coal	coal	gas	gas	gas	gas	gas	gas	gas	coal

The emission level of SO_2 at different values of P.E.C. are shown in Fig. 2. The graph indicates a significant difference in SO_2 emission for the same value of P.E.C. in the two studies. A larger relative weight assigned to SO_2 in the Pace study have led to more emphasis being placed on controlling SO_2 emission. Subsequently, less SO_2 is emitted when compared to the Mass study. The vastly different dispatches resulted from the two distinct sets of relative weight has illustrated the importance of assigning appropriate relative weight for each pollutant under different situations. The determination of relative weight largely depends on local regulations, geographical and meteorological factors.

The trade-off curves between the total fuel cost and the emission of individual pollutants for the case of Pace study are presented in Fig. 3. The trade-off curves exhibit the conflicting property between the economic and environmental aspects of power generation as anticipated. The points on the curve are defined as the optimal points. Each point is associated with an optimal dispatch solution for a particular value of P.E.C. The accuracy of the trade-off curve can be improved further by decreasing the increment of P.E.C. at which evaluations are carried out.

6. Conclusion

Two hybrid algorithms developed by combining GA and SA have been proposed and developed for evaluating the trade-off between fuel cost and pollutant emissions in power dispatch. In the absence of an environmental cost for the emission, the problem is formulated as a bi-criterion function accounting for both the cost and emission consideration. The points on the trade-off curves are found by evaluating the bi-criterion objective function using the developed algorithms. The application example has shown that both hybrid algorithms have the ability to deal with multiple fuels and multiple pollutants where conventional methods will have difficulties in finding the optimal solution. The GAA2 algorithm however requires much less memory than GAA during computation. The results of the two studies in the application example have also indicated that the values of the relative weight assigned to each pollutants have direct bearing on the generation of the optimal dispatch solution. This implies that the determination of appropriate relative weights is important in reflecting the environmental impact of power generation under different situations. The trade-off curves evaluated are useful in providing alternative dispatch solutions for engineers in daily operations.

FIGURE 2 : SO_2 AS A FUNCTION OF P.E.C. (1-W)/W

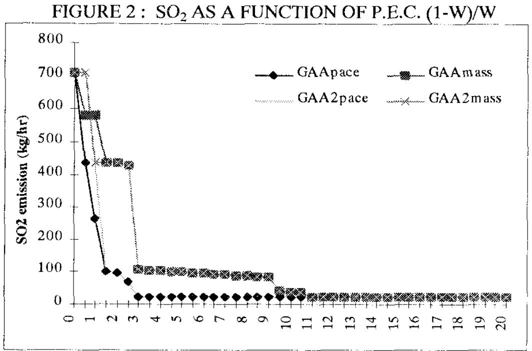
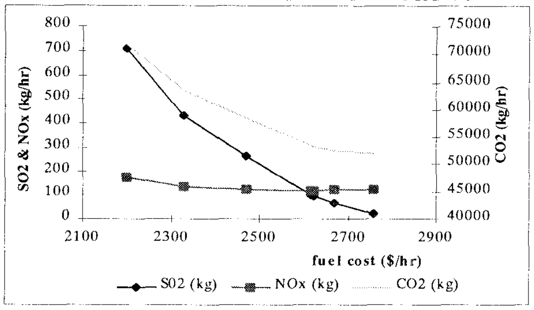


FIGURE 3 : TRADE-OFF CURVES BETWEEN FUEL COST AND THE THREE INDIVIDUAL POLLUTANTS



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