Proceedings of the 2001 IEEE Congress on Evolutionary Computation Seoul, Korea • May 27-30, 2001

Using Evolutionary Computation to Solve the Economic Load Dispatch Problem

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Abstract. The classical approach to the Economic Load Dispatch Problem (ELDP) seeks to minimize the cost of generation subject to the usual constraints. If the transmission losses are also to be taken care of, a common method (λ - iteration procedure) involves adding the cost of transmission losses charged at incremental cost of received power to the cost of generation. This combined cost function forms the objective function to be minimized. However it is desirable that the transmission losses be dealt with separately in the minimization process, without computing the incremental cost of received power. Genetic Algorithms (GAs) offer a suitable and robust approach to meet the twin objectives of cost minimization and loss minimization simultaneously. This paper presents the development of the GA for solving the ELDP. It also suggests a convenient technique for representing the search space. Finally, the results of the algorithm are analyzed by comparing them with those obtained from a direct random search algorithm, called the LJ algorithm.

1 Introduction

The energy crisis, rising prices of fuel, disparate sources of energy, and interconnection of electric networks have made it essential to reduce the running charges of producing electrical energy.

The ELDP involves the solution of two different problems [1]. The first is the predispatch problem wherein it is required to select optimally out of the available generating resources to meet the expected load. The second aspect is the on-line economic dispatch wherein it is required to distribute the load among the generation units paralleled with the system, in such a manner as to minimize the total cost of supplying the requirements of the system. In the ELDP each generator's generation is not kept fixed but is allowed to take values within certain limits so as to meet a particular load demand with minimum cost.

The location of generating plants far away from load centers also brings to fore the need to reduce transmission losses. Any solution to the ELDP must include a strategy to take into account transmission losses as well.

Thus the problem of scheduling generation considering transmission losses involves the minimization of cost of generation, with the losses taken care of either implicitly or explicitly. In the non-linear programming approach the losses are minimized indirectly by adding the cost of transmission losses to the cost of generation, and minimizing this combined cost subject to constraints. This involves finding the incremental cost of received power [2], which is a complicated procedure. When compared to the cost of generation, the cost of losses doesn't amount to much. The unnecessary computation of incremental cost of received power can be avoided by following the proposed method in which losses are directly minimized along with the cost of generation.

GAs are search procedures that mimic natural processes of selection, reproduction, and mutation spread across generations of population, as a means of solving problems. [3] and [4] are useful references to this regard.

The GA presented here is extremely efficient, robust, and fast. It avoids the laborious calculation of the loss coefficients and incremental costs by using the line losses calculated from data obtained from load flow studies.

2 Encoding and Decoding

2.1 Encoding

Encoding refers to the process of coding the members of the solution set as a number of finite strings (chromosomes). It typically utilizes the binary alphabet {0,1}. Unlike in ordinary encoding schemes in which each string represents a particular value, in the novel coding system we have designed, each string represents a region of the search space. This region is the sum of the ranges of power generation (in MW) the generators must confine themselves to, in order to satisfy the objective function and constraints. For the 5-generator problem investigated, a structure in the form of a string of length five is used, with each position in the string corresponding to one generator. Besides representing the

0-7803-6657-3/01/$10.00

number of the generator, the loci have no other influence on the string's value. The string is made up of 1s and 0s whose meaning changes with every new generation i.e. the range of values they represent decreases progressively. The data structure used to represent each member of the string is provided below.

```
Struct member {
        float lower, upper, midvalue;
        int digit; // takes values {0,1}
        };
```

lower stores the lower bound of the range of values represented by *digit*, while *upper* stores the upper bound. *midvalue* is the average of *lower* and *upper*. The initial range of power generation for each generator is the generation constraints given by $UPPER_{initial}$ and $LOWER_{initial}$. In our problem and in all the results presented in this paper the value of $UPPER_{initial}$ is 600MW while that of $LOWER_{initial}$ is 200MW. A pictorial representation of the initial search region is given in Figure 1.

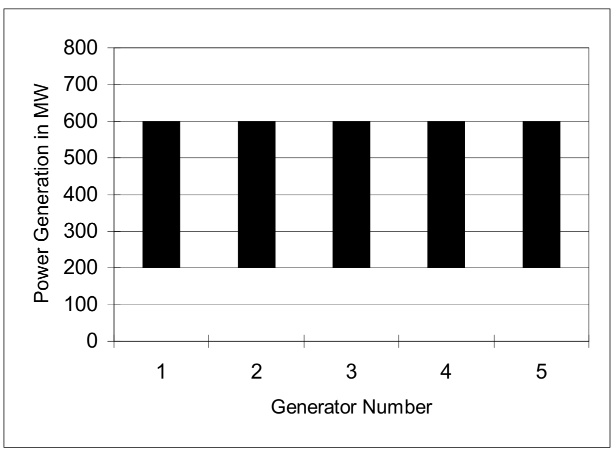

Fig. 1. Initial search region

2.2 Population Creation Procedure

To create the population random strings are generated. A '1' in a new string is considered to represent the upper half of the range of the values represented in the corresponding position in the previous generation. Similarly a '0' represents the lower half of the range represented in the corresponding position in the previous generation. Corresponding changes to *upper*, *lower*, and *midvalue* are made. For the generation following from the region shown in Figure 1., a '1' in the new string represents the range 400-600MW while a '0' represents the range 200-400MW. Suppose the string generated is 01101, then the new regions will be as depicted in Figure 2.

As can be observed, the string will represent five integral values of power generation after some generations. This is because of the range contraction by half with every new generation.

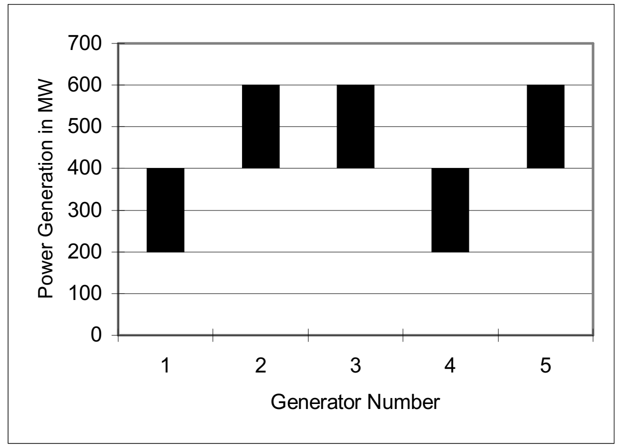

Fig. 2. Note the contracted region represented by the new string 01101. Future generations will also comprise of 0s and 1s, but their interpretation will be different

The number of generations required to reach an integral solution is given by equation (1).

$$\log_2\left(UPPER_{initial} - LOWER_{initial}\right). \quad \textbf{(1)}$$

The encoding scheme we have developed is extremely convenient for many reasons.

i. The constraints (7) on generation are straightaway incorporated into the strings. This automatically prevents generation constraint violation.
ii. The memory requirements are very low compared to the huge and unwieldy strings used in [2] that require special operators.
iii. The level of accuracy required of the answer can be controlled by simply varying the number of generations. As the number of generations increases, the region of space where the solution is most likely to be found narrows down. Thus the accuracy of the solution increases.
iv. A good solution can be obtained in a fixed number of generations.
v. A generator can be added by simply increasing the string length by one. Dropping a generator is easier, it just requires setting $UPPER_{initial}$ and $LOWER_{initial}$ for that generator to zero.

2.3 Decoding

Since it is otherwise impossible to decode the string as it represents a region in space, *midvalue*s of all the characters in the string are sampled. The actual power generation value for a generator will lie anywhere between *upper* and *lower* for that generator. The inherent nature of the algorithm to drive the current solution towards the best by search region contraction obviates any concern regarding the sampling of *midvalue* to decode the string.

Other advantages of our encoding scheme include the doing away with of penalty factors and fitness mapping in the objective function – procedures that are key in [5].

3 Problem Formulation

In the ELDP we seek

(a) to minimize the generation cost i.e.

$$Minimize\ \ Z = \sum_{i=1}^{k} F_i \ . \qquad \textbf{(2)}$$

where

$$F_i = \sum_{j=1}^{4} A_{ij} P_i^{4-j} \ . \qquad \textbf{(3)}$$

Equation (3) is the cubic cost curve.

and (b) minimize the transmission losses i.e.

$$Minimize\ \ P_L = \sum\sum P_m B_{mn} P_n \ . \qquad \textbf{(4)}$$

subject to the constraints

$$P_T - P_D - P_L = 0 \ . \qquad \textbf{(5)}$$

and

$$0 \le P_L \le 0.1 P_D \ . \qquad \textbf{(6)}$$

and

$$P_{\min} \le P_i \le P_{\max} \ \ for\ i = 1,2,3,...m \ . \qquad \textbf{(7)}$$

where

k is the number of generators; in our sample problem its value is five.

F_i is the cost of generation for the i^{th} generator,

A_{ij} is the general element in the cost coefficient matrix,

B_{mn} is the general element in the loss coefficient matrix,

P_m and P_n are the source loadings,

P_i is the power generated by the i^{th} generator, ranging between $P_{\min}$ and $P_{\max}$,

P_T is the total power generated,

P_L is the total power loss,

and P_D is the desired power.

Although scheduling is possible with extremely high values of losses, such situations are infeasible. There are countless solutions that satisfy (5), some with very high loss values. The constraint (6) has been introduced to contain losses within realistic limits.

4 Data

The cost coefficient matrix A for the system is

$$\begin{bmatrix} 1.270\text{E - 7} & 9.680\text{E - 4} & 6.950 & 749.55 \\ 6.453\text{E - 8} & 7.375\text{E - 4} & 7.051 & 1285.00 \\ 9.980\text{E - 8} & 1.040\text{E - 3} & 6.531 & 1531.00 \\ 1.270\text{E - 7} & 9.680\text{E - 4} & 6.950 & 749.55 \\ 6.453\text{E - 8} & 7.375\text{E - 4} & 7.051 & 1285.00 \end{bmatrix}$$

The loss coefficient matrix B for the system is

$$\begin{bmatrix} 0.0003 & 0 & 0 & 0 & 0 \\ 0 & 0.00005 & 0 & 0 & 0 \\ 0 & 0 & 0.00012 & 0 & 0 \\ 0 & 0 & 0 & 0.0007 & 0 \\ 0 & 0 & 0 & 0 & 0.00009 \end{bmatrix}$$

5 Fitness function

In order to evaluate members of a population a simple weighted sum approach is followed. Since all the objectives are assumed to be equally important, they are assigned equal weights. The fitness value for each objective is computed individually, and the values are summed to create an overall fitness score given by $figure\_of\_merit = x + y + z$. The values of x , y , and z are calculated as described below.

To meet the constraint (5), we use the value

$$x = \left(1 - \left(P_D \big/ P_T - P_L\right)\right) \ . \qquad \textbf{(8)}$$

Solutions in which $P_T - P_L < P_D$ are unacceptable. So the solution is checked and in such cases x is assigned the value $\left(P_D / \left(P_T - P_L\right)\right)$. This prevents the assignment of lower scores to unsuitable solutions.

To minimize the cost (2), another member-specific value y is computed.

$$y = \text{cost}\,[\text{member}] \Big/ \begin{matrix}\text{average cost of} \\ \text{population members}\end{matrix} \quad (9)$$

Naturally, low values of y are desirable.

To minimize the losses (4) the procedure used to tackle the equality constraint is followed again. Another member-specific value z is calculated as

$$z = \left(1 - {P_D}\Big/{P_T}\right) . \quad (10)$$

The closer the value z is to zero i.e. when $P_T \approx P_D$, the lower will be the losses P_L.

The constraint (6) is checked only after the final solution is available. Solutions not satisfying the constraint are simply rejected.

Finally we arrive at a figure of merit given by

$$figure\_of\_merit = x + y + z \ . \quad (11)$$

This figure of merit is used to rank members of the population – the lower the value of the figure of merit, the fitter the individual.

6 Algorithm Description

The algorithm is the standard GA with several modifications. An outline of the modified algorithm is presented.

6.1 Creation of archetype population

This is the first step in which the original members (search regions) that are most promising are determined. A typical member is shown in Figure 4. The method used to find the best members is the standard GA with some interesting modifications. In the initial generations, we found that the conventional mutation process was ineffective in preventing premature convergence. As an alternative, we simply replaced some weaker members with fitter members. This effectively aided mutation in prevented premature convergence. Another interesting aspect was that this supplement to mutation completely dominated it as the region of space represented by the population members reduced generation after generation. In the final generations, when premature convergence was no longer a problem, this concept of direct replacement still served to help provide better solutions.

6.2 Application of GA to the search regions represented by the archetype members

i. Within the region represented by each member of the old (in the first instance, the archetype members) population, a random population of individuals is created.

ii. GA is applied to these individuals and the population ranked according to fitness (figure of merit).

iii. The number of runs is decided by trial and error and finally the best members (sub-regions) are selected.

iv. The best member replaces the corresponding member in the old population.
Finally a new set of promising (contracted) search regions replace the older generation. In the particular run offer as an example, the string that replaced the population member depicted in Figure 4. is shown in Figure 5.

v. Steps (i) to (iv) are repeated till the search region contracts to the desired limit.

For a power demand of 1800MW supplied by a 5-generator system, the search region contraction for the first member of the archetype is presented. The solution for the particular run is **X = {201.17,396.48,305.07,428.51,469.14} MW** after nine generations. **P** (crossover) = 0.8, while **P** (mutation) = 0.04.

Figures 3. to 8. show the parallel search region contraction across five generations for all generators till a solution of desired accuracy is found. Only five generations are shown.

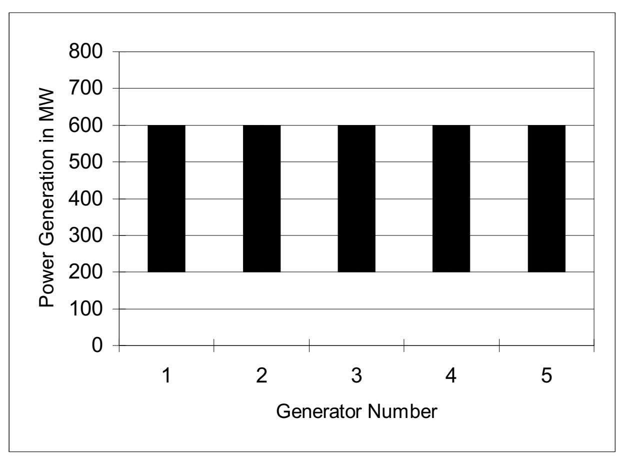

Fig. 3. Initial search region

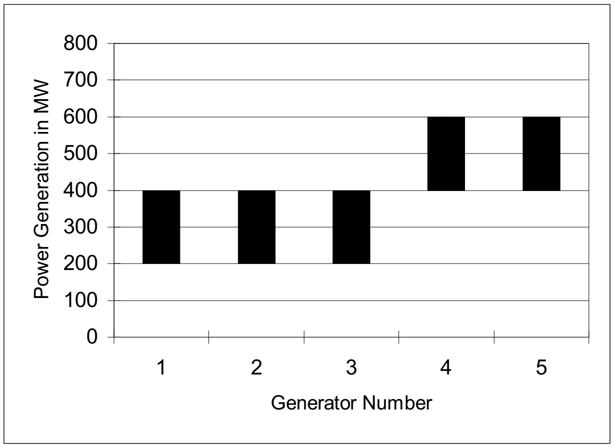

Fig. 4. Search region in the first generation

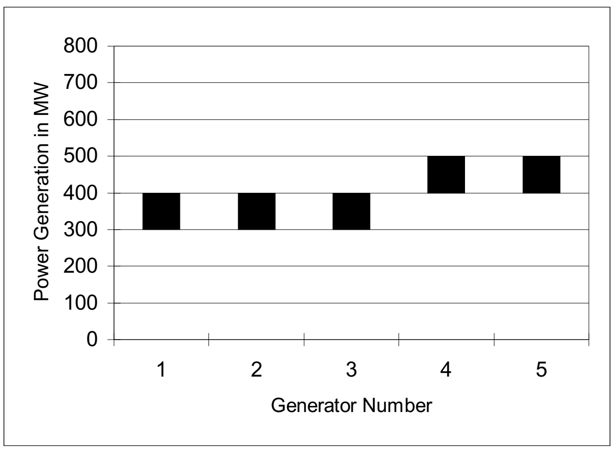

Fig. 5. Search region in the second generation

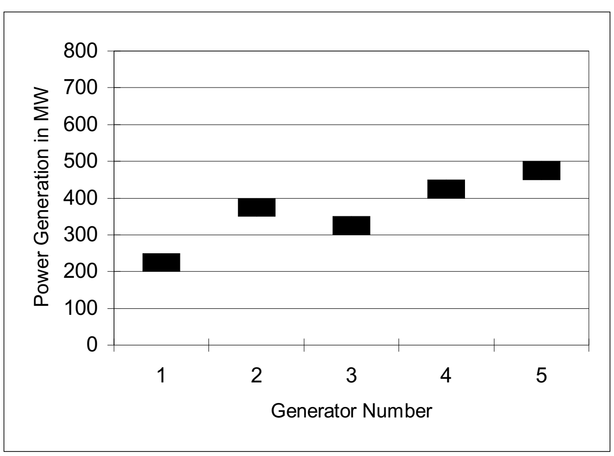

Fig. 6. Search region in the third generation

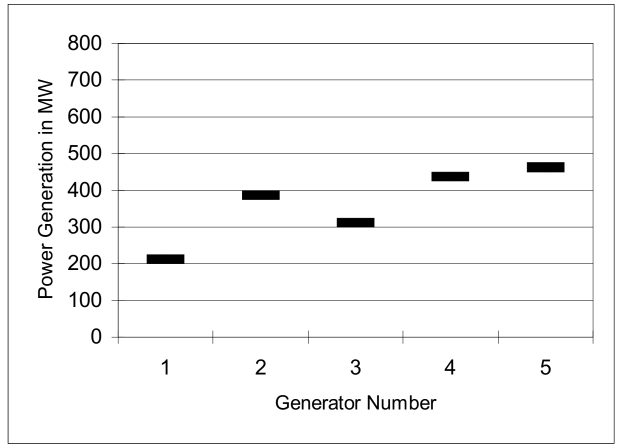

Fig. 7. Search region in the fourth generation

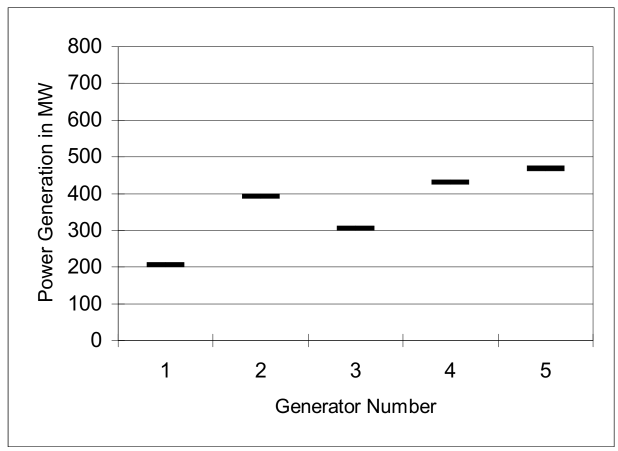

Fig. 8. Search region in the fifth generation

7 Discussion of results

The results of solving the same 5 – generator problem using the (a) GA and (b) LJ algorithm (by calculating incremental costs) [6,7] are shown in Table 1. and Table 2. respectively. It is evident form Table 2. that the cost of losses does not amount to much – around 5% of the generation cost. The solutions derived from the GA compare well with those from the LJ algorithm, and in all cases are superior to them. It is now obvious that calculation of incremental costs is unnecessary.

8 Conclusions

The robustness, parallelism, and versatility of GAs has been exploited in our proposed solution to the ELDP. It has been shown that it is possible to altogether avoid the computationally expensive calculation of incremental costs. A consequence of this is the high speed of the GA we have developed. The unique encoding scheme allows us to arrive at an acceptable solution within a fixed number of iterations(generations). Unlike in most comparable evolutionary algorithms, changes in the system do not need to be met with corresponding modifications to the core GA. All such changes can be incorporated by giving suitable new values to $UPPER_{initial}$ and $LOWER_{initial}$. The GA also provides a diverse set of solutions, while a number of runs are required to get the same number of solutions using the LJ method.

Solution Number	Power Generated in MW	Power Loss in MW	Power Demand in MW	Cost of Generation
1	1926.171875	126.013947	1800.157928	19351.04
2	1962.890625	162.835281	1800.055344	19669.83
3	1962.890625	163.097656	1799.792969	19669.73
4	1914.84375	114.787605	1800.056145	19278.34
5	1939.453125	139.138611	1800.314514	19486.79

Table 1. The result of one run of the GA for a power demand of 1800MW supplied by a 5-generator system is shown. Number of members of the population = 5, **P** (crossover) = 0.8 and **P** (mutation) = 0.04.

Solution Number	Incremental Cost	Power Generated in MW	Power Loss in MW	Power Demand in MW	Cost of Generation	Cost of Losses	Total Cost
1	8.05	1979.77	179.99	1799.95	20013.02	1449.83	21462.85
2	8.02	1925.87	126	1800.05	19586.7	1010.49	20597.25
3	8.03	1943.82	144	1800	19739.7	1156.82	20896.57
4	8.05	1961.82	162	1800	19875.1	1304.02	21179.11
5	8.05	1979.82	180	1800	20013.4	1449.87	21463.33

Table 2. The results of five runs of the LJ algorithm for meeting a power demand of 1800MW supplied by the same 5-generator system is shown. The LJ algorithm is used to solve the ELDP using incremental costs.

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