IEEE Transactions on Power Systems, Vol. 12, No. 2, May 1997

HYBRID GENETIC/SIMULATED ANNEALING APPROACH TO SHORT-TERM MULTIPLE-FUEL-CONSTRAINED GENERATION SCHEDULING

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***Abstract*—This paper develops a new formulation for short-term multiple-fuel-constrained generation scheduling. In the formulation, the power balance constraint, generator operation limits, fuel availability factors of generators, efficiency factors of fuels and the supply limits of fuels are taken fully into account. A fuzzy set approach is included in the formulation to find the fuel schedules, which meet the take-or-pay fuel consumption as closely as possible or maximise the utilisation of the cheap fuels, within a generation schedule. The new formulation is combined with genetic algorithms, simulated-annealing and hybrid genetic/simulated-annealing optimisation methods to establish new algorithms for solving the problem. A method for forming the initial candidate solutions in the genetic-based and hybrid-based algorithms is also developed. This method has also been incorporated into the simulated-annealing-based algorithm. The new algorithms are demonstrated by applying them to determine the most economical generation schedule for 25 generators in a local power system and its fuel schedule for 4 different types of fuels.**

I. INTRODUCTION

The objective of the short-term multiple-fuel-constrained generation scheduling problem is to determine the most economical generation and fuel schedule in meeting the load demands in a schedule horizon of one or few days. The need for short-term fuel scheduling in generation scheduling has been addressed in Reference 1. In the multiple-fuel-constrained generation scheduling problem, each generator can be fuelled by more than one type of fuels. For a given loading of the generator, it is necessary to determine the appropriate ratio of the different types of fuels available to the generator. For any type of fuel, its total consumption by different generators over the schedule horizon is subject to the fuel supply limits and the take-or-pay contracts.

96 SM 499-4 PWRS A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for presentation at the 1996 IEEE/PES Summer Meeting, July 28 - August 1, 1996, in Denver, Colorado. Manuscript submitted October 20, 1995; made available for printing June 27, 1996.

Methods based on the Lagrange multiplier, linear programming and network flow algorithm for determining the most economical generation and fuel schedule have previously been proposed [2, 3, 4]. While the Lagrange multiplier method has difficulties in dealing with the operation limits and the non-convexity of the incremental heat-rate curves of generators, the network flow technique may provide impractical solutions [3]. Linear programming is inefficient in solving the present problem because of the large number of variables in the problem even over a 24-hour schedule horizon [4].

Work has been performed by the authors on solving a simpler fuel-constrained generation scheduling problem [5], in which each generator is fuelled by only one type of fuel and the supply of the fuel may be under the take-or-pay contract. Some new algorithms [5] based on genetic algorithms [6], simulated annealing [7, 8] and fuzzy set theory [9] have been established for that problem and have been found to be capable of solving non-convex optimisation problems.

Owing to their ability of dealing with combinatorial optimisation problems, genetic algorithms and simulated annealing methods are adopted here to solve the much larger and more complex problem of short-term multiple-fuel-constrained generation scheduling problem, which is combinatorial and non-convex.

This paper develops a new formulation for short-term multiple-fuel-constrained generation scheduling. In the formulation, the power balance constraint, generator operation limits, fuel availability factors of generators, efficiency factors of fuels and the supply limits of fuels are taken fully into account. A fuzzy set approach is included in the formulation to find the fuel schedules, which meet the take-or-pay fuel consumption as closely as possible or maximise the utilisation of the cheap fuels, within a generation schedule. The new formulation is combined with genetic algorithms (GAs), simulated-annealing (SA) and hybrid genetic/simulated-annealing optimisation methods to establish new algorithms for solving the problem. A method for forming the initial candidate solutions in the GA-based and hybrid-based algorithms is also developed. This method has also been incorporated into the simulated-annealing-based algorithm. The new algorithms are demonstrated by applying them to determine the most economical generation schedule for 25 generators in a local power system and its fuel schedule for 4 different types of fuels.

II. THE PROBLEM

The basic short-term multiple-fuel-constrained generation scheduling problem over a schedule horizon is to determine the most economical generation schedule of T generators and its fuel schedule of K types of fuels. Here each generator can consume one or more types of fuels. The problem can be described mathematically as follows:

$$\text{Minimise } F = \sum_{k=1}^{K} C_k * F_k \qquad (1)$$

in which F is the fuel cost function over a schedule horizon in dollars and C_k is the price of fuel k in dollar per MBtu. The total amount of consumption of fuel k in MBtu by all the generators is given by the double summation term in (2) below. When this amount exceeds $\mathbf{Q_k}$, the minimum amount agreed under the take-or-pay contract, the value of F_k in (1) is given by the total amount of consumption. Otherwise, the value of F_k is taken to be that of $\mathbf{Q_k}$. The expression for F_k therefore is:

$$F_k = \{ \max (Q_k , \sum_{j=1}^{J} \sum_{t=1}^{T} (1/\beta_{kt})\, n_j\, \rho_{tjk}\, f_{tk}(\delta_{tjk} * P_{tj})) \} \qquad (2)$$

In the above equation,

J : total number of intervals in schedule horizon

n_j : number of hours in the jth interval

P_{tj} : the loading of generator t in interval j.

δ_{tjk} : fuel allocation factor, ranging from 0 to 1, gives the fraction of the P_{tj} loading level when fuel k is used in interval j. In interval j, for generator t and for all k, the summation of δ_{tjk} is equal to 1.

$f_{tk}(\delta_{tjk} * P_{tj})$: the heat rate function of generator t using fuel k at power level of $(\delta_{tjk} * P_{tj})$.

ρ_{tjk}: fuel availability factor, the value of which is 1 if fuel k is available to generator, and is 0 if unavailable during interval j.

β_{kt} : efficiency factor of fuel k to generator t.

The minimisation of F in (1) is subject to the power balance constraint

$$D_j = \sum_{t=1}^{T} P_{tj} \qquad j = 1, 2,..., J \qquad (3)$$

where D_j is the total load demand at interval j

It is also subject to the constraints imposed by the minimum and maximum operation limits of the generators. For the t^{th} generator, the constraint is

$$P_{t,min} \le P_t \le P_{t,max} \qquad (4)$$

The minimisation is also subject to the supply delivery constraints of the fuels. The supply delivery constraint for fuel k is

$$F_{k,min} \le F_k \le F_{k,max} \qquad (5)$$

III. FORMULATION FOR SOLVING THE PROBLEM

To solve the multiple-fuel-constrained generation scheduling problem, a formulation is developed in the following. First a generator is selected randomly. Let this generator be r and is here referred to as the *dependent generator*. The loadings and the fuel allocation factors of the dependent generator r in all intervals in the schedule horizon are to be determined so that the power balance requirement will be met in all intervals and a generation and fuel schedule for the generators can be formed.

Assume the loadings, P_{tj}, and the fuel allocation factors, ρ_{tjk}, of all the generators in all intervals except the dependent generator r, that is t=1, 2...., T and $t \neq r$, have been determined by the optimisation techniques in Section V. In any interval j, from the power balance constraint in (3), the loading P_{rj} of the dependent generator r can be found from

$$P_{rj} = D_j - \sum_{t=1,\, t\neq r}^{T} P_{tj} \qquad \text{for } j = 1,2, ...,f,..,J \qquad (6)$$

If the value of P_{rj} is not within the operation limits, the assumed loadings, P_{tj}, are invalid and another set of loadings is to be assumed by the optimisation techniques in Section V such that P_{rj} is within the limits.

To determine the fuel allocation factors for the dependent generator r in any interval j, first select arbitrarily an available fuel k'. The allocation factor of fuel k', $\delta_{rjk'}$, to generator r is given by 1 minus the sum of the allocation factors of other fuels as in

$$\delta_{rjk'} = 1 - \sum_{k=1,\, k\neq k'}^{K} \delta_{rjk} \qquad \text{for } j = 1,2, ...,f,..,J \qquad (7)$$

In the above equation, the value of the δ_{rjk} is 0, if fuel k is not available to generator r. Otherwise, it is set to a random number generated within the range of 0 to 1. This method is used in the mutation operation to assign values to the fuel allocation factors of a generator in the genetic-based algorithms and hybrid-based algorithms to be developed in Sections V.A and V.C respectively and it is also employed in the simulated-annealing-based algorithm in Section V.B. If the value of $\delta_{rjk'}$ of generator r is found to be negative, the sum of the values of δ_{rjk} of the non-dependent generators is invalid and another set of values of δ_{rjk} is to be set by the above method such that $\delta_{rjk'}$ is either 0 or positive.

At this point, for all intervals, the values of P_{tj} and δ_{tjk} for all the generators including that for the dependent generator are known. In order to obtain better fuel schedules which either (a) meet the take-or-pay contracts on the fuels or (b) consume cheaper fuels as much as possible, it is here proposed that an interval *f*, called the *take-or-max interval*, in the schedule horizon is randomly selected and the values of the fuel allocation factors of all the generators, in this interval are modified. A fuzzy set approach is here proposed for the modification process and is presented in the next section.

IV. MODIFICATION OF FUEL ALLOCATION FACTORS BY FUZZY SET APPROACH

Requirements (a) and (b) in the last section can be viewed as 'soft' constraints. This means that candidate solutions which do not quite satisfy the constraints but are otherwise economical will not be discarded by the optimisation procedure. The presence of these economical solutions will enhance the ability of the genetic-based algorithms to be developed in later sections to determine the optimum solution.

The take-or-pay constraint in (a) can now be expressed as: if the contracted minimum amount of a fuel is not exceeded, the total consumption of this fuel by all the generators should be as close to the contracted amount as possible. Owing to the inexactness of this statement, it has been described using fuzzy set theory [5].

The constraint in (b) can be stated as: if it is found that the required amount of the fuel exceeds the minimum amount in the take-or-pay contract and the fuel is a less expensive fuel, it should be consumed as much as possible by the generators. Again, this statement can also be described using a fuzzy set theory. The fuzzy sets representing requirements (a) and (b) above are presented in the next section.

A. Fuzzy Set

Let U be a set with elements x, then a fuzzy set F in U is a set of ordered pairs, defined as follows:

$$F = \{(x, \mu_F(x)) | \, x \in U\} \tag{8}$$

where $\mu_F(x)$ is the membership function of an element x. The membership function $\mu_F(x)$ gives the degree of belonging of x to the fuzzy set F.

To represent the requirements (a) and (b), x in (8) is assigned to be the total consumption of a fuel. The total consumption of fuel k in the schedule horizon is here denoted by x_k and is given by the double summation term in (2). The total consumption x_k has three components: f1, f2 and f3. Component f1 is the fuel k consumption by all generators in all the intervals except the take-or-max interval *f*. Component f2 is the amount consumed by any generator t' in *f*, while component f3 is the total amount consumed by the remaining generators in *f*.

As mentioned in Section 0, to satisfy either the take-or-pay contract in requirement (a) or the maximum utilisation of the cheaper fuels in requirement (b), the fuel allocation factors of all the generators, δ_{tfk}, in the take-or-max interval need to be adjusted. The adjustment is reflected by the variation of the values of f2. When the value of f2 varies, the degrees of satisfaction of requirements (a) and (b) are changed and are indicated by the closeness of the value of x_k (= f1 + f2 + f3) to the value of Q_k and to the value of $F_{k,max}$ respectively.

