Simulated annealing based economic dispatch algorithm

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Indexing terms: Algorithms, Annealing, B-matrix, Simulated annealing, Economic dispatch

Abstract: This paper develops an economic dispatch algorithm for the determination of the global or near global optimum dispatch solution. The algorithm is based on the simulated annealing technique. In the algorithm, the load balance constraint and the operating limit constraints of the generators are fully accounted for. In the development of the algorithm, transmission losses are first discounted and they are subsequently incorporated in the algorithm through the use of the B-matrix loss formula. The algorithm is demonstrated by its application to a test system. The results determined by the new algorithm are compared to those found by dynamic programming with a zoom feature.

List of principal symbols

B = loss coefficient matrix
B_0 = loss coefficient vector
B_{00} = loss constant
D = total system demand
ΔC^+ = average increment in cost
ΔF_t = increment in fuel cost
$f_i(P_i)$ = fuel cost of the ith generator operating at power level P_i
F_t = total fuel cost
I = maximum number of iteration
k = iteration number in solution process
K_B = Boltzmann's constant
m = number of trials in an iteration
N = vector of perturbation
P = vector of generator power loadings
$P(\Delta)$ = probability of acceptance
$P_{i,max}$ = maximum operation limits of the ith generator
$P_{i,min}$ = minimum operation limits of the ith generator
P_L = total transmission network loss
P_r = dependent generator loading
r = reduction factor for control parameter
T = temperature
X_0 = acceptance ratio
Δ = increment in energy level
γ = scaling factor
σ = control parameter
σ_f = final value of control parameter
σ_k = control parameter at iteration k

Paper 9594C (P9), first received 21st September 1992 and in revised form 7th April 1993

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1 Introduction

One of the most important aspects of power system operation is to supply power to the customers economically. The problem of deciding how power supplies are shared among generators in a system in the most economic manner has been studied extensively [1, 2], and various mathematical programming methods and optimisation techniques [3–11] have been developed and applied.

In the above methods, the fuel cost characteristic of a thermal generator is usually approximated by (i) a quadratic function, (ii) piecewise quadratic functions, or (iii) a polynomial function with order higher than two. When functions in (ii) or (iii) are adopted, the economic dispatch problem may have several local optimum solutions with one being the global optimum solution. In these cases, conventional methods may have difficulties in the determination of the global optimum solution. To find the global or near-global optimum solution, a more general method for solving the economic dispatch problem is needed.

The simulated annealing method [12] is a powerful optimisation technique and it has the ability to find global or near global optimum solutions for large combinatorial optimisation problems. This method is similar to the local search technique [13] in optimisation, which can only guarantee a local optimum solution. However, the simulated annealing method in addition employs a probabilistic approach in accepting candidate solutions in its solution process such that it can 'jump' out of the local optimum solutions. The simulated annealing technique has previously been applied to some optimisation problems [14—16] in power engineering. However, it has not been used to solve the problem of economic dispatch.

This paper first develops an economic dispatch algorithm using the local search approach [13]. Based on the initial development, a simulated annealing based economic dispatch algorithm to find the global or near global optimum solution for the economic dispatch problem is developed. Transmission losses are first discounted in the development and they are subsequently incorporated in the simulated annealing based algorithm through the use of the B-matrix loss formula [10].

The developed algorithm is validated by applying it to a test system [11] having three generators. The fuel cost characteristics of the generators are expressed as third-

The support given to the work reported in this paper by the Australian Research Council is gratefully acknowledged.

order polynomials. The results obtained by the new algorithm are compared to those found by the method of dynamic programming with a zoom feature reported recently [11].

2 Economic dispatch problem

When transmission losses are discounted, for a total system load demand D, the total fuel cost F_t for running n generators to meet the system load is given by

$$F_t = f_1(P_1) + f_2(P_2) + \cdots + f_n(P_n) \tag{1}$$

and the total load is

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

In eqn. 1, $f_i(P_i)$ is the fuel cost of the ith generator operating at power level P_i. To solve for the economic loadings of all the n generators, F_t in eqn. 1 is minimised subject to the equality constraint in eqn. 2 and the inequality constraint

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

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum operation limits of the ith generators, respectively.

