OPTIMIZATION OF PIECEWISE NON-LINEAR MULTI-CONSTRAINED ECONOMIC POWER DISPATCH PROBLEM USING AN IMPROVED GENETIC ALGORITHM

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Abstract—In this paper, a more realistic formulation of the Economic Dispatch problem is proposed, which considers practical constraints and non linear characteristics. The proposed ED formulation includes ramp rate limits, valve loading effects, equality and inequality constraints, which usually are found simultaneously in realistic power systems. This paper presents a novel Genetic Algorithm to solve the economic load dispatch (ELD) problem of thermal generators of a power system. This method provides an almost global optimal solution, since they don’t get stuck at local optimum. The proposed method and its variants are validated for the two test systems consisting of 3 and 10 thermal units whose incremental fuel cost functions takes into account the valve-point loading effects.

Keywords—Economic load Dispatch, Genetic Algorithm, Valve-point loading, Ramp rate limits, Roulette selection.

I. INTRODUCTION

ECONOMIC Load Dispatch (ELD) seeks “the best” generation for the generating plants to supply the required demand plus transmission losses with the minimum production cost. Improvement in scheduling the units output can lead to significant cost savings. In traditional ELD problems, the cost function of each generator is approximately represented by a simple quadratic function and is solved using mathematical programming based on several optimization techniques such as dynamic programming, Linear programming, homogenous linear programming and quadratic programming methods[1],[3],[4]. However none of these methods may be able to provide an optimal solution and they usually get stuck at a local optimum. Normally the input-output characteristic of modern generating units are highly non-linear in nature due to valve-point effect [14], [15], [16], [18], [19] ramp-rate limits, Fuel switching [11], [20] etc, having multiple local minimum points in the cost function. To overcome such difficulties many heuristic search algorithms, such as Genetic algorithm [5], Differential Evolution [6], Tabu search [7], [19], etc., have been proposed to solve ELD problem. These techniques can be used to search the global optimum with any type of objective function and constraints [22]. In this paper, two ED problem for 3 and 10 thermal units with a non smooth fuel cost function [8] are employed to demonstrate the performance of the proposed method. This paper employs genetic algorithm to solve the non convex and non smooth cost function.

The rest of this paper is organized as follows; Section II describes the formulation of an ED problem; while section III explains the standards in GA. Section IV then details the procedure of handling the GA. Section V gives the flow chart. Section VI gives the Data’s and Section VII gives the results of the optimization. Section VIII outlines our conclusion and future research.

II. PROBLEM DESCRIPTION

The objective of ED is to determine the generation levels for all on-line units which minimize the total fuel cost, while satisfying a set of constraints. It can be formulated as follows:

A. ECONOMIC DISPATCH (ED) PROBLEM FORMULATION

The fuel cost functions of the generating units are usually described by a quadratic function of power output [13]. Thus the objective function is given as:
Minimize:
\[ F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \]  
(1)

Where
- \( a_i, b_i, c_i \) - the fuel cost coefficients of the \( i \)th unit
- \( N \) - Number of generating units in the system
- \( P_i \) - output generation of \( i \)th unit.

1. Power balance constraint:
\[ \sum_{i=1}^{N} P_i = P_D + P_L \]  
(2)

Where
- \( P_D \) – Total power demand
- \( P_L \) – Total network losses

2. Capacity limits constraints:
\[ P^\text{min}_i \leq P_i \leq P^\text{max}_i \]  
(3)

Where
- \( P^\text{min}_i \) – minimum generation limit
- \( P^\text{max}_i \) – maximum generation limit

B. VALVE POINT EFFECT

Large steam turbine generators will have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the unit. As the unit loading increases the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves [9], however, when a valve is first opened, the throttling losses increases rapidly and the incremental heat rate rises suddenly. This is “valve point” effect which leads to non-smooth, non-convex input-output characteristics [12], to be solved using the heuristic techniques.

The valve point effect is incorporated in ED problem by superimposing the sine component model on the quadratic cost curve which is given below,
\[ F_i^*(P_i) = F_i(P_i) + e_i \sin(f_i[P^\text{min}_i - P_i]) \]  
(4)

Where
- \( F_i^*(P_i) \) – fuel cost if \( i \)th unit with valve point effect
- \( e_i, f_i \) – the fuel cost coefficients of the \( i \)th unit with valve point effect.

C. RAMP RATE LIMITS:

The Ramp-Up and Ramp-Down rate limits of \( i \)th generator are given by

As generation increases,
\[ P_i - P_{i0} \leq UR_i \]  
(5)

As generation decreases
\[ P_i - P_{i0} \leq DR_i \]  
(6)

and
\[ \max(P^\text{min}_i, P_i - DR_i) \leq P_i \leq \min(P^\text{max}_i, P_{i0} + UR_i) \]  
(7)

Where \( P_i \) is the current output power and \( P_{i0} \) is the output power in the previous interval of the \( i \)th generator. \( UR_i \) is the up-ramp rate limit of the \( i \)th generator and \( DR_i \) is the down-ramp rate limit of the \( i \)th generator.

III. OPTIMIZATION USING GENETIC ALGORITHM

A. BASIC FUNDAMENTALS OF GA

Genetic Algorithm (GA) is a search algorithm based on the conjecture of natural selection and genetics. The features of genetic algorithm are different from other search techniques in several aspects [6].
First, the algorithm is a multi-path that searches many peaks in parallel, and hence reducing the possibility of local minimum trapping.

Secondly, GA works with a coding of parameters instead of the parameters themselves. The coding of parameter will help the genetic operator to evolve the current state into the next state with minimum computations.

Thirdly, GA evaluates the fitness of each string to guide its search instead of the optimization function.

Three basic operators of GA are reproduction, crossover, and mutation

B. BASIC OPERATORS OF GA

Reproduction: A mechanism by which the most highly fit members in a population is selected to pass on information to the next population of members. It effectively selects the fittest of the springs in the current population to be used in generating the next population. In this way, relevant information concerning the fitness of a string is passed along to successive generations.

Crossover: A mechanism by which strings can exchange information, possibly creating more highly fit strings in the process and allowing the exploration of new regions of the search space.

Mutation: It ensures that a string position will never be fixed at a certain value for all time.

C. PROPOSED SOLUTION METHOD

1. Code the problem variables into binary strings.
2. Randomly generate initial population strings. Tossing of a coin can be used.
3. Evaluate fitness values of population members
4. Is solution available among the population?
   If yes then GOTO step 9
5. Select highly fit strings as parents and produce offspring’s according to their fitness.
6. Create new string by mating current offspring. Apply crossover and mutation operators to introduce variations and form new strings.
7. New springs replace existing one.
8. GOTO step 4 and repeat
9. Stop.

IV. IMPLEMENTATION OF GA

A. CODING:

Implementation of problem in a genetic problem starts from the parameter encoding. It is carefully done to utilize the genetic algorithm’s ability to efficiently transfer information between chromosome strings and objective function of the problem. Binary coded strings 1s and 0s are used.

B. FITNESS FUNCTION:

Genetic algorithm mimics the survival of the fittest principle of nature to make a search process. Therefore, the Genetic Algorithm problems are naturally suitable for maximization problems. Minimization problems are usually converted into the maximization problems using some suitable transformations, The fitness function for maximization problem is given by

\[ f_i(x) = \frac{1}{1+F(x)} \]

In order to emphasize the best chromosome and speed up the convergence of the evolutionary process, fitness function is normalized into the range between 0 and 1. The fitness function of the ith chromosome is given by

\[ f_i(x) = \frac{1}{1 + k \left( \frac{F_i(x)}{F} - 1 \right)} \]

Where

- \( F_i(x) \) is the solution corresponding to the ith chromosome
- \( F_i^{\text{min}} \) is the solution of the highest ranking chromosome
- \( k \) is the scaling constant

C. REPRODUCTION

The reproduction genetic algorithm operator selects the good strings in a population and forms a matting pool. The commonly used selection operator is the proportionate reproduction operator where a string is selected from the mating pool with a probability proportional to its fitness.