When x_k is less than Q_k, requirement (a) is to be satisfied. To indicate the closeness of the value of x_k to Q_k, the membership function in (9) [5, 10] below is suggested.

$$\mu_F(x_k) = (1 + (f1 + f2 + f3 - Q_k)^4)^{-1} \tag{9}$$

Fig. 1 shows the variation of the value of the membership function $\mu_F(x_k)$ with the value of f2 when Q_k is set to 10000 and f1+f3 is set to 9990.

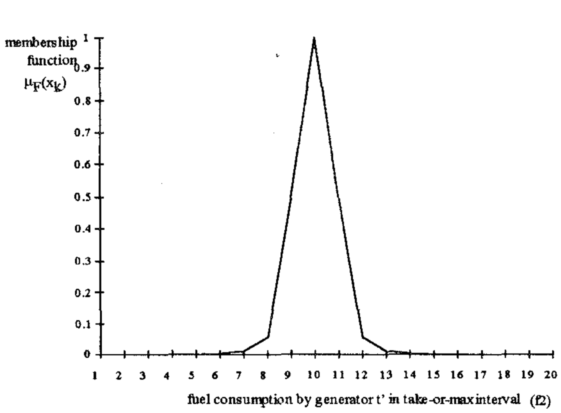

Fig. 1: Membership function showing the closeness of the fuel consumption f2 of generator t' to the minimum consumption in the take-or-pay contract

When x_k exceeds Q_k and fuel k is not the most expensive type of fuel consumed by generator t', requirement (b) is to be satisfied. To indicate the closeness of the value of x_k to $F_{k,max}$, the membership functions in (10) and (11) below are suggested.

$$\mu_F(x_k) = 0 \qquad \text{for } (f1 + f2 + f3) > F_{k,max} \tag{10}$$

$$\mu_F(x_k) = (1 + ((F_{k,max} - (f1 + f2 + f3))^3)^{-1} \qquad \text{for } (f1 + f2 + f3) \le F_{k,max} \tag{11}$$

The membership function in (10) states that the membership value of the total fuel consumption of fuel k, x_k, is 0 when $x_k > F_{k,max}$, the upper supply limit of the fuel. The second membership function in (11) describes the degree of closeness of the value of x_k to the value of $F_{k,max}$ when $x_k \le F_{k,max}$. This function is suggested since the range $F_{k,min} \le x_k \le F_{k,max}$ is of immediate interest here and an odd function suffices. Moreover, although the power index of the term ($F_{k,max}$ -(f1 + f2 + f3)) is 3 in this function, the function is very similar to the case when the power index is 4. By adopting 3 as the value of the power index, some gains in computational time can be achieved since the function needs to be evaluated many times during the optimisation process.

For $F_{k,max}$ = 10000 and f1+f3 = 9990, Fig. 2 shows the variation of the value of the membership function $\mu_F(x_k)$ in the y-axis when f2 varies from 1 to 20 in the x-axis.

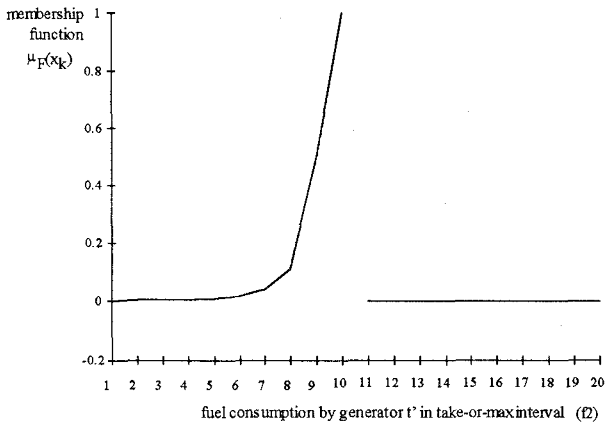

Fig. 2: Membership function of the closeness of the fuel consumption f2 of generator t' to the upper supply limit of the fuel

B. Changing the Value of Fuel Allocation Factors

B.1. Changing the value of δt'fk

To change the value of the fuel k allocation factor of any generator t', $\delta_{t'fk}$, in the take-or-max interval *f*, the range of value 0 to 1 of $\delta_{t'fk}$ is first divided into *m* equal sub-ranges. In the present work, *m* is taken to be 5. For each sub-range, a value within the sub-range is chosen randomly and is assigned to be the value of $\delta_{t'fk}$ and this in turn sets the value of f2. The corresponding membership value will be found from the membership functions in the last section. The value of $\delta_{t'fk}$ and the corresponding value of f2, which produce the greatest membership value among the *m* values are adopted.

B.2.Dependent fuel

In any interval, the sum of the fuel allocation factors of all the fuels to generator t' must be 1. This constraint must also be satisfied in the take-or-max interval. After the fuel k allocation factor of t' is adjusted in that interval, the above constraint is satisfied by selecting arbitrarily among the available fuel to t', a *dependent fuel* k' and modify the fuel k' allocation factor, $\delta_{t'fk'}$, to t' according to the following expression.

$$\delta_{t'fk'} = 1 - \sum_{k=1,\, k \neq k'}^{K} \delta_{t'fk} \qquad (12)$$

C. Procedures For The Satisfaction Of Requirements (a) And (b)

The procedure to satisfy requirement (a) can be summarised in the following. For any generator t' in interval f and for any *non-dependent fuel* k of t', calculate the fuel consumption (f1+f3) by all the generators in the schedule horizon except t'. If (f1+f3) $\geq Q_k$, further process will be taken to satisfy requirement (b). Otherwise, the take-or-pay minimum amount of consumption has not been reached and the fuel k allocation factor $\delta_{t'fk}$ of t' is then increased by the fuzzy set method in Section IV.B1 to meet the minimum amount Q_k. Repeat this process until all the non-dependent fuel allocation factors have been adjusted. Update the dependent fuel allocation factor $\delta_{t'fk'}$ using (12).