When transmission losses are considered, the system load demand is given by

$$D = \sum_{i=1}^{n} P_i - P_L \tag{4}$$

where P_L is the total loss in the transmission network. While this loss can be found from a load flow study, it can also be approximated by the B-matrix loss formula [10] below.

$$P_L = P^t BP + P^t B_0 + B_{00} \tag{5}$$

where P^t is the vector of generator loadings ($P_1, P_2, \ldots, P_n$). B, B_0 and B_{00} are the loss coefficient matrix, the loss coefficient vector and the loss contant, respectively.

3 The local search technique

The local search technique [13] is widely used in the area of optimisation and it guarantees to find a local optimum solution. This metod also gives some of the foundations of the simulated annealing based economic dispatch algorithm to be developed in this paper.

Central to the local search method is the concept of local optimality. This concept can be defined in the following way. Let S be the solution space of a combinatorial optimisation problem and i is a solution state in S. Let R be a possible set of solution states in the neighbourhood of state i. When the cost associated with state i is less than, or equal to, all its neighbouring solutions in R, then solution state i is a local optimum wrt R. Based on the above concept, the local search method iterates on a number of solutions until a maximum number of iterations is reached or no further improvement is found after a fixed number of iterations has been carried out. This local search method can be applied to find the local optimum solution of the economic dispatch problem.

3.1 Determination of a local optimum solution

Consider the case where there are n thermal generators for economic dispatch and transmission losses are discounted. Assume that the power loadings of any $n - 1$ generators are specified, from the equality constraint in eqn. 2, the power level of the remaining generator (i.e. the dependent generator) is given by

$$P_r = D - \sum_{\substack{i=1 \\ i \neq r}}^{n} P_i \tag{6}$$

The loading levels of all the generators are then taken as the starting values in the iterative solution process provided that they satisfy the constraint in eqn. 3 on the operation limits of the generators. The generation of a neighbourhood solution of power loadings in an iteration is now described.

3.1.1 Generation of a neighbourhood solution

At any iteration k, let the solution of the power loadings of any $n - 1$ generators be held in vector P. To find a solution in the neighbourhood of the loadings in P, the amount of perturbation for each loading in P is first found according to a probability distribution function (PDF). In the present work, the Gaussian PDF [17] is assumed and its standard deviation is set to the product of the control parameter σ, and a scaling factor γ. This means that the probability of generating a perturbation of the amount in the range between $-\gamma\sigma$ and $+\gamma\sigma$ is 68.26%.

Let the perturbations be stored in vector N. A solution in the neighbourhood of the loadings in P is then given by $(P + N)$. The power loading of the dependent generator is calculated according to eqn. 6. The complete set of power loadings of the n generators generated is then a new solution in the neighbourhood of the current solution.

3.1.2 Control parameter

The primary function of the control parameter in the local search algorithm is to regulate the amount of perturbation in the neighbourhood of the current solution. In the present work, the value of the control parameter σ_k at any iteration k is calculated [12] from

$$\sigma_k = r^{(k-1)} \bullet \sigma_1 \tag{7}$$

where σ_1 is the initial value when $k = 1$ and r is a constant, the value of which is slightly less than 1. The value of the control parameter is reduced as the number of iteration increases, and its rate of reduction is dependent on the value of r. Since the amount of perturbation is proportional to the control parameter, this will effectively reduce the range of the neighbourhood space of the current solution as the number of iteration increases.

3.1.3 Generation of a local optimum solution

Within each iteration, a chain of neighbourhood solutions are generated one by one. When a neighbourhood solution is found, it is tested against an acceptance criterion. The acceptance criterion is that, when the cost associated with a most recently generated neighbourhood solution is lower, this solution is accepted and is taken as the current solution for the generation of the next neighbourhood solution. When the specified size of the chain of solutions is reached, the last accepted solution will be the starting solution for the next iteration. The solution process is terminated when a termination criterion is met.

3.1.4 Termination criterion

The iterative solution process can be terminated by one of the following ways: (i) when the specified number of iterations is reached; (ii) when there is no improvement in the solution over a specified number of iterations.

