Genetic Algorithm Approach to Solve Economic Load Dispatch Problem on Three Thermal Plants and A Combined Cycle Co-Generation Plant

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Abstract — This paper presents an approach based on Genetic Algorithm to solve the economic load dispatch problem with losses for three thermal plant system and combined cycle co-generation plant. Genetic algorithms are adaptive search methods that simulate some of the natural processes: selection, inheritance, random mutation and population dynamics. This approach is used to test for an example of three thermal plant system and one combined cycle co-generation plant in two ways of dispatching load between three thermal plants and among two thermal plus one combined cycle co-generation plant and the results are compared. In this paper, the results are obtained through the genetic algorithms developed in C Language.

Index Terms — About four key words or phrases in order of importance, separated by commas.

I. Introduction

Economic load dispatch (ELD) is a sub-problem of the optimal power flow (OPF) having the objective of fuel-cost minimization. The classical solutions for ELD problems have used equal incremental criterion for the loss-less system and the use of penalty factors for considering the system losses. However, all these methods are based on the assumption of continuity and differentiability of cost functions. Hence, the cost functions have been approximated in the differentiable form, mostly in the quadratic form. Further, these methods also suffer on two main counts. One is their inability to provide global optimal solution and getting stuck at local optima. The second problem is handling the integer or discrete variables.

Genetic algorithms (GAs) have been proved to be effective and quite robust in solving the optimization problems. GAs can provide near global solutions and also can handle effectively the discrete control variables. Discontinuity and non-differentiability of cost characteristics can be effectively handled by GAs.

Combined cycle co-generation plants (CCCP) have the following advantages over the thermal plants, namely,

1. Higher overall thermal efficiency.
2. Minimum air pollution by nox, dust etc.
3. Independent operation of gas turbine for peak loads.
4. Quick start-up and less capital cost per kw and
5. Less water requirement per unit of electrical output.

This paper proposes the application of GAs to solve the economic load dispatch for two types, that is,

1. The thermal plant systems and the results are compared with conventional method, and
2. Two thermal plant systems and third plant as a combined cycle co-generation plant and the results are included.
II. Theoretical Analysis on Genetic Algorithm and Economic Load Dispatch

A. Genetic Algorithm

1) Introduction

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search [1]. In every generation,

![Figure 1 The Single Peak function which is easy for Calculus-Based Methods](image)

A new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure.

2) A Simple Genetic Algorithm

The mechanics of simple genetic algorithm are surprisingly simple, involving nothing more complex than copying strings and swapping partial strings. Simplicity of operation and power of effect are two of the main attractions of the genetic algorithm approach.

A simple genetic algorithm that yields good results in many practical problems is composed of three operators:

- a. Reproduction
- b. Crossover
- c. Mutation

A) Reproduction

Reproduction is a process in which individual strings are copied according to their objective function values, f (biologists call this function the fittest function). This operator is artificial version of natural selection, a Darwinian survival of fittest among string creatures. In natural populations fitness is determined by a creature’s ability to survive predators, pestilence and the other obstacles to adulthood and subsequent reproduction. In our artificial setting the objective function is the final arbiter of the string creature's life or death.
The reproduction operator may be implemented in an algorithmic form in a number of ways. The easiest is to create a biased roulette wheel where each current string in the population has a roulette wheel slot sized in proportion to its fitness. Suppose the sample population of four strings in the black box problem has objective or fitness function values as shown in Table 1.

Summing the fitness over all four strings, one obtains a total of 1170. The percentage of population total fitness is also shown in the table. To reproduce, one simply spins the biased roulette wheel thus defined four times. For the example problem, string number 1 has a fitness value of 169, which represents 14.4 percent of the total fitness. As a result, string 1 is given 14.4 percent of the biased roulette wheel, and each spin turns up string 1 with probability 0.144.

### B) Crossover

After reproduction, simple crossover may proceed into two steps. First, members of the newly reproduced strings in the matting pool are matted at random. Second, each pair of strings undergoes crossing over as follows: an integer position \( k \) along the string is selected uniformly at random between 1 and the string length less 1 (1 to \( l-1 \)). Swapping all characters between positions \( k+1 \) and \( l \) inclusively creates two new strings. For example consider strings \( A_1 \) and \( A_2 \) from the initial population:

\[
A_1 = 0110/1 \\
A_2 = 1101/0
\]

Suppose in choosing a random number between 1 and 4, we obtain a \( k=4 \) (as indicated by a separator symbol '/'). The resulting crossover yields two new strings where the prime ('') means the strings are part of the new generation.

\[
A_1' = 01100 \\
A_2' = 11011
\]

Consider a population of \( n \) strings over some appropriate alphabet, coded so that each is a complete idea or prescription for performing a particular task. Sub strings within each string (idea) contain various notions of what is important or relevant to the task. Genetic algorithms ruthlessly exploit this wealth of information by

1. Reproducing high-quality notions according to their performance and
2. Crossing these notions with many other high-performance notions from other strings.

Thus, the action of crossover with previous reproductions speculates on new ideas constructed from the high-performance building blocks (notions) of past trials.
C) Mutation

Mutation plays a decidedly secondary role in the operation of genetic algorithms. Mutation is needed because, even though reproduction and crossover effectively search and recombine extant notions, occasionally they may become overzealous and lose some potentially useful genetic material (1’s or 0’s at particular locations).

One may notice that the fitness or objective function values are the same as the black box values (compare Tables 1 and 2). There is no coincidence, and the black box optimization problem was well represented by the particular function \( f(x) \), and coding one is now using. A generation of the genetic algorithm begins with reproduction. One select the mating pool of the next generation by spinning the weighted roulette wheel four times.

![Image of Tables and Data]

**Table 2**

Actual simulation of this process using coin tosses has resulted in string 1 and string 4 receiving one copy in the mating pool, string 2 receiving two copies, and string 3 receiving no copies, as shown[9] in the center of Table 2.

B. Economic Load Dispatch

1) Introduction

An early method of attempting to minimize the cost of delivered power called for supplying power from only the most efficient plant at light loads. As load is increased, the most efficient plant would supply power until the point of maximum efficiency of that plant was reached. Even with transmission losses neglected this methods fail to minimize the cost.

Thus, because of the following trends in the growth of power systems it has become progressively important to give increasing attention to economic operation of power systems.

1. In many cases, economic factors and the availability of primary essential such as coal, water etc., dictate that new generating plants be located at greater distances from the load centre.
2. The installation of larger blocks of power has resulted in the necessity of transmitting power out of a given area until the load in that area is equal to new block of installed capacity.
3. Power systems are interconnecting for purposes of economy interchange and reduction of reserve capacity.
4. In a number of areas of the country the cost of fuel is rapidly increasing.

The main factor controlling the most desirable load allocation between various generating units is the total running cost. The operating cost of a thermal plant is mainly the cost of the fuel. Fuel supplies for thermal plants can be coal/natural gas, oil or nuclear fuel. The other costs such as cost of labour, supplies,
maintenance etc., being difficult to be determined and approximate, are assumed to vary as affixed percentage of the fuel cost.

2) Economic Dispatch Neglecting Losses

When transmission distances are very small and load density is very high, transmission losses may be neglected and the optimal dispatch of generation is achieved with all plants operating at equal incremental production cost. The common for including the effect of transmission losses is to express the total transmission losses as quadratic function of the generator power outputs. The simplest quadratic form is:

\[ P_l = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \]  
\[ \cdots \cdots \cdot (1) \]

Here the coefficients Bij are called loss coefficients or B-coefficients. B-coefficients are assumed constant and reasonable accuracy can be expected provided the actual operating conditions are close to the base values where the B-constants are computed.

For a system with 'n' generating units let

\[ F_t = f_1 + f_2 + \cdots + f_n \]

Where \( F_t \) is the cost function giving all the fuel for the entire system and is the sum of the fuel cost of the individual units \( f_1, f_2, \cdots, f_n \).

The total megawatt power input to the network from all units is the sum

\[ P_{G1} + P_{G2} + P_{G3} + \cdots + P_{Gn} \]

Where \( P_{G1}, P_{G2}, \cdots, P_{Gn} \) are the individual outputs of the units injected into the network. The total \( F_t \) of the system is a function of all the power plant outputs. The constraining equation on the minimum value of \( F_t \) is given by the power balance equation:

\[ P_1 + P_d - \sum_{i=1}^{n} P_{Gi} = 0 \]  
\[ \cdots \cdots \cdot (2) \]

Where \( P_d \) is the total power received by the loads and \( P_1 \) is the transmission loss of the system. The objective is to obtain a minimum \( F_t \) for affixed system load \( P_d \) subjected to the above power balance constraint.

The procedure for solving such minimization problems is called the method of Lagrange's multipliers.

The new cost function \( F \) is formed by combining the fuel cost and the equality constraint in the following manner:

\[ F = F_t + \lambda ( P_1 + P_d - \sum P_{Gi} ) \]  
\[ \cdots \cdots \cdot (3) \]

The augmented cost function \( F \) is also called the Lagrangian and the parameter, which is called the Lagrange multiplier is the effective incremental fuel cost of the system when transmission line losses are taken into account.
The original problem of minimizing $F_t$ subjected to the constraint given by Eq 3.2.4.2 is transformed into an unconstrained problem given by $F$, where it is required to minimize $F$ with respect to and the generator outputs.

$$\frac{n}{F/PG_i} = \frac{F_t/PG_i + \lambda}{1-(P_l/PG_i)} = 0 \quad \dots \quad (4)$$

Since, $P_d$ is fixed and the fuel cost of any one unit varies only if the power output of that unit is varied. So the above equation yields:

$$\frac{F/PG_i}{F_t/PG_i + \lambda(P_l/PG_i-1)} = 0 \quad \dots \quad (5)$$

for each of the generating unit outputs $PG_1, PG_2, \ldots, PG_n$.

Because $F_t$ depends on only $PG_i$, the partial derivatives of $F_t$ can be replaced by the full derivative and the Eq 3.2.4.5 gives

$$\lambda = \frac{(dF_t/dPG_i)}{1-(P_l/PG_i)} \quad \dots \quad (6)$$

for every value of $i$.

This equation can also be written in the form

$$\lambda = L_i \frac{(dF_t /dPG_i)}{1-(P_l/PG_i)} \quad \dots \quad (7)$$

where $L_i$ is called penalty factor of plant $i$, and is given by

$$L_i = \frac{1}{1-(P_l/PG_i)} \quad \dots \quad (8)$$

The result for Eq (7) means that the minimum fuel cost is obtained when the incremental fuel cost of each unit multiplied by its penalty factor is the same for all the generating units in the system. The products $L_i (dF_t/dPG_i)$ are each equal to called the system, which are approximately the cost in Rs/h to increase the total delivered load by one MW.

Eq (7) governs the coordination of transmission loss into the problem of economic loading of units in plants, which are geographically dispersed throughout the system.

### 3) Combined Cycle Co-Generation Plant

Combined cycle co generation plants have the following advantages over the thermal plants, namely,

1. higher overall thermal efficiency
2. minimum air pollution by nox, dust etc.
3. independent operation of gas turbine for peak loads.
4. quick start-up and less capital cost per KW and
5. less water requirement per unit of electrical output.

The fuel consumption and the cost characteristics of such plants, in general, are not differentiable. The application of the genetic algorithms is the only viable solution for power system with combined cycle cogeneration plants and it is not possible to solve such a ELD problem by conventional technique. Till date only limited work has been reported in the area of CCCP economic load dispatch.
4) Two Thermal Plants and One CCCP System

In the three thermal plant systems, the third thermal plant is to be replaced by combined cycle cogeneration plant CCCP (two 75MW gas turbines and one 50 MW steam turbines). The fuel cost characteristics of this plant is shown in figure below[6]:

Figure 2: Fuel characteristics of co-generation plant

<table>
<thead>
<tr>
<th>Power (MW)</th>
<th>Cost (Rs/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>490</td>
</tr>
<tr>
<td>52.5</td>
<td>505</td>
</tr>
<tr>
<td>55</td>
<td>520</td>
</tr>
<tr>
<td>57.5</td>
<td>570</td>
</tr>
<tr>
<td>60.75</td>
<td>605</td>
</tr>
<tr>
<td>62.88</td>
<td>605</td>
</tr>
<tr>
<td>83.94</td>
<td>625</td>
</tr>
<tr>
<td>85</td>
<td>650</td>
</tr>
<tr>
<td>90</td>
<td>770</td>
</tr>
<tr>
<td>93.75</td>
<td>880</td>
</tr>
<tr>
<td>100</td>
<td>920</td>
</tr>
<tr>
<td>110</td>
<td>1020</td>
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<tr>
<td>120</td>
<td>1120</td>
</tr>
<tr>
<td>130</td>
<td>1200</td>
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<td>140</td>
<td>1280</td>
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<tr>
<td>157.5</td>
<td>1460</td>
</tr>
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<td>166</td>
<td>1460</td>
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<td>176.63</td>
<td>1460</td>
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<tr>
<td>178.32</td>
<td>1490</td>
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<td>180</td>
<td>1520</td>
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<tr>
<td>185</td>
<td>1600</td>
</tr>
<tr>
<td>190</td>
<td>1720</td>
</tr>
<tr>
<td>200</td>
<td>1850</td>
</tr>
</tbody>
</table>

Table 3
Using the given set of points, a polynomial of specific order can be fitted using polynomial regression technique. We assume that the quadratic is to be fitted here for the cost curve. Assume that n pairs of coordinates (xi, yi) are given which are to be approximated by a quadratic. Let the quadratic be represented as

\[ Y = AX^2 + BX + C \]

When \( X = X_i \) The left hand side of the above equation is represented by \( Y_{ci} \)

\[ Y_{ci} = AX_i^2 + BX_i + C \]

The sum of squares of the deviations is given by

\[ S = \sum (Y_i - Y_{ci})^2 = \sum (Y_i - A X_i^2 - B X_i - C)^2 \]

Differentiating \( S \) w.r.t. \( A, B, C \) respectively and setting each of the co-efficient equal to zero, we get

\[
\begin{align*}
    nC + B\sum X_i + A\sum X_i^2 &= \sum Y_i \\
    C\sum X_i + B\sum X_i^2 + A\sum X_i^3 &= \sum X_i Y_i \\
    C\sum X_i^2 + B\sum X_i^3 + A\sum X_i^4 &= \sum X_i^2 Y_i
\end{align*}
\]

These are three linear equations in three unknowns. These are called normal equations for quadratic regression. These may be solved by Gauss–Jordan procedure.

Finally we obtain the curve as

\[ F = A P_{Gi}^2 + B P_{Gi} + C \]

For the problem, the solution was obtained through the genetic algorithms developed in c language. It is observed that this method is accurate and may replace effectively the conventional practices presently performed in different central load dispatch centers.

**III. Classical Economic Load Dispatch Problem**

The object of ELD problem is to minimize the total fuel cost at thermal plants

\[ OBJ = \sum_{i=1}^{n} F_i(P_i) \]

Subject to the constraint of equality in real power balance

\[ \sum_{i=1}^{n} P_i - P_L - P_d = 0 \]

The inequalities of real power limits on the generator outputs are

\[ P_{imin} < P_i < P_{imax} \]

Where \( F_i(P_i) \) is the individual generation production in terms of its real power generation \( P_i \), \( P_i \) is the output generation for unit \( i \), \( n \) the number of generators in the system, \( P_d \) the total current system load demand, and \( P_l \) the total system transmission losses.
The thermal plant can be expressed as input-output models (cost function), where the input is the fuel cost and the output the power output of each unit. In practice, the cost function could be represented by a quadratic function.

\[ F_i(P_i) = A_i P_i^2 + B_i P_i + C_i \]

The incremental cost curve data are obtained by taking the derivative of the unit input-output equation resulting in the following equation for each generator:

\[ \frac{dF_i(P_i)}{dP_i} = 2A_i P_i + B_i \]

Transmission losses are a function of the unit generations and are based on the system topology. Solving the ELD equation for a specified system requires an iterative approach since all unit generation allocation are embedded in the equation for each unit.

\[ P_i = P_i B_{ij} P_j \]

Where \( B_{ij} \) are coefficients, constant for certain conditions.

Application of GA to economic load dispatch problem.

Value = \( \text{bit}_0 \times 2^0 + \text{bit}_1 \times 2^1 + \ldots + \text{bit}_i \times 2^i + \ldots + \text{bit}_{\text{chrom-length}} \times 2^{\text{chrom-length}} \)

If the optimized parameter belongs to \((P_{\text{imax}}, P_{\text{imin}})\), decoding value of the parameter is computed by equation (4.1.1).

\[ \frac{\text{Value} \times (P_{\text{imax}} - P_{\text{imin}})}{2^{\text{chrom-length} - 1}} \]

**Objective Function and Fitness Function Formulation**

In the ELD problem, the goal is to minimize the objective function

\[ F_t = \sum_{i=1}^{n} F_i(P_i) \]

with the constraint of equality

\[ \sum_{i=1}^{n} P_i - P_L - P_d = 0 \]

is changed to constrained optimization problem and thus forming fitness function

\[ F_c = F_t + P_f (\sum P_i - P_L - P_d) \]

where \( P_f \) is penalty factor. The penalty function is placed into the objective function in such away that it penalizes any violation of the constraint and forces that unconstrained optima toward the feasible region. In the ELD problem the goal is to minimize the objective function \( F_c \), while the objective when using GAs is to maximize a fitness function \( F_t \) in the given form [10].

\[ F_t = \exp(-K_t F_c) k_2 \]
K1 and K2 are constants and the value is problem dependent. Considering the evolutionary process of the GAs, the solution is improved through the generation and also to decrease the penalty function over successive iterations can be adapted with the penalty function varying directly with the number of generations.

IV. Software and Results

The cost functions of the three thermal plants considered in this paper are obtained from Sheble and Britting [11] and they are as follows.

\[ F_1 = (0.00156)P_1^2 + (7.92)P_1 + 561 \text{ Rs/h} \]
\[ F_2 = (0.00194)P_2^2 + (7.85)P_2 + 310 \text{ Rs/h} \]
\[ F_3 = (0.00482)P_3^2 + (7.97)P_3 + 78 \text{ Rs/h} \]

The loss coefficients of the considered system are:

\[
\begin{array}{ccc}
0.000075 & 0.000005 & 0.000008 \\
0.000005 & 0.000015 & 0.000010 \\
0.000008 & 0.000010 & 0.000045 \\
\end{array}
\]

The operating ranges for three plants are:

100MW < P1 < 600MW
100MW < P2 < 400MW
50MW < P3 < 200MW

Population size: 30
Chromosome length: 36
Maximum number of generations: 1000
Crossover probability: 0.50
Mutation probability: 0.01
Table 4

Here the range of limits for the load can be taken as 250MW – 1200 MW.

Genetic Algorithm claims to provide near optimal or optimal solution for computationally intensive problems. Therefore the effectiveness of the genetic algorithm solutions should always be evaluated by experimental results. For economic load dispatch problem, the results obtained through genetic algorithms developed in C language was tested for three thermal plant systems and extended to one plant as combined cycle co-generation plant in three thermal plant systems. The execution time takes two seconds in Pentium 120 MHz processor.

The performance of GA approach is compared with the classical Kirchmayr method as given in table 5.1. For the load of 585.33 MW, \( \Sigma P_i - PD - PL = 592.297 - 585.33 - 6.962 = 0.005 \) MW in Classical Kirchmayr method, and it is 592.850 – 585.330 – 7.25 = 0 in GA approach. For the load of 869 MW \( \Sigma P_i - PD - PL = 884.390 - 869.000 - 15.420 = -0.030 \) in conventional method and it is 884.811 – 869.000 – 15.812 = -0.001 MW in GA approach. The constraint of equality \( \Sigma P_i - PD - PL = 0 \) does not hold good for classical Kirchmayr method. But this constraint is almost equal to or nearer to zero in GA approach. It at all it is having some value, it is multiplied by the penalty factor (PF) which is placed into the objective function in such a way that it penalizes any violation of the constraints and forces that unconstrained optima towards the feasible region. The solution of GA is improved through the generations, and also by decreasing the penalty function.

In conventional method, the values of \( PG_1, PG_2, PG_3 \) are not optimal values as the constraint of equality does not hold good and also the cost functions of the plants are non-linear and they are approximated as either linear or quadratic.

It is observed that for any load, GA approach provides optimal values as the constraint of equality is almost zero or nearer to zero to minimize the objective function and there is no need of approximating the cost functions. Hence it is more accurate method and may replace effectively the conventional methods.

The cost functions of two thermal plants of taken as same as in the case of three thermal plants and the cost function of combined cycle co-generation plant (CCCP) can be taken as \( F_3=(0.003210) P_3^2+(7.927738) P_3+56.6678.04 \) Rs/h. The loss co-efficients, operating ranges and the other data used in GA are same as in the first case.

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As combined cycle co-generation plant (CCCP) is having low cost, total cost of two thermal plants with one combined cycle co-generation plant is lower than the total cost of three thermal plant system for any load and it is proved by the GA approach given in the table 5.2. The method is accurate and may replay effectively the conventional practices presently performed in different central load dispatched centers. This approach is only viable solution for power system with combined cycle co-generation plants and it is not possible to solve such a ELD problem by conventional technique and it is given in the Table 5.2.

V. Conclusions

The genetic algorithm is a searching or optimizing algorithm based on the natural evolution principles. Because of its capability to solve nonlinear optimization problems the application of GAs to power system is a promising area to explore.

There is no need of approximating the cost functions of the plants in the differentiable form or quadratic form as in the case of conventional methods as Genetic Algorithms are used for solving the functions whether they are differentiable or not, continuous or not effectively. They do not stuck into local optima, because these begin with many initial points and search for the most optimum in parallel and these have been proved to be effective and quite robust in solving the optimization problems and can handle discrete control variable effectively and provide global solutions.

VI. Scope for Enhancement

Movement in the simple genetic algorithm is accomplished using three primary operators: reproduction, crossover and mutation. A genetic algorithm works with a population of chromosomes.

Refined genetic algorithms differ from simple genetic algorithms by some improvements made to ensure faster convergence. They are elitism, changing probabilities of mutation and crossover.

It is having a wide variety of current applications in science, engineering business and the social sciences. For other applications like multi-objective optimization etc. the advanced operators like Dominance, Diploid and Invasance, Inversion and other Recording operators may be used.

VII. References