The above process is repeated until all the generators in interval f have been processed. If the process does not lead to any fuel consumption such that (f1+f3) $\geq Q_k$, a fuel schedule has been formed. Otherwise, some allocated fuels have exceeded their contracted minimum quantities and the following procedure is performed to satisfy the maximum utilisation of cheap fuels in requirement (b):

In each interval, the value of the fuel allocation factor of the cheapest non-dependent fuel to generator t' is increased by the value of factor of the most expensive fuel to t'. Here the most expensive fuel takes on the role of the dependent fuel k' and it is set to be unavailable to t'. If the revised fuel schedule for t' does not violate the fuel supply constraints, it will be accepted.

If the revised fuel schedule for t' is infeasible, it is discarded. Then starting from the original fuel schedule for t', the allocation factor of the next cheapest non-dependent fuel for t' will then be modified in the same manner described above. This process is repeated until all the non-dependent fuels for t' have been processed or the revised fuel schedule is feasible. If a feasible revised fuel schedule for t' cannot be found when the process is terminated, the most expensive fuel is now taken as the dependent fuel k' and the remaining fuels are modified by the fuzzy set approach described in Section IV.B1 to achieve the maximum utilisation of the cheaper fuels. The allocation factor of the most expensive fuel k' to t' is calculated according to (12) in Section IV.B2.

The procedure above is repeated for other generators in the take-or-max interval until all the generators have been processed.

V. APPROACHES BASED ON GENETIC ALGORITHMS, SIMULATED ANNEALING AND THEIR COMBINATION

Simulated annealing (SA) technique and genetic algorithms (GAs) and the hybrid GA/SA algorithms [11] have been applied by the authors to determine global optimum solutions for economic dispatch [12], generation scheduling with take-or-pay contracts [5] and unit commitment [13]. SA and GAs have also been applied to power system problems by other researchers [14 - 17].

The formulation and the fuzzy approach described in the previous sections can now be combined with GAs, SA, or the hybrid algorithms, GAA and GAA2, to seek for the global or near-global optimal short-term multiple-fuel-constrained generation schedule. As mentioned in Section 0, the generator loadings and the fuel allocation factors of the generators in all the intervals except that of the dependent generator r are determined by GAs, SA or the hybrid algorithms.

The GA-based algorithms, SA-based technique and the hybrid-based algorithms for the present problem are developed in the following sections.

A. Genetic-Algorithm-Based Algorithms

GAs [6] are optimisation techniques which can determine the global optimum solution of a combinatorial optimisation problem. They are based on the mechanics of natural genetics and natural selection. The basic GA (BGA) is made up of four components: (a) the representation of candidate solutions by chromosomes; (b) the fitness function for the evaluation of the degree of fitness of the solutions; (c) the crossover operator as a mechanism for generating new candidate solutions (child chromosomes) from selected old candidate solutions (parent chromosomes); and (d) the mutation operator which operates on chromosomes to introduce new information in the chromosomes.

In adopting GAs to the present problem, a chromosome represents a candidate solution which consists of the loadings and the fuel allocation factors of all the generators in the schedule horizon. Each element in a chromosome consists of the loading of a generator at an interval and the allocation factors of all the fuels in that interval. Consequently, for J intervals and T generators, there will be T*J elements. The elements in a chromosomes are all coded using floating-point numbers [18].

For the present problem, the objective function is the total fuel cost function F in (1). The fitness function is expressed as K/F, where K is the maximum floating-point number that can be represented in the computer. K magnifies the values of (1/F), which are usually small, and spreads the fitness values of the chromosomes in a wider range.

In the generation of new candidate solutions, the 2-point crossover method [19] is adopted in the present work. In 2-point crossover, the points are randomly decided as in single-point crossover. The elements in between the 2 randomly selected points are swapped between two parent chromosomes to form two child chromosomes. The crossover operation is initiated when a random number generated between 0 and 1, rand [0,1], is less than the preset value of the probability of crossover.

When mutation is applied to a chromosome, the values of the loading and fuel allocation factors in a randomly selected element, *m*, in the chromosome are changed. A random number generated between the lower and upper operation limits of the generator is used as the value of the loading. The method for assigning the values of the fuel allocation factors is the same as that described in Section 0. Similar to crossover, mutation is initiated only if rand[0,1] is less than the pre-specified value of the probability of mutation. After crossover and mutation, the formulation in Section 0 is adopted to determine the loadings and fuel allocation factors of generator r in all the intervals, while the fuzzy approach of Section IV is employed to modify the fuel allocation factors at the take-or-max interval *f*.

To initiate the execution of the algorithm, a population of *s* chromosomes is first initialised randomly or by the process described in Section VI. A new generation of *s* chromosomes is produced in each iteration by crossover. Mutation is then applied on each chromosome to introduce new information into the population. When the pre-specified number of iterations has been reached, the algorithm is terminated.

The BGA can be modified in a way that new child chromosomes replace chosen chromosomes in the current generation instead of being stored in the next generation [20]. Consequently, the memory requirement to store the *s* chromosomes is reduced and the population of a generation of chromosomes consists of parent and child chromosomes. The modified BGA will be named as the incremental GA (IGA).

B. Simulated Annealing Technique

SA is an optimisation technique which simulates the physical annealing process of a molten particle starting from a high temperature. This techniques consists of three components: (i) generation of candidate solutions by perturbation of current solutions; (ii) checking for acceptance of the solutions and (iii) an iterative procedure.

A candidate solution consists of the loadings and fuel allocation factors of all the generators in all the intervals. In component (i), a new candidate solution is generated by perturbing the loadings and the fuel allocation factors of the generators in the current solution. The loadings of the non-dependent generators are perturbed in the following manner. In the high temperature region, the loadings are perturbed randomly in the range given by the operation limits of the thermal generators. By this means, the chance of generating feasible solutions will be very high although the new solutions may not be in the neighbourhood of the current solution. At the low temperature region, it is important to ensure the new solutions are in the neighbourhood of the current solution. This can be achieved by perturbing the current solution according to the Gaussian probabilistic distribution function (g.p.d.f.) [21]. After the new loadings of the non-dependent generators are found, the loadings of the dependent generator is determined by the method in Section 0.

The method of perturbing the fuel allocation factors in the current solution is as follows. Since the range of the value of the fuel allocation factor of the generator is from 0 to 1 and it is a small range, the value of the factor can be set efficiently to a random number within 0 to 1 as described in Section 0. A new and complete candidate solution of generation dispatch with a fuel schedule is now formed. The candidate fuel schedule can then be further refined to satisfy the take-or-pay contracts in requirement (a) or the maximum utilisation in requirement (b) by the fuzzy approach developed in Section IV.

In component (ii), a new solution is accepted deterministically as the current solution when its cost is lower than that of the current solution, otherwise, it is probablistically accepted with the following probability of acceptance $\Pr(\Delta F)$ [22]

$$\Pr(\Delta F) = [1 / (1 + \exp(\Delta F / T))] \tag{13}$$

where ΔF is the increment of cost of the new solution compared to the current solution and T is the temperature level. The accepted solution will be used to generate another new solution.

In component (iii), components (i) and (ii) are executed repeatedly for a temperature level until a specified number of trial solutions is reached. The last accepted candidate solution becomes the initial solution for the next iteration. The temperature in the next iteration is reduced according to the following geometric cooling schedule [8]:

$$T_k = r^{(k-1)} T_0 \tag{14}$$

in which T_k is the temperature at the k^{th} iteration. T_0 is the initial temperature and its value can be determined by trial and error method or estimated by the method described in Reference 21. The iterative process in component (iii) is terminated when there is no significant improvement in the solution after a pre-specified number of iterations or when the maximum allowable number of iterations is reached. The latter way is adopted in the present work.

C. Hybrid Genetic/Simulated Annealing Algorithms

The performance of IGA can be improved by introducing more diversity in the chromosomes in the early stage of the solution process. This can be achieved by replacing fitter chromosomes by weaker child chromosomes in a controlled way. To accomplish this, the probabilistic acceptance test technique in component (ii) of SA is now employed as the probabilistic replacement test and is incorporated into IGA. In the replacement test, the probability of replacement is given by (13). As the solution process progresses, the temperature level T in (13) is reduced according to (14). The probability of replacement therefore will also be reduced gradually. This means that at the later stage of the solution process, the chance of a fitter chromosome being replaced becomes less. In addition, the probabilistic replacement test is also adopted to check whether a mutated chromosome should be included in a population. The resultant algorithm is here referred to as Genetic Annealing Algorithm (GAA).

It should be noted here that although mutation can introduce new information to chromosomes, it can also destroy useful information. In the GAA algorithm, to preserve the positive effects and to counter the adverse effects of the mutation operator, after an element of generator loading in the chromosome is chosen for mutation, the value of the loading is changed by perturbing its present value according to the g.p.d.f. The mean value of g.p.d.f. is set to the present value of the element and its standard deviation is set proportional to the temperature level T_k in (14). As the iteration increases, the amount of perturbation to the present value decreases and the change in value of the loading of the selected element for mutation is also reduced and regulated. The method of mutation of the values of the fuel allocation factors, however, remains the same as that of the GA-based process in Section V.A since the method is efficient for dealing with the range of the values of the fuel allocation factors.

The memory requirement of GAA can be reduced greatly by restricting the size of the population of chromosomes to 2. The modified algorithm is called GAA2. In GAA2, to achieve more diversity, the fittest chromosome generated so far is always stored and is re-introduced into the population at the end of each generation in a probabilistic manner. To compensate for the smaller population size, the values of probability of crossover and mutation are set at higher values in GAA2 than in other GA-based algorithms in Section V.A. Despite a larger mutation rate, because of the probabilistic replacement test and the regulation of the amount of change in value of the selected loading in a chromosome to be mutated, the adverse effect of mutation can still be reduced greatly. The detailed development of the GAA and GAA2 hybrid algorithms can be found in the paper by the authors in Reference 11.

VI. A METHOD FOR IMPROVING THE ALGORITHMS

The efficiency of the developed new algorithms can be greatly improved if a cheaper generation schedule can be formed based on a generation schedule in which the take-or-pay contracts for the expensive fuels are satisfied. The cheaper schedule can be generated by reducing the loadings of generators that consume the expensive fuels and by increasing the loadings of generators that utilise the cheaper fuels. This can be incorporated in the formation of the solution chromosomes in the initial population of the GAs and the hybrid algorithms. However, generation schedules, in which the take-or-pay contracts for the expensive fuels are not satisfied, are still included in the initial population. For the SA-based algorithm, the above mechanism is incorporated in the solution generation process in component (i).

Since in all the new algorithms, the setting of the generator loading depends on the specified operating limits of the generators, in the formation of a cheaper generation schedule, the reduction of the loading of an expensive generator can be effectively implemented by setting arbitrarily the maximum operation limit of the generator to a lower value. Similarly, the increment of the loading of a generator using cheap fuels can be effectively implemented by setting arbitrarily the minimum operation limit to a higher value.

After the new generator loadings are determined, the fuel allocation factors of the generators are then determined by the methods in Sections 0 and IV. A complete candidate solution of generation dispatch with a fuel schedule is now formed.

VII. APPLICATION EXAMPLE

The developed algorithms for short-term multiple-fuel-constrained generation scheduling have been implemented using the C programming language and the software systems are run on a PC/486 computer with an I860 Co-processor. Owing to the randomness of the algorithms, they are executed 30 times. To validate the algorithms, they have been first applied to a simple test example in Reference 3. In the test example, there are 4 generators and there are 4 contracted fuels. In Reference 3, the test example was solved by the network flow technique. The new algorithms in this paper obtained identical results with that by the network flow technique. This confirms the validity of the new algorithms.

A. Application Studies

To demonstrate the power and the usefulness of the new algorithms, however, the algorithms with and without fuzzy approach have been applied to a local power system and three application studies have been performed. In the first study, Study (1), the take-or-pay contracts on the fuels and the maximum supply limits of the fuels are discounted. In the second study, Study (2), the contracts and the limits are accounted for. To show the ability of the algorithms in seeking for the global optimum solution, in the third study, Study (3), the effects of valve-point loading in the heat rate functions of the generators are also included in addition to including the limits and take-or-pay contracts of the fuels.

In the three studies, 25 thermal generators and 4 different types of fuels are scheduled over a schedule horizon of 24 hours. The generator commitment schedule in the schedule horizon is assumed to have been determined and it is given in Table 1. The horizon is divided into 48 half-hour intervals. The study results obtained using the BGA, IGA, GAA, GAA2 and SA are presented later in this section. As the generation and fuel scheduling problems in the three studies are highly combinatorial, conventional mathematical programming methods would require excessive computational resources to find the optimum solutions and hence have not been employed for comparison purposes.

Table 1: 24-hour generator schedule for studies

gen. no.	1	2	3	4	5	6	7	8	9	10	11	12	13
up (hr)	8:30	6:00	0:00	5:30	7:30	0:00	0:00	0:00	-	0:00	0:00	0:00	0:00
down (hr)	18:00	+	+	22:00	21:00	+	23:30	+	0:00	+	+	+	+
gen. no.	14	15	16	17	18	19	20	21	22	23	24	25	
up (hr)	0:00	0:00	7:00	8:30	8:30	-	15:00	-	6:30	6:30	8:00	-	
down (hr)	+	+	14:00	15:00	15:00	0:00	16:30	0:00	18:00	23:00	20:30	0:00	

'-' denotes not committed within the time horizon

'+' denotes not decommitted within the time horizon

The settings of the parameters of the algorithms are summarised in Table 2. They are suggested by De Jong [23] except the number of iterations, which is found experimentally. In the table, the population size of 100 means a population of 100 feasible chromosomes. To ensure the specified population size is reached, a maximum of 10,000 crossover operations is allowed in each iteration. For the hybrid algorithm GAA2, the population size and the probability of crossover are 2 and 1 respectively and 40 feasible chromosomes are allowed to be produced in an iteration. For the execution of the hybrid algorithms GAA2 and GAA, the initial temperature T_0 and the temperature reduction rate r in (14) are set respectively to the values of 5000 and 0.98 after some experimentation.

When the SA technique is applied to the studies, the temperature reduction factor is set to 0.98. The initial temperature T_0 is set to 50,000. The maximum number of iteration is 200 and the number of trials per iteration is 3000. The method of perturbation is changed from the random approach to the g.p.d.f. approach at the 150th iteration.

Table 2: Parameter settings of GA-based and hybrid algorithms

algorithms	BGA, IGA, GAA	GAA2
population size	100	2
no. of iterations	900	270
probability of crossover	0.6	1
probability of mutation	0.001	0.01

Table 3: Fuel types and data

Fuel	Type 1 (coal)	Type 2 (coal)	Type 3 (gas)	Type 4 (gas)
price($/MBtu)	2.75	2.25	2.00	3.00
Q_k(MBtu)				3000
F_{min}(MBtu)	500	500	500	0
F_{max}(MBtu)	--	--	130000	--
available to gen.	1	8-15	2-7, 16-25	16-25

'--' indicates unlimited supply
Type 1 to 3 fuels not under take-or-pay contract

In the studies, each generator uses only one kind of fuel throughout the schedule horizon. For each kind of fuel, there are 2 different types of fuels. As shown in Table 3, Type-1 and Type-2 fuels are coal and Type-3 and Type-4 fuels are gas. The heat-rate function of the generator is assumed to be the same for different types of the same kind of fuel. Table 3 also summarises the fuel prices, the fuel supply limits, the take-or-pay contracted amount for Type 4 and the availability of the fuels to the generators.

The coefficients of the heat-rate functions and the operation limits of the generators are summarised in Table 4. Coefficients 'e' and 'f' in Table 4 are the coefficients of the sine term which is used to superimpose on the quadratic heat-rate function to simulate the valve-loading points [15]. Table 5 summarises the efficiency factors of the fuels.

For Study (3), as shown in Table 6, in the determined solution schedule, GAA2 with fuzzy approach has allocated 129985.28 MBtu of the cheaper Type-3 fuel to Generators 2 to 7 and Generators 16 to 25 and 4128.32 MBtu of the dearer Type-4 fuel to Generators 16 to 25. The allocated amount of Type-3 fuel is very close to its maximum supply limit of 130000 MBtu. Moreover, by allocating the cheaper fuel, Type-2 fuel, to Generators 8 to 15, the algorithm has been able to reduce greatly the consumption of the dearer Type-4 fuel. Comparing these results with that obtained by GAA2 without fuzzy approach in Table 6, it can be observed that GAA2 with fuzzy approach performs better.

For the three studies, the total fuel consumption and the total costs in Australian dollars of the best schedule solutions found by new algorithms are tabulated in Tables 6-8. From the results in Table 7, it can be seen that the new algorithms successfully preclude the use of the dearer Type-4 fuel for Study (1). For Studies (2) and (3), the results in Tables 8 and 6 indicate better solution quality can be achieved by the algorithms with the fuzzy approach. The improvement is more prominent in Study (2) as the fuzzy approach assists the algorithms to utilise larger amount of Type-3 fuel, which is the cheapest. The improvement, however, is less prominent in Study (3) than Study (2). It is because in Study (3), the effects of valve-loading points lead to higher consumption of all the fuels. In particular, the Type-3 fuel consumption is already very close to its maximum supply limit and it cannot be increased any more to further reduce the consumption of the Type-4 fuel.

Table 4: Heat rate coefficients and operation limits of generators

gen	Pmin	Pmax	a	b	c	e	f
1	11	16	0.0586	10.32	36.53	0	0
	16	32	0.1172	10.32	18.27	0	0
2	36	114	0.0069	6.7378	94.7055	100	0.084
3	36	114	0.0069	6.7378	94.7055	100	0.084
4	47	97	0.0114	5.3519	148.8907	120	0.077
5	47	97	0.0035	7.2038	83.1773	120	0.077
6	60	190	0.0016	6.4352	222.9258	150	0.063
7	60	190	0.0009	6.5651	233.4006	150	0.063
8	43	60	0.000052	11.1222	15.723	0	0
9	43	60	0.000052	11.1222	15.723	0	0
10	43	60	0.000052	11.1222	15.723	0	0
11	43	60	0.000052	11.1222	15.723	0	0
12	90	200	0.000109	8.9545	107.874	200	0.042
13	90	200	0.000109	8.9545	107.874	200	0.042
14	90	200	0.000126	8.621	116.58	200	0.042
15	90	200	0.000126	8.621	116.58	200	0.042
16	13	37	0.0084	8.0625	85.4140	0	0
17	13	37	0.0084	8.0625	85.4140	0	0
18	10	38	0.0192	7.4987	99.1089	0	0
19	10	38	0.0192	7.4987	99.1089	0	0
20	10	38	0.0192	7.4987	99.1089	0	0
21	10	38	0.0192	7.4987	99.1089	0	0
22	25	110	0.0161	5.8801	307.4522	80	0.098
23	13	37	0.0084	8.0625	85.4140	0	0
24	13	37	0.0084	8.0625	85.4140	0	0
25	10	38	0.0192	7.4987	99.1089	0	0

$F(P) = a * P^2 + b * P + c + |e \sin(f (P_{min} - P))|$ in MBtu/hr with P in MW

Table 5: Fuel efficiency factors of generators

	coal		gas			coal		gas	
	Type 1	Type 2	Type 3	Type 4		Type 1	Type 2	Type 3	Type 4
gen no.	eff.	eff.	eff.	eff.	gen no.	eff.	eff.	eff.	eff.
1	1.075	-	-	-	14	-	1.075	-	-
2	-	-	1.075	-	15	-	1.075	-	-
3	-	-	1.075	-	16	-	-	1	1
4	-	-	1.075	-	17	-	-	1	1
5	-	-	1.075	-	18	-	-	1	1
6	-	-	1.075	-	19	-	-	1	1
7	-	-	1.075	-	20	-	-	1	1
8	-	1.075	-	-	21	-	-	1	1
9	-	1.075	-	-	22	-	-	1	1
10	-	1.075	-	-	23	-	-	1	1
11	-	1.075	-	-	24	-	-	1	1
12	-	1.075	-	-	25	-	-	1	1
13	-	1.075	-	-					

Table 6: Fuel consumption and costs of Study (3) by new algorithms

algorithm	fuel				cost
	Type 1	Type 2	Type 3	Type 4	
BGA	2127.91	196307.56	129923.10	12679.07	745427.12
BGA**	2116.68	203075.95	129992.64	6901.84	743432.50
IGA	1859.52	193624.58	129993.47	11781.50	736100.44
IGA**	2000.17	196694.02	129976.7	8993.00	734994.50
GAA	2066.07	193001.08	129892.93	12593.25	737499.75
GAA**	2056.39	198201.34	129952.62	8176.53	736043.00
GAA2	2162.83	192512.84	129803.54	13226.26	738387.56
GAA2**	2078.79	202549.30	129985.28	4128.32	733808.06
SA	2626.91	122931.44	122931.44	76966.21	760581.25
SA**	2826.80	208606.36	129572.67	5983.25	754233.13

** indicates algorithm with fuzzy approach

Table 7: Fuel consumption and costs of Study (1) by new algorithms

algorithm	fuel				cost
	Type 1	Type 2	Type 3	Type 4	
BGA	1905.43	176006.39	142446.48	0.00	686147.25
BGA**	1905.43	176006.39	142446.48	0.00	686147.25
IGA	1772.86	167926.44	149030.39	0.00	680770.63
IGA**	1749.66	167427.86	149615.89	0.00	680756.00
GAA	1671.24	168308.81	148795.03	0.00	680880.81
GAA**	1671.24	168308.81	148795.03	0.00	680880.81
GAA2	1676.42	166543.94	150277.86	0.00	679889.25
GAA2**	1676.42	166543.94	150277.86	0.00	679889.25
SA	2449.42	191454.20	130151.81	0.00	697039.87
SA**	2484..70	190757.70	130501.07	0.00	697039.87

** indicates algorithm with fuzzy approach

Table 8: Fuel consumption and costs of Study (2) by new algorithms

algorithm	fuel				cost
	Type 1	Type 2	Type 3	Type 4	
BGA	1879.11	197667.91	109988.04	14785.53	714253.00
BGA**	2080.90	189405.44	128916.18	2991.52*	698717.00
IGA	1703.62	197080.30	109994.42	14368.31	711209.38
IGA**	1605.55	186098.98	129998.51	3068.47	692340.38
GAA	1725.38	197411.40	109970.18	14251.60	711615.56
GAA**	1681.93	185985.27	129985.70	3115.89	692411.25
GAA2	1684.28	197185.30	109994.65	14206.91	710908.75
GAA2**	1587.93	185922.61	129978.20	3000.2	691650.00
SA	2657.77	192655.02	115922.64	13025.25	711703.69
SA**	2285.36	192961.91	114875.00	13908.24	711923.75

** indicates algorithm with fuzzy approach

* denotes the total fuel consumption is less the minimum contracted take-or-pay amount

Table 9 shows the cheapest and the most expensive costs associated with the solution schedules found by the new algorithms with or without the fuzzy approach. The results in Table 9 indicate that GAA2 with the fuzzy approach has the best performance among the new algorithms. They also show that the new algorithms with the fuzzy approach are more reliable than when they are without. Table 10 summaries the execution time required by the new algorithms in the three studies. Again, the GAA2 algorithm with fuzzy approach is the most promising algorithm in terms of the execution time.

Table 9: Comparison of best and worst solutions

	Study (1)		Study (2)		Study (3)	
algorithm	best cost	worst cost	best cost	worst cost	best cost	worst cost
BGA	686147.25	689139.13	714253.00	715863.00	745427.12	751280.81
BGA**	686147.25	688299.69	698717.00	702984.38	743432.50	747475.63
IGA	680770.63	681642.88	711209.38	712143.32	736100.44	738026.13
IGA**	680756.00	681410.50	692340.38	692954.88	734994.50	736592.81
GAA	680880.82	681601.50	711615.56	712541.19	737499.75	739479.63
GAA**	680880.81	681474.75	692411.25	693169.75	736043.00	737592.37
GAA2	679889.75	680532.57	710908.75	711551.88	738387.56	741337.19
GAA2**	679889.25	680315.25	691650.00	692653.57	733808.06	736091.81
SA	697039.87	697811.50	711703.69	716464.25	760581.25	763436.75
SA**	697039.88	697814.25	711923.75	712182.38	754233.13	755449.38

Table 10: Comparison of execution time

	Study (1)	time	(min)	Study (2)	time	(min)	Study (3)	time	(min)
algorithm	shortest	longest	average	shortest	longest	average	shortest	longest	average
BGA **	13.189	15.57	14.28	57.58	128.40	70.14	70.72	108.23	91.48
IGA**	117.76	121.91	120.31	142.88	340.09	176.89	230.26	239.48	234.68
GAA**	94.38	96.21	95.38	121.09	125.69	122.86	174.70	180.83	177.05
GAA2**	40.48	41.14	40.92	45.68	45.91	46.25	56.59	60.00	58.28
SA**	697.65	697.78	697.72	696.79	913.41	704.06	1644.79	1645.17	1645.03

B. Convergence Characteristics Of New Algorithms

The problem in Study (3) is more non-linear than that in the other studies. The typical convergence characteristics of the new algorithms with the fuzzy approach for this study are therefore presented here in Fig. 3. Each characteristic shows the variation of the cost of the cheapest schedule found as the number of iterations increases in the optimisation process. The typical convergence characteristics in Fig. 3 show that GAA2 converges much faster than the other algorithms. The typical convergence characteristic of GAA2 is shown again in Fig. 4 as characteristic 'a', which is bounded by the upper and lower envelopes 'b' and 'c'. These envelopes respectively trace the minimum and the maximum costs of the best solutions that can be found in each iteration of GAA2 in 30 executions. At the 270th iteration, which is the last iteration in an execution, the maximum difference in cost between the best and the worst solutions is only 0.34% confirming that the reliability of the GAA2 algorithm is very high.

VIII. CONCLUSION

A formulation has been established for solving the short-term multiple-fuel-constrained generation scheduling problem. The formulation has been augmented with the GA and SA techniques in forming GA-based, SA-based and GA/SA-based algorithms for the scheduling problem. A fuzzy set approach for representing the requirements of the take-or-pay contracts and the maximum utilisation of cheaper fuels has been developed. The GA-based and the hybrid algorithms have been enhanced by an efficient method developed for forming the initial candidate solutions for the initial population. This method has also been incorporated into the SA-based algorithm. While the power of the new algorithms have been validated and compared with the network flow technique [3], their practicability is demonstrated by three application studies on a practical system.

The algorithms have been found to have the ability to seek for the global optimum solution. The power balance constraint and the constraints on the generator operation limits and the fuel supply delivery limits are always satisfied. The hybrid GAA2 with fuzzy approach has the best performance and the least memory requirement. Although the computational requirement of this hybrid algorithm is high, it can be reduced greatly by adopting the parallel form of this algorithm [24] previously developed by the authors.

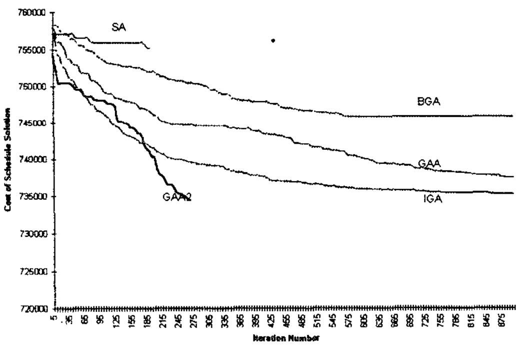

Fig. 3: Comparison of convergence characteristics of the new algorithms

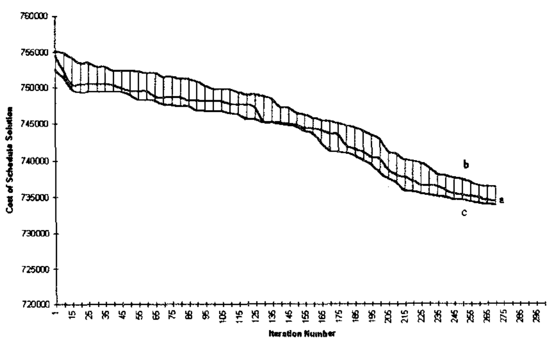

Fig. 4: Convergence characteristics of GAA2

IX. ACKNOWLEDGMENTS

The authors wish to express their sincere gratitude to the Electricity Supply Association of Australia, and to the Energy Research and Development Corporation for their generous support to the work reported in the paper. The authors are also grateful to A. Bateman, E. Goddard, and P. Kelloway of Western Power, Western Australia, for their valuable discussions on the problem and for making their valuable data available.

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XI. BIOGRAPHIES

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