Evolutionary Computational Techniques to Solve Economic Load Dispatch Problem Considering Generator Operating Constraints

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Abstract— **The economic load dispatch plays an important role in the operation of power system, and several models by using different techniques have been used to solve these problems. More recently, the soft computing techniques have received more attention and were used in a number of successful and practical applications. The purpose of this work is to find out the advantages of application of the evolutionary computing techniques in particular to the economic load dispatch problem. Here, an attempt has been made to find out the minimum cost by using PSO & GA considering generator operating constraints. These included are continuous prohibited zones, ramp rate limits, and cost functions which are non smooth or convex. The results are compared with the traditional technique and GA, PSO seems to give a better result with better convergence characteristic.**

***Keywords*— Economic Load Dispatch, Genetic Algorithm, Particle Swarm Optimisation.**

I. INTRODUCTION

Electrical energy cannot be stored, but is generated from natural sources and delivered as demand arises. A transmission system used for the delivery of bulk power over considerable distances, and a distribution system is used for local deliveries. Such configuration applies to all interconnected networks (regional, national, international), where the number of elements may vary. The transmission networks are interconnected through ties so that utilities can exchange power, share reserves and render assistance to one another in times of need. For an interconnected system, the fundamental problem is one of minimizing the source expenses [1].

Economic dispatch (ED) problem is one of the fundamental issues in power system operation. In essence, it is an optimization problem and its objective is to reduce the total generation cost of units, while satisfying constraints. Previous efforts on solving ED problems have employed various mathematical programming methods and optimization techniques. These conventional methods include the lambda-iteration method, the base point and participation factors method, and the gradient method. In these numerical methods for solution of ED problems, an essential assumption is that the incremental cost curves of the units are monotonically increasing piecewise-linear functions. The proposed method considers the nonlinear characteristics of a generator such as ramp rate limits and prohibited operating zone for actual power system operation. The feasibility of the proposed method was demonstrated for three different systems respectively, as compared with the real-coded GA method in the solution quality and computation efficiency [2].

In this respect, evolutionary computational techniques such as GAs (GAs), may prove to be very effective in solving nonlinear ELD problems without any restrictions on the shape of the cost curves [3]. These evolutionary algorithms (EAs) are search algorithms based on the simulated evolutionary process of natural selection, variation, and genetics. EAs are more flexible and robust than conventional calculus-based methods. Evolutionary Programming differs from traditional GAs in two aspects: Evolutionary Programming uses the control parameters (real values), but not their coding as in traditional GAs, and Evolutionary Programming relies primarily on mutation and selection, but not crossover, as in traditional GAs. Hence, considerable computation time may be saved in EP [3].

Chen and Chang presented a GA method that used the system incremented cost as encoded parameter for solving ED problems that can take into account network losses, ramp rate limits, and valve-point zone [4]. The GA methods have been employed successfully to solve complex optimization problem, recent research has identified some deficiencies in GA performance.

Particle Swarm Optimisation (PSO), first introduced by Kennedy and Eberhart, is one of the evolutionary computational techniques. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [5]. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods [6]. Although the PSO seems to be sensitive to the tuning of some weights or parameters, many researches are still in progress for proving its potential in solving complex power system problems [7].

The programs are developed in MATLAB and Spread Sheet, to solve economic load dispatch problem and to verify the solutions by using Evolutionary Computational Techniques (GA and PSO) considering generator operating constraints such as Power Balance equation,Transmission loss, Minimum and Maximum Power limits ,Generator ramp rate limits & Generator prohibited operating zone by varying above constraints ELD problems are solved.

Initially to check the effectiveness of PSO, ELD problems were solved by using Conventional Method, GAs and by PSO.

Later on more focus is given on PSO method due to its effectiveness over others.

II. PROBLEM STATEMENT

The Economic Load Dispatch (ELD) is generating adequate electricity to meet the continuously varying consumer load demand at the least possible cost under a seven of constraints. Practically, while the scheduled combination of units at each specific period of operation are listed, the ELD planning must perform the optimal generation dispatch among the operating units to satisfy the load demand, spinning reserve capacity, and practical operation constraints of generators.

A. Objective Function

The objective of the economic dispatch problem is to minimize the total fuel cost of thermal power plants subjected to the operating constraints of a power system. The simplified cost function of each generator can be represented as a quadratic function as

$$\text{Minimize} \quad F_t = \sum_{i=1}^{n} F_i(P_i) \quad --[1]$$

$$F_t = F_i(P_i) = A_i P_i^2 + B_i P_i + C_i \quad --[2]$$

Where, F_t Total generation cost,
F_i Cost function of generator i,
P_i Power of generator i,
n Number of generators
A_i, B_i, C_i Cost coefficients of generator i,

B. Constraints

The Economic load Dispatch is subjected to the following Constraints

1) Power balance equation

a) Without considering transmission loss

$$\sum_{i=1}^{NG} \left(P_{gi}\right) = P_D \; --[3]$$

b) With considering transmission loss

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{NG} \left(P_{gi}\right) = P_D + P_L \; --[4]$$

Where P_D is the total system demand and

P_L is the total line loss.

c) Constraint Satisfaction Technique

To satisfy the equality constraint of equation (3), a loading of any one of the units is selected as the dependent loading Pd and its present value is replaced by the value calculated according to the following equation,

$$P_d = P_D + P_L - \sum_{\substack{i=1 \\ i\neq 1}}^{n} P_i \; --[5]$$

Where P_d can be calculated directly from the equation (5) with the known power demand P_D and the known values of remaining loading of the generators. Therefore the dispatch solution will always satisfy the power balance constraint provided that P_d also satisfies the operation limit constraint as given in equation (5). An infeasible solution is omitted and above procedure is repeated until P_d satisfies its operation limit. Because P_L also depends on P_d, we can substitute an expression for P_L in terms of P_1, P_2….P_d…..P_n and B_{mn} coefficients. After substituting it in the equation (.5), separate the independent and dependent generator terms to obtain a quadratic equation for Pd. Solving the quadratic equation for Pd, the power balance equality condition is exactly satisfied.

2) Transmission Loss

The total transmission loss,

i) The general form of the loss formula using B-coefficients is

$$P_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gi} \; --[6]$$

The transmission loss formula is known as the George's formula

ii) The accurate form of the loss formula

$$P_L = B_{00} + \sum_{i=1}^{NG} B_{i0} P_{gi} + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gi} --[7]$$

Where P_{gi} and P_{gj} are the real power injections at the i^{th} and j^{th} buses respectively. B_{00}, B_{i0} and B_{ij} are the loss coefficients which are constant under certain assumed conditions. NG is number of generation buses.

The transmission loss formula is known as the Kron's formula.

3) Minimum and maximum power limits

Generation output of each generator should be laid between maximum and minimum limits. The corresponding inequality constraints for each generator are

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \; --[8]$$

Where P_{gi}, $^{\min}$ and P_{gi}, $^{\max}$ are the minimum and maximum output

4) Generator ramp limits

In ELD research, a number of studies have focused upon the economical aspects of the problem under the assumption that unit generation output can be adjusted instantaneously. Even though this assumption simplifies the problem, it does not reflect the actual operating processes of the generating unit.

The operating range of all on-line units is restricted by their ramp rate limits [2]. Fig.1 shows three possible situations when a unit is on-line from hour t-1 to t. Fig l (a) shows that the unit is in a steady operating status. Fig l (b) shows that the unit is in an increasing power generation status. Fig. l (c) shows that the unit is in a decreasing power generation status.

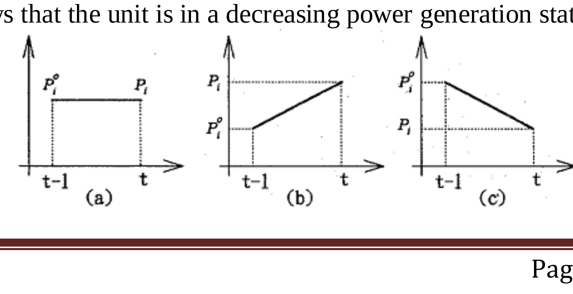

Fig. 1 Three possible situations of an on-line unit

Then the inequality constraints due to ramp rate limits are given,

1) If generation increases $P_i - P_i^0 \le UR_i \quad --[9]$

2) If generation decreases $P_i^0 - P_i \le DR_i \quad --[10]$

Where P_i^0 is the previous output power of unit i.

DR_i and UR_i are the down ramp and up ramp limits Combining (9), (10) and (1) the constrained optimization problem is modified as follows,

$$Max\left(P_i, P_i^0 - DR_i\right) \le P_i \le Min\left(P_i, P_i^0 + UR_i\right) \quad --[11]$$

5) Generator prohibited operating zones

The operating zone of a generating unit may not be available always for power generation due to limitations in practical operating constraints as shown in Fig.2

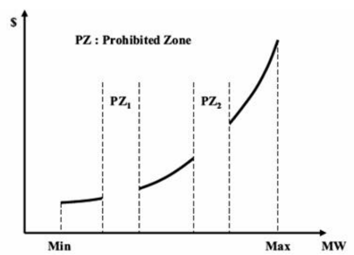

Fig. 2 Cost functions with 2 prohibited operating zones

$$P_i \in \begin{cases} P_{i,\min} \le P_i \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i \le P_{i,k}^l \qquad k = 2,3,.....N_{PZ,i} \\ P_{i,N_{PZ,i}}^u \le P_i \le P_{i,\max}^l \end{cases} \quad ----[12]$$

Where $P^l i,k$, and $P^u ik$, are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. $N_{PZ,i}$ is the number of prohibited zones of unit *i*.

6) Valve Point Effects:

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. Since the valve point results in the ripples as shown in Fig.3

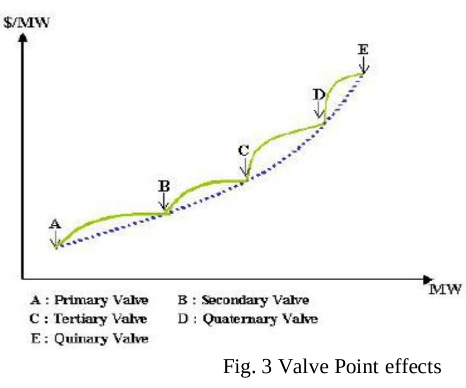

Fig. 3 Valve Point effects

The valve-point effect, sinusoidal functions are added to the quadratic const functions. Therefore, quadratic functions equation should be replaced follows:

$$F_i(P_i) = A_i P_i^2 + B_i P_i + C_i + \left| e_i \times \sin\left(f_i \times \left(P_{\min} - P_i \right) \right) \right| --[13]$$

where *ei* and *f i* are the coefficients of unit *i* reflecting valve point effects.

The generating units with multivalve steam turbines exhibit a greater variation in the fuel-cost functions. The valve-point effects introduce ripples in the heat-rate curves.

III. METHODS TO SOLVE ECONOMIC LOAD DISPATCH

In this work economic load dispatch problem is solved by evolutionary computational techniques (GA and PSO) and compared with the conventional method i.e. Lagrangian method.

A. GENETIC ALGORITHM

The GA is a stochastic global search method introduced by John Holland of Michigan University in 1970's.that mimics the metaphor of natural biological evolution such as selection, crossover, and mutation. The GA combines an artificial principal with genetic operation. The artificial principal is the Darwinians survival of fittest principal and the genetic operation is abstracted from nature to form a robust mechanism that is very effective at finding optimal solutions to complex real world problems.

GA is operates on string structures. The string is binary digits representing a coding of control parameters for a given problem. The each parameter of the given problem is coded with strings of bits. The individual bit is called 'gene' and the content of the each gene is called 'allele'. The total strings of such genes of all parameters written in a sequence are called a 'chromosome' so there exists a chromosome for each point in the search space. Here we have to know about search space. In this approach, a GA candidate solution is represented as a linear string analogous to a biological chromosome. The general scheme of GAs starts from a population of randomly generated candidate solutions (chromosomes). Each chromosome is then evaluated and given a value which corresponds to a fitness level in objective function space. In each generation, chromosomes are chosen based on their fitness to reproduce offspring. Chromosomes with a high level of fitness are more likely to be retained while the ones with low fitness tend to be discarded. This process is called selection. After selection, offspring chromosomes are constructed from parent chromosomes using operators that resemble crossover and mutation mechanisms in evolutionary biology. The crossover operator, sometimes called recombination, produces new offspring chromosomes that inherit information from both sides of parents by combining partial sets of elements from them. The mutation operator randomly hangs elements of a chromosome with a low probability. Over multiple generations, chromosomes with higher fitness values are left based on the survival of the fittest.

B. PARTICLE SWARM OPTIMISATION:

Particle Swarm Optimisation (PSO) is a population based stochastic optimization technique developed by Dr. Ebehart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as GAs (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities,which direct the flying of the particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called *gbest*. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called p-best. After finding the two best values, the particle updates its velocity and positions with following equation (14) and (15).

$$V_{id}^{(t+1)} = \omega.v_i^{(t)} + C_1.rand().\left[Pbest_{id} - P_{gid}^{(t)}\right] + C_2.Rand().\left[gbest_{id}(t) - P_{gid}^{(t)}\right] \quad --[14]$$

$$P_{gid}^{(t+1)} = P_{gid}^{(t)} + V_{id}^{(t+1)} \qquad --[15]$$

In the above equation,

The term $rand0.\left[pbest_{id} - P_{g_{id}}^{(t)}\right]$ is called particle memory influence. The term $rand0.\left[gbest_{id}(t) - P_{g_{id}}^{(t)}\right]$ is called swarm influence. $v_i(t)$ which is the velocity of i^{th} particle at iteration 't' must lie in the range $V_{min} \le V_i(t) \le V_{max}$. The parameter V_{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position .If V_{max} is too high, particles may fly past good solutions. If V_{min} is too small, particles may not explore sufficiently beyond local solutions. The constants C_1 and C_2 pull each particle towards *Pbest* and *gbest* positions.

The acceleration constants C_1 and C_2 are often set to be 1.5 to 2.2 according to past experiences. In general, the inertia weight **ω** is set according to the following equation,

$$\omega = \omega_{max} - \left[\frac{\omega_{max} - \omega_{min}}{iter_{max}}\right] \times iter$$

Where

ω is the inertia weighting factor
ω_{max} - maximum value of weighting factor
ω_{min} - minimum value of weighting factor
$iter_{max}$ - maximum number of iterations
iter - current number of iteration

IV. CASE STUDY EXAMPLES AND RESULTS

PARAMETERS:

The Lagrangian Method parameters are

Convergence tolerance ε	0.001
Step size α	0.005
Maximum allowed iterations	20

The GA Method parameters are

Length of string, i	16 bits
Population size L	20
Crossover probability, P_c	0.8
Mutation probability, P_m	0.01

The PSO method parameters are

Population size	10
No. of Iterations	10
Inertia weight factor ω is set by	$\omega_{max} = 0.9$ and $\omega_{min} = 0.4$
limit of change in velocity of each member in an individual was as	$Vd_{max} = +0.5\ Pg_{min}$, $Vd_{min} = -0.5\ Pg_{min}$
Acceleration constant	$C_1 = 1.5$ and $C_2 = 2.2$

***EXAMPLES OF GENERATING RAMP RATE LIMITS AND PROHIBITED ZONES CONSTRAINTS*:**

EXAMPLE 1: THREE UNIT SYSTEM

The cost characteristics of the three units are given as

$F_1 = 0.00525\ P_1^2 + 8.663\ P_1 + 328.13$ Rs/h

$F_2 = 0.00609\ P_2^2 + 10.040\ P_2 + 136.91$ Rs/h

$F_3 = 0.00592\ P_3^2 + 9.760\ P_3 + 59.16$ Rs/h

The unit operating ranges are:

$50\ MW \le P_1 \le 250\ MW$ $\qquad$ $5\ MW \le P_2 \le 150\ MW$

$15\ MW \le P_3 \le 100\ MW$

Generating units ramp rate limits and prohibited zones

Sr. No.	P^0_i (MW)	UR_i (Mw/ Hr)	DR_i (Mw/ Hr)	Prohibited zones (MW)
1	215	55	95	[105,117] [165,177]
2	72	55	78	[50,60] [92,102]
3	98	45	64	[25,32] [60,67]

B_{mn} Coefficient matrix

$$B_{mn} = \begin{matrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.0000175 & 0.000154 & 0.000283 \\ 0.000184 & 0.000283 & 0.000161 \end{matrix}$$

For the system load of 300 MW the GA and PSO method is applied

RESULT OF POWER GENERATION AND TOTAL FUEL COST

The results for 300 MW power and fuel cost with transmission loss are obtained as

Power Output (MW)	GA Method	PSO Method
P_1 (MW)	194.265	189.572
P_2 (MW)	50.00	66.8044
P_3 (MW)	79.627	54.5355
Total Power output (MW)	323.892	310.919
Power loss P_L (MW)	24.011	10.9119
Total generation cost (Rs /Hr)	3737.1669	3603.1633
No. of Iteration	18	10

Table 1: Comparison of Power and fuel cost of 300 MW with loss

The comparison of results of total fuel cost for 300 MW with loss, Prohibited zone and ramp rate between GA Method and PSO Method as shown in figure 4

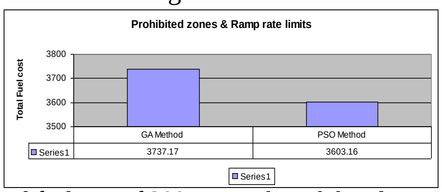

Figure 4 Total fuel cost of 300MW with Prohibited Zone & Ramp rate limits

EXAMPLE 2: SIX UNIT SYSTEM

This example adapted from [2] comprises six generating units with ramp rate and prohibited zone.

RESULT OF POWER GENERATION AND TOTAL FUEL COST:

The results for 1263 MW power and fuel cost with transmission loss, ramp rate and prohibited zone are obtained as

Power Output(MW)	**GA Method**	**PSO Method**
P_1 (MW)	474.80	442.747
P_2 (MW)	178.63	200
P_3 (MW)	262.20	259.6578
P_4 (MW)	134.28	130.9213
P_5 (MW)	151.90	150.265
P_6 (MW)	74.18	91.7842
Total Power output (MW)	1275.99	1275.37
Power loss P_L (MW)	13.02	12.3759
Total generation cost (Rs /Hr)	15459	15452.71
No. of Iteration	18	10

Table 2: Comparison of Power and fuel cost of 1263 MW with loss

The comparison of results of total fuel cost for 1263 MW with loss between Conventional method, Genetic Algorithm Method and PSO Method as shown in figure 6.15

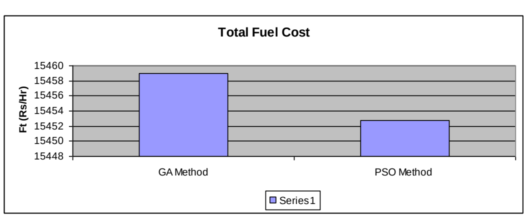

Fig. 5 Comparison of Power and fuel cost of 1263 MW with loss

EXAMPLE OF VALVE POINT EFFECTS

This example adapted from [5] comprises three generating units with quadratic cost functions together with the effects of valve – point loadings.

RESULT OF TOTAL FUEL COST

The results for 850 MW total fuel cost with valve point loadings as

Power Output(MW)	**GA Method**	**PSO Method**
Total generation cost (Rs /Hr)	8234.08	8232.57
No. of Iteration	18	15

Table 3: Comparison of total fuel cost of 850MW

V. CONCLUSIONS

Based on the observations and results obtained from simulation studies carried out for three units, systems for Lambda Iteration, GA and PSO the following conclusions are drawn,

Lambda Iteration method requires large number of iterations converges slowly and is not cost effective. GA method provides fast convergence and requires less number of iterations and is cost effective. The PSO method requires less number of iterations is cost effective and provides fastest convergence among the three.PSO method is efficient for both, with and without loss problems and constraints.

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