In the present work, approach (i) is adopted. The maximum number of iteration I for a specified final value of the control parameter denoted by σ_f can be determined in the following way. From eqn. 7 and at $k = I$

$$I = \frac{\log(\sigma_f/\sigma_1)}{\log(r)} + 1 \tag{8}$$

The size of the neighbourhood space in the final iteration depends on the choice of σ_f and hence σ_f governs the resolution or closeness of the solution to the optimum point.

4 Economic dispatch algorithm based on local search

The economic dispatch algorithm based on the local search method when transmission losses are discounted can be summarised in the following steps

(i) Select a set of initial power loadings for the n generators such that the constraints in eqns. 2 and 3 are satisfied. Initialise k to 1 and calculate the total fuel cost using eqn. 1.

(ii) Calculate the control parameter using eqn. 7.

(iii) For any iteration k and for a prespecified number of trials in the chain of neighbourhood solutions within that iteration, determine the best loadings of all the generators in the neighbourhood of the current loading settings by the following steps.

At iteration k and trial m

(*a*) Select randomly a generator as a dependent generator. From the known current loadings of the generators, set dependent generator loading to P_r and set the loadings of the remaining $(n-1)$ generators in $P^{(k,m)}$.

(*b*) Generate vector $N^{(k,m)}$.

(*c*) Form new power loading vector P' using $(P^{(k,m)} + N^{(k,m)})$.

(*d*) Using eqn. 6, find the new power loading, P'_r of the dependent generator.

(*e*) If the power loadings satisfy the operating limits in the inequality constraints in eqn. 3, calculate the new total cost using eqn. 1. Otherwise, discard the new power loadings and return to Step (iii.*a*).

(*f*) Calculate the increment in total fuel cost ΔF_t, by subtracting the cost associated with the old loading levels from the cost associated with the new loading levels.

(*g*) Check whether the new power loadings can be accepted:

(1) If $(\Delta F_t \leqslant 0)$, the new power loadings are accepted as the current solution in the next trial as described by

$$P^{(k,m+1)} = P^{(k,m)} + N^{(k,m)}$$

and

$$P_r^{(k,m+1)} = P'_r$$

(2) If $(\Delta F_t > 0)$, the new loadings are discarded. The old loadings of the current solution are retained and used in the next trial as described by

$$P^{(k,m+1)} = P^{(k,m)}$$

and

$$P_r^{(k,m+1)} = P_r$$

(iv) If k is greater than the maximum number of iterations, stop. Otherwise, increment iteration counter k by 1, and go to Step (ii).

4.1 Local and global optimum solutions

The algorithm in the last Section always finds a local optimum solution for the economic dispatch problem. It will find the global optimum dispatch solution only if the composite fuel cost charactersistic is unimodal.

When the composite characteristic is multimodal, the concept of the local optimality in local search can be extended in the following way. If a local optimum solution is also the local optimum solution wrt all the possible sets of neighbourhood solutions, the local optimum solution is also the global optimum.

It follows that, when the neighbourhood solution space is small, the local search based algorithm may not find the global optimum solution, and the solution process may be trapped in a local optimum point. If this local optimum point is also the global optimum point and the initial settings of the loadings of the generators are close to this point, the global optimum solution may be found. In general, the chances for the algorithm to find the global optimum solution starting from any initial settings of loadings can be greatly increased by one of the three ways below.

(i) Enlarge the neighbourhood solution space.

(ii) Repeat executions with different initial settings of loadings.

(iii) Assist the algorithm to 'jump' out of the local optimum point by accepting in a limited way a solution in a trial having an increased value of cost. When this acceptance criterion is included, the algorithm becomes the simulated annealing based algorithm.

The enlargement of the neighbourhood space in item (i) can be achieved by setting the initial control parameter σ_1 in eqn. 7 to a very large value. However, this will lead to the generation of a large number of unfeasible neighbourhood solutions resulting in long computing time. While general guidelines for the determination of the appropriate initial settings of loadings are not available, the approach in item (ii) is impractical.

5 The simulated annealing technique

The simulated annealing method [12] takes the analogy between the physical annealing process of solids and the process of solving combinatorial optimisation problems such as the economic dispatch problem. In physical annealing, when a molten particle at a very high temperature is cooled slowly, the particle can reach the state of thermal equilibrium at each temperature. At any temperature T, the thermal equilibrium state is characterised by the Boltzmann probability factor (BPF), $\exp(-E_i/K_B T)$ where E_i is the energy of the configuration of the particle, K_B is the Boltzmann's constant and T is the temperature. The probability of the particle having energy E_i, $P(E_i)$ is given by

$$P(E_i) = \frac{\exp(-E_i/K_B T)}{\sum_j \exp(-E_j/K_B T)} \tag{9}$$

where the summation term is the sum of BPFs of all the possible states that the particle can have at temperature T.

The denominator in eqn. 9 suggests the examination of all the possible states of the particle at temperature T. This is computationally equivalent to generating a large number of trials for the particle, as in the case of the local search method described previously. By checking the energy levels of the states of the particle against the acceptance criteria in the next Section, a state will be accepted as the current state of the particle for the next temperature. The cooling process continues in the same manner until the temperature is sufficiently low for the particle to become a solid.

5.1 Acceptance criteria

The acceptance criteria for accepting a state of the particle within a number of trials consist of a deterministic criterion and a probabilistic criterion. They are summarised below.

(i) The state with a lower energy level will be accepted.

(ii) The state with a higher energy level will be accepted in a limited way with a probability of acceptance, $P(\Delta)$ [18]. The expression of the probability of acceptance adopted in the present work is

$$P(\Delta) = 1/(1 + \exp(\Delta/K_B T)) \quad (10)$$

where Δ is the increment in energy level between the current state of the particle and the state formed by a small random displacement of the current state.

Metropolis [19] proposed that the acceptance of the new state with higher energy level is determined by comparing a random number generated from a uniform distribution on the interval between 0 and 1 with the value of the acceptance probability $P(\Delta)$. If the random number is less than the value of $P(\Delta)$, the new state is accepted as the current state.

5.2 Cooling schedule

The rate of cooling in the annealing process can be controlled by a number of different schedules [20]. The cooling schedule [12] adopted here is

$$T_k = r^{(k-1)} * T_1 \quad (11)$$

where k is the cooling step counter and r is a scaling factor less than 1. T_1 is the initial temperature.

5.3 Application to optimisation problems

As the concept of the temperature in physical annealing has no equivalent in the problem being optimised [12], the temperature can be taken as the control parameter σ previously described. Moreover, the cooling step counter k in the last Section can be regarded as the iteration counter k as in the local search method.

With the above considerations, the control parameter in eqn. 7 and the cooling schedule in eqn. 11 are therefore identical and $\sigma_k = T_k$. Replacing $(K_B T)$ by σ_k, the probabilistic acceptance criterion in eqn. 10 can now be reexpressed as

$$P(\Delta) = 1/(1 + \exp(\Delta/\sigma_k)) \quad (12)$$

The deterministic acceptance criterion (i) above is equivalent to the acceptance criterion used in the local search method.

6 Simulated annealing based economic dispatch algorithm

From the discussion above, the simulated annealing technique is similar to the local search method described, but it also has the probabilistic acceptance criterion. For the economic dispatch problem, the increment in energy level Δ in eqn. 12 is equivalent to the increment in fuel cost. Denoting the change in fuel cost by ΔF_t, eqn. 12 becomes

$$P(\Delta F_t) = 1/(1 + \exp(\Delta F_t/\sigma_k)) \quad (13)$$

Representing the random number uniformly distributed in the interval [0, 1] by random (0, 1) and based on the steps in the local search based algorithm, the simulated annealing based economic dispatch algorithm can be established by replacing step (iii.g.2) with the following step:

If ($\Delta F_t > 0$) and ($P(\Delta F_t) >$ random (0, 1))

$$P^{(k, m+1)} = P^{(k, m)} + N^{(k, m)}$$

and

$$P_r^{(k, m+1)} = P'_r$$

Otherwise

$$P^{(k, m+1)} = P^{(k, m)}$$

and

$$P_r^{(k, m+1)} = P_r$$

6.1 Initial loadings and initial control parameter

While the values of generator loadings may be set arbitrarily at the beginning of the solution process in the simulated annealing based algorithm above, the initial settings of the loadings can be set on the basis that the generators share the total load demand in proportion to their ratings.

The initial value of the control parameter is usually set to a large value so that neighbourhood solutions with higher costs can be accepted. Consequently, as the control parameter is reduced gradually from this very high initial value, it is possible for the solution process to 'jump' out of many local optimum points in seeking for the global optimum solution. However, the control parameter value should not be too high as many unfeasible solutions will be generated in a very large neighbourhood space. To determine the appropriate initial control parameter values, the probability of acceptance in eqn. 13 can be approximated by a ratio X_0, such that

$$X_0 = 1/(1 + \exp(\Delta C^+/\sigma_1)) \quad (14)$$

The ratio X_0 is defined as the ratio of the number of accepted higher cost solutions to the total number of higher cost solutions generated. In the above equation, ΔC^+ is the average increment in cost of the higher cost solutions.

The value of X_0 can be obtained numerically by performing an iteration according to the simulated annealing based algorithm prior to the actual first iteration. With the known value of X_0, the value of the initial control parameter can then be estimated from

$$\sigma_1 = |\Delta C^+/\ln((1/X_0) - 1)| \quad (15)$$

7 Incorporation of transmission losses

In Step (iii.d) in the algorithm of Section 4, the loading level of the dependent generator is found from eqn. 6 for the lossless case. When transmission losses are required to be reflected in the algorithm, from eqn. 4, the loading of the dependent generator P_r is given by

$$P_r = D - \sum_{\substack{i=1 \\ i \neq r}}^{n} P_i + P_L \quad (16)$$

If the value of the total transmission loss P_L is available from load flow studies, P_r can be calculated using eqn. 16.

Alternatively, the network losses can be approximated using the B-matrix loss formula in eqn. 5 and this approach is adopted in the present work.

7.1 Expression for dependent generator loading

The transmission loss P_L in eqn. 5 is a function of the loadings of all the generators including that of the dependent generator. Partitioning P, B, and B_0 in eqn. 5

$$P_L = [P_a^t | P_r]\left[\frac{B_{aa}}{B_{ra}} \middle| \frac{B_{ar}}{B_{rr}}\right]\left[\frac{P_a}{P_r}\right] + [P_a^t | P_r]\left[\frac{B_{0a}}{B_{0r}}\right] + B_{00} \tag{17}$$

where P_a^t is the row vector of the loadings of the $(n-1)$ generators, $(P_1, P_2, \ldots, P_n)$ excluding P_r. B_{aa} is a $(n-1) \times (n-1)$ matrix. B_{0a} and B_{ar} are $(n-1)$ column vectors. B_{ra} is a $(n-1)$ row vector. B_{rr}, B_{0r} and B_{00} are scalars.

Expanding and rearranging, eqn. 17 becomes

$$P_L = aP_r^2 + bP_r + c \tag{18}$$

where

$$a = B_{rr} \tag{19}$$

$$b = B_{ra}P_a + P_a^t B_{ar} + B_{0r} \tag{20}$$

$$c = P_a^t B_{aa} P_a + P_a^t B_{0a} + B_{00} \tag{21}$$

From eqn. 16

$$P_r - P_L = D - \sum_{\substack{i=1 \\ i \neq r}}^{n} P_i \tag{22}$$

In the above equation, the difference between P_r and P_L can be evaluated since the total system demand D and the new loadings of the $(n-1)$ generators formed by perturbing the current solution loadings are known. Let the known value of the difference be denoted by P_d. Therefore P_d is equal to $(P_r - P_L)$ and on using eqn. 18 it can be shown that

$$aP_r^2 + (b-1)P_r + (c + P_d) = 0 \tag{23}$$

The loading of the dependent generator P_r can then be found by solving the above equation using standard algebraic method.

8 Application example

The developed simulated annealing based economic dispatch algorithm has been implemented using the C programming language. The software system runs on a PC/486 computer. The new algorithm is applied to a test system having three generators. The optimum dispatch solution of the test system, when the load demand is 1400 MW, has previously been solved by the dynamic programming method with a zoom feature incorporated [11]. The third-order fuel cost functions of the generators in the test system and the B-matrix coefficients can be found in Reference 11. The incremental fuel cost functions of the generators are nonmonotonic.

In applying the new algorithm to the test system, the calculation of the initial generator settings is based upon the proportional approach described in Section 6.1. The initial control parameter is calculated using eqn. 15. The value of γ is set to 0.01. The effect of enlarging the neighbourhood solution space has been investigated by increasing the value of γ to 0.1. The final value of the control parameter is chosen to be 1. The reduction rate of the control parameter r in eqn. 11 is 0.95 and the number of trials in an iteration is 1000.

Table 1 summarises the dispatch solutions found by the new method and that by the recent dynamic programming method. From the Table, for scaling factor

Table 1: Comparison of dispatch solutions

a	Solutions from Ref. 11		
Gen	Loadings	Fuel cost	
	MW	\$/h	λ
1	360.2	1661.956	4.82517
2	406.4	1843.420	4.81883
3	676.8	3137.083	4.82366
Total	1443.4	6642.459	
losses	43.4		
b	**Solutions from new algorithm when $\gamma = 0.01$**		
Gen	Loadings	Fuel cost	
	MW	\$/h	λ
1	359.5459	1659.016	4.82237
2	406.7342	1844.985	4.82583
3	677.1525	3138.656	4.82377
Total	1443.4339	6642.657	
losses	43.4339		
c	**Solutions from new algorithm when $\gamma = 0.1$**		
Gen	Loadings	Fuel cost	
	MW	\$/h	λ
1	376.1226	1733.799	4.88146
2	100.0521	397.030	8.10834
3	986.2728	4508.675	4.85014
Total	1462.448	6639.504	
losses	62.448		

$\gamma = 0.01$, the solution obtained by the two methods are almost identical, and the percentage difference in costs determined by both is only 0.00296. However, when the neighbourhood solution space is enlarged by a factor of 10 by setting γ to 0.1, the dispatch solution obtained by the new algorithm leads to a lower cost of 6639.504 as compared to 6642.459 found by the dynamic programming method, although the transmission loss is now 62.4475 MW instead of 43.4 MW. The loading of generator 2 is very close to the 100 MW limit, and the loading of generator 3 is close to its upper limit of 1000 MW. The respective incremental fuel costs of these two generators are 7.8935 and 4.3825, and the respective values of the Lagrange multipliers λ are 8.1083 and 4.850 as shown in Table 1. These results confirm that the new algorithm has the ability to determine the global or the near global optimum solution.

Assuming that the three generators are the only generators used to supply the range of load demands from 450 MW to 1900 MW, the generator loadings, fuel costs and transmission losses in this range in steps of 50 MW have been determined by the new algorithm. The results are tabulated in Tables 2 and 3 in steps of 100 MW. Table 2 is for the case that the scaling factor γ is set to 0.1. Table 3 is for the case that γ is set to 0.01.

From Tables 2 and 3, solutions for the loadings, fuel costs and transmission losses are similar for load demands in the range of 450 MW to 750 MW, and in the range of 1450 MW to 1900 MW. This shows that a near global optimum solution can be determined when the

Table 2: Dispatch solutions with $\gamma = 0.1$

Load demand	Generator loadings			Fuel cost	Losses
	Gen 1	Gen 2	Gen 3		
MW	MW	MW	MW	$/h	MW
500	100.0086	100.0016	306.2836	2379.9622	6.2936
600	100.0597	100.0007	409.9377	2840.6670	9.9983
700	261.5951	100.0081	351.5866	3307.3391	13.1895
800	298.4908	100.3291	418.9266	3772.0664	17.7465
900	330.1606	100.0245	492.8260	4239.6001	23.0118
1000	348.1436	100.7676	580.0187	4715.2363	28.9303
1100	361.1604	100.1610	674.4479	5190.7461	35.7694
1200	381.5067	100.2550	761.6805	5672.4136	43.4424
1300	414.7176	100.6995	836.4216	6160.3027	51.8388
1400	376.1226	100.0521	986.2728	6639.5043	62.4480
1500	368.0314	407.7335	776.1051	7126.6680	51.8714
1600	371.7842	407.9640	881.7268	7613.2847	61.4764
1700	371.1941	407.8110	993.3748	8101.3330	72.3812
1800	457.5262	423.1195	999.9993	8605.0674	80.6463
1900	499.9968	486.9898	999.9942	9190.2998	86.9812

Table 3: Dispatch solutions with $\gamma = 0.01$

Load demand	Generator loadings			Fuel cost	Losses
	Gen 1	Gen 2	Gen 3		
MW	MW	MW	MW	$/h	MW
500	100.0050	100.0007	306.2873	2379.9546	6.2937
600	100.0642	100.0007	409.9324	2840.6648	9.9982
700	282.9852	100.0325	330.3979	3307.7041	13.4150
800	100.0048	397.9365	312.9480	3817.3701	10.8906
900	100.0024	400.8333	414.3950	4281.3169	15.2321
1000	275.1006	399.3372	344.2293	4748.3428	18.6686
1100	309.8751	400.3426	413.5573	5214.6982	23.7763
1200	330.8108	403.5294	495.1281	5686.0342	29.4699
1300	347.6868	405.3712	582.9395	6162.1973	35.9989
1400	359.5459	406.7342	677.1525	6642.6562	43.4339
1500	367.8181	407.5905	776.4725	7126.6680	51.8825
1600	371.7213	408.1905	881.5497	7613.2842	61.4629
1700	371.4536	407.7474	993.1752	8101.3330	72.3777
1800	457.7585	422.9009	999.9979	8605.0693	80.6584
1900	499.9997	486.9839	999.9966	9190.2832	86.9815

value of γ is in the range of 0.01 to 0.1. In the range of 800 MW to 1400 MW, however, dispatch solutions with lower fuel costs are found when γ is 0.1. At 800 MW, the difference in fuel cost is 45 $/h or 1.2%.The difference in cost gradually reduces to zero at 1450 MW as shown in Fig. 1. The difference in transmission losses, however, increases from 6.856 MW to 18.87 MW when the load demand is increased from 800 MW to 1400 MW. This is also shown in Fig. 1. The results of transmission losses

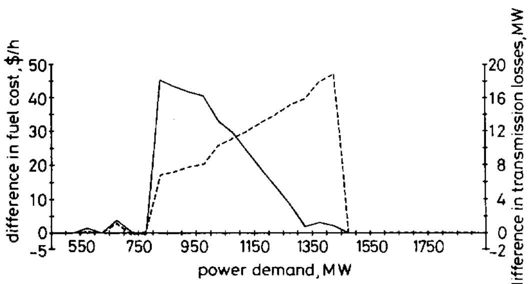

Fig. 1 *Differences in fuel cost and transmission losses*
——— difference in fuel cost
- - - - difference in transmission losses

indicate that a more economical dispatch solution can lead to higher transmission losses in this range. The average number of iteration and computing time for the solutions in Table 1 are 95 and 27.253 seconds, respectively. In this test example, the optimum dispatch solutions have been found after 6 and 20 iterations for $\gamma = 0.1$ and $\gamma = 0.01$, respectively.

9 Conclusion

A general simulated annealing based economic dispatch algorithm has been developed. A method for incorporating the effects of transmission losses into the algorithm based on the B-matrix loss formula has also been developed. The ability of this algorithm to find the global or near global optimum solution has been demonstrated by a test example. The dispatch results obtained for the test system by the new algorithm are more economical than those found by the dynamic programming technique with a zoom feature recently reported. The advantages of the new algorithm are summarised below.

(i) The solution process is independent of the fuel cost characteristic function of the generators.

(ii) Its convergence property is not affected by the inclusion of the inequality constraints due to the operation limits of generators.

(iii) Exact dispatch solution to meet the load demand and transmission losses is guaranteed.

(iv) The need to evaluate the Lagrange multipliers and penalty factors is avoided.

(v) The computer memory requirement is low.

The main disadvantage of the new algorithm is that the computing time requirement is high. However, the speed of the algorithm can be greatly reduced by means of parallel processing. This can be achieved by further developing the present algorithm into a form suitable for execution in a multiprocessor system.

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