The probability of selecting the \( i^{\text{th}} \) string is

\[ p_i = \frac{f_i}{\sum_{j=1}^{n} f_j} \]
Where

\[ L \] is the population size

\[ f_i \] is the fitness function of the ith population

This selection scheme is implemented by using the roulette-wheel [2] with its circumference marked for each string proportionate to the string’s fitness.

D. COMPEITION AND SELECTION

Each individual in the combined population has to compete with some other individuals to have a chance to be copied to the next generation. The score of each trial vector after stochastic competition is given by

\[ w_i = \sum_{n=1}^{L} w_n \] (10)

E. CROSSOVER OPERATOR

In crossover the information is exchanged among stings of the mating pool to create new strings. In the crossover operator the good substrings from parent strings will be combined to form a better child offspring. There are three forms of crossover:

- One point crossover
- Uniform crossover
- Multi point crossover

The effect of crossover may be detrimental or beneficial. The crossover has three distinct sub-steps, namely:

- Slice each of parent in the substrings
- Exchange a pair of corresponding substrings of parents
- Merge the two respective substrings to form offspring.

F. MUTATION

Mutation is the important operator, because newly created individuals have no new inheritance information and the number of alleles is decreasing. This process results in the contraction of the population to one point. Diversity is necessary to search a big part of the search space. It is achieved by the mutation.

V. FLOW CHART

![Flowchart for Genetic Algorithm](Fig.5.1)

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Fig. 5.1 Flowchart for Genetic Algorithm.
VI. DATA’S AND RESULT

A. TEST CASE I

3-generator System: The unit characteristics data are given in Table 1, 2 and 3. The load demand is 850MW. The B loss coefficients are given in the Table 4. [10]

Table I
CAPACITY AND COST CO-EFFICIENT

<table>
<thead>
<tr>
<th>Quantities</th>
<th>Unit-1</th>
<th>Unit-2</th>
<th>Unit-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ai</td>
<td>0.004820</td>
<td>0.001940</td>
<td>0.001562</td>
</tr>
<tr>
<td>bi</td>
<td>7.97</td>
<td>7.85</td>
<td>7.92</td>
</tr>
<tr>
<td>ci</td>
<td>78</td>
<td>310</td>
<td>562</td>
</tr>
<tr>
<td>Pimin</td>
<td>50</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Pimax</td>
<td>200</td>
<td>400</td>
<td>600</td>
</tr>
</tbody>
</table>

Table II
VALVE-POINT LOADING

<table>
<thead>
<tr>
<th>Quantities</th>
<th>Unit-1</th>
<th>Unit-2</th>
<th>Unit-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ei</td>
<td>150</td>
<td>200</td>
<td>300</td>
</tr>
<tr>
<td>Fi</td>
<td>0.063</td>
<td>0.042</td>
<td>0.0315</td>
</tr>
</tbody>
</table>

Table III
RAMP RATE LIMITS

<table>
<thead>
<tr>
<th>Unit</th>
<th>Pio</th>
<th>URi</th>
<th>DRi</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>170</td>
<td>50</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>350</td>
<td>80</td>
<td>120</td>
</tr>
<tr>
<td>3</td>
<td>440</td>
<td>80</td>
<td>120</td>
</tr>
</tbody>
</table>

Table IV
B-COEFFICIENTS

\[ B = \begin{bmatrix} 0.0006760 & 0.0000953 & -0.0000507 \\ 0.0000953 & 0.0005210 & 0.0000901 \\ -0.0000507 & 0.0000901 & 0.0002940 \end{bmatrix} \text{ MW}^{-1} \]

\[ B_{00} = \begin{bmatrix} -0.07660 & -0.00342 & 0.01890 \end{bmatrix} \]

\[ B_{0} = \begin{bmatrix} 4.0357 \end{bmatrix} \text{ MW} \]

B. TEST CASE II

10-generator Systems: The load demand is 2000MW. The unit characteristics data are given in the Table 5, 6 and 7. The system B loss coefficients are given in the Table 8.
B0 = \begin{bmatrix} 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 \end{bmatrix}

Table IX

CONVERGENCE RESULTS FOR 3 GENERATING UNITS WITH VALVE POINT EFFECT & LOSSES

PD = 850MW
No. of Trials = 50
No. of Population = 5
Crossoverrate=0.8; MutRate=0.001

<table>
<thead>
<tr>
<th>Quantities</th>
<th>Res-1</th>
<th>Res-2</th>
<th>Res-3</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1(MW)</td>
<td>148.67</td>
<td>146.75</td>
<td>146.56</td>
</tr>
<tr>
<td>P2(MW)</td>
<td>297.33</td>
<td>293.5</td>
<td>293.12</td>
</tr>
<tr>
<td>P3(MW)</td>
<td>428.88</td>
<td>422.5</td>
<td>421.87</td>
</tr>
<tr>
<td>F1(Rs/hr)</td>
<td>1379.5</td>
<td>1379.4</td>
<td>1379.4</td>
</tr>
<tr>
<td>F2(Rs/hr)</td>
<td>2643.1</td>
<td>2588.5</td>
<td>2584.3</td>
</tr>
<tr>
<td>F3(Rs/hr)</td>
<td>4487.5</td>
<td>4388</td>
<td>4377.7</td>
</tr>
<tr>
<td>Ploss(MW)</td>
<td>13.361</td>
<td>13.159</td>
<td>13.139</td>
</tr>
<tr>
<td>Total Gen(MW)</td>
<td>874.88</td>
<td>862.76</td>
<td>861.55</td>
</tr>
<tr>
<td>Total Fuel Cost(Rs/hr)</td>
<td>8510.1</td>
<td>8355.9</td>
<td>8341.4</td>
</tr>
<tr>
<td>CPU Time(sec)</td>
<td>6.25</td>
<td>6</td>
<td>6.0313</td>
</tr>
<tr>
<td>Best Trial</td>
<td>13</td>
<td>28</td>
<td>50</td>
</tr>
</tbody>
</table>

Table X

CONVERGENCE RESULTS FOR 10 GENERATING UNITS WITH VALVE POINT EFFECT

PD = 2000MW
No. of Trials = 50
No. of Population = 5
Crossoverrate=0.8; MutRate=0.001

<table>
<thead>
<tr>
<th>Unit power output</th>
<th>Optimal Values by GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1(MW)</td>
<td>225.6242</td>
</tr>
<tr>
<td>P2(MW)</td>
<td>233.7826</td>
</tr>
<tr>
<td>P3(MW)</td>
<td>330</td>
</tr>
<tr>
<td>P4(MW)</td>
<td>300</td>
</tr>
<tr>
<td>P5(MW)</td>
<td>242</td>
</tr>
<tr>
<td>P6(MW)</td>
<td>160</td>
</tr>
<tr>
<td>P7(MW)</td>
<td>130</td>
</tr>
<tr>
<td>P8(MW)</td>
<td>118</td>
</tr>
<tr>
<td>P9(MW)</td>
<td>80</td>
</tr>
<tr>
<td>P10(MW)</td>
<td>245.9484</td>
</tr>
<tr>
<td>Total Power Output(MW)</td>
<td>2065.3552</td>
</tr>
<tr>
<td>Ploss(MW)</td>
<td>56.872</td>
</tr>
<tr>
<td>Total Generation Cost(Rs/hr)</td>
<td>125975.5063</td>
</tr>
<tr>
<td>CPU time(sec)</td>
<td>23.547</td>
</tr>
<tr>
<td>Best Trial</td>
<td>47</td>
</tr>
</tbody>
</table>

VIII. CONCLUSION

In this paper, a comprehensives ED model including ramp rate limits, valve loading effects and transmission losses together is presented. In this method, the genetic algorithm method is found best suited for the fuel cost functions of non-smooth, non-continuous valve point curves. The proposed GA can provide a more diverse search of solution space and so better optimum solutions with low computation burden can be found. The research work is under way in order to incorporate more security issues of power system in the ED model with other constraints.

IX. REFERENCES

(a) Books:

(b) Periodicals:

(c) Articles from published conference proceedings: