Comparative Study of Economic Dispatch by Using Various Optimization Techniques

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***Abstract*- This paper presents various optimization techniques to solve the problem of Economic Dispatch (ED). The optimization techniques used in this paper to do the comparison are Quadratic Programming (QP), Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Differential Evolution (DE) and Genetic Algorithm (GA). The objective of Economic Dispatch is to minimize the fuel cost at the same time to determine the optimum power generation. Optimization technique is used for ED so that the better convergence could be approached to solve the problem effectively as well as by considering the constraints. To do the comparison, the six generating unit system was used and the experimental results are compared. The experimental result indicates that the Differential Evolution is the most efficient technique compared to others in terms of fuel cost and total losses.**

I. Introduction

Economic Dispatch (ED) is the scheduling of generators to minimize the total operating cost and to meet load demand of the power system over some appropriate period while satisfying various equality and inequality constraint. The ED basically considers the load balance constraint beside the generating capacity limits. However, in practical ED, ramp rate limits as well as prohibited operating zones (POZ), valve point effects, and multi-fuel option must taken into the account[1].

Many conventional and nonconventional optimization techniques available in literature are applied to solve the problem in ED. Quadratic linear programming, Mathematical linear programming, dynamic programming are the conventional methods. However, conventional method failed to solve the problem because they have the drawbacks of multiple local minimum points in the cost function. Conventional method usually have simple mathematical model and high search speed. But, it will use approximation to search for the algorithms that have the required characteristics. This may cause to suboptimal operation and huge revenue loss over time[2].

Hence, to solve the Economic Dispatch problem more efficiently, method based on artificial intelligence have been proposed. The optimization techniques based artificial intelligence includes Genetic Algorithm (GA), Articial Bee Colony (ABC), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Differential Evolution (DE), Tabu search and etc. These methods solve variety of power system problem because have better convergence characteristic, high solution quality and simple to use.

II. Problem Formulation

The Objective of Economic Dispatch is to minimize the fuel cost while satisfying several equality and inequality constraints. Hence, the problem is formulated as below.

A. *Economic Load Dispatch formulation*

Consider a power system having N generating units, the objective function is formulated as

$$\text{Min}\, F_t = Min \sum_{i=1}^{N} F(P_i)$$

B. *Minimization of Fuel Cost*

The generator cost curve are represented by quadratic functions and the total fuel cost F(PG) in (RM/h) can be expressed as

$$F(P_G) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2$$

Where N is the number of generators; a_i, b_i, c_i are the cost coefficients of the i^{th} generator and P_G is the vector of real power outputs of generators and defined as

$$P_{Gi} = [P_{G1}, P_{G2}, \dots \dots, P_{GN}]$$

C. *Constraints*

1.) Power Balance/Equality Constraint

The total generated power must cover the total power demand P_D and the real power of transmission loss P_{loss} which can be defined as

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_{loss} = 0$$

To achieve accurate economic dispatch, the transmission loss can be formulated by B-matrix method.

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00}$$

Where,
P_j = the output generation of unit j (MW).
B_{ij} = the ij^{th} element of the loss coefficient square matrix.
B_{i0} = the i^{th} element of the loss coefficient.
B_{00} = the loss coefficient constant.

2.) Generation Capacity/Inequality Constraint

For stable operation, the real power outputs of each generator is restricted by lower and upper limits as follows:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, \qquad i = 1,2, \dots, N$$

III. OVERVIEW OF OPTIMIZATION TECHNIQUES

A. Quadratic Programming (QP)

Quadratic Programming is an effective optimization method to fid the global solution if the objective function is quadratic and the constraints are linear. It can be applied to optimization problems having non-quadratic objective and non-linear constraints by approximating the objective to quadratic function and the constraints are linear. For all the four problems the objective is quadratic and the constraints also quadratic so the constraints are to be made linear. Transformation of variables technique is incorporated for making the constraints linear. Quadratic Programming solution was implemented in Economic and emission dispatch problem by R.M.S Danaraj and Dr.F.Gajendran in 2005.

B. Differential Evolution (DE)

Differential Evolution algorithm is a method of optimization proposed by Price and Storn which is a population-based stochastic parallel search technique. DE has the ability to handle optimization problems with non-smooth or non-convex objective functions. It has a simple structure and a good convergence property and requires a few robust control parameters [3]. This algorithm using three operators which are mutation, cross-over and selection to evolve from randomly generated initial population to final individual solution. The main part of this DE is it starts with an initial population of feasible target vectors (parents) and new solutions (offspring) are generated (by mutation, crossover and selection operation) until the optimal solution is reached. In the mutation operation, three different vectors are selected randomly from the population and a mutant vector is created by perturbing one vector with the difference of the two other vectors. Whereas, in the crossover operation certain parameters of the targeted vector is replaced by the corresponding parameter of the mutant vector based on a probability distribution to create a new trial vector (offspring). In DE, the parent will compete one to one with the offspring. The individual with best fitness will remain until the next generation. The iterative process will only end when user-specific stopping criteria was met. The control parameter of DE algorithms are differentiation (or mutation) factor *F*, crossover constant *CR*, and size of population N_P [4].

C. Simulated Annealing (SA)

The idea of the simulated annealing algorithm is actually evaluated from the annealing process of metals. Annealing is the process of heating up a metal to a high temperature followed by slow cooling which will be done by decreasing the temperature step by step. At each step, the temperature is fixed for a period of time until the system reach thermal equilibrium. Finally the system reaches to its minimum energy crystalline structure. SA technique is a random search technique for optimization developed by Kirkpatrick et al. which simulates the physical annealing process. In SA, the objective function corresponds to the energy of the metal and the number of iterations is equivalent to the temperature level in the annealing process. The SA technique consists of three stages which are generation of candidates solution by perturbations the current solutions, checking for acceptance of the solution and an iterative procedure. SA is able to generate global or near global optimal solutions without restriction on the shape of the objective functions. Moreover, SA is not memory intensive. However, the setting of control parameters of the SA algorithm is difficult task and the computation time is high [7]&[8].

D. Artificial Bee Colony (ABC)

Artificial Bee Colony method was first introduced to solve economic load dispatch by Gaurav Prasad et.al in 2011. If compared with other heuristic methods, ABC have highly superior feature in terms of quality of solution, stable convergence characteristics and good computational efficiency. The solution of ABC is by the location of a food source and the quality of the solution is represented by the nectar amount of the source (fitness). At the initial step of ABC, the location of the food source will be produced randomly [6].

E. Genetic Algorithm (GA)

Genetic algorithms were formally introduced in the United States in the 1970s by John Holland at University of Michigan. The continuing performance improvement of computational systems has made them attractive for some types of optimization. In particular, genetic algorithms work very well on mixed (continuous *and* discrete), combinatorial problems. Combinatorial Optimization problem usually consist high number of solution which makes the perfect solution is impossible to achieve. They are less susceptible to getting 'stuck' at local optima than gradient search methods. But they tend to be computationally expensive. To use a genetic algorithm, a solution must be presented to the problem as a *genome* (or *chromosome*). GA is done by random search or heuristic search technique based on the conjecture of natural selection and genetics. The analogy of GA is similar to an actual chromosome. Firstly, it will only search the maximum value and avoid trapping of minimum values. The genetic algorithm then creates a population of solutions and applies genetic operators such as selection, mutation and crossover to evolve the solutions in order to find the best one. Lastly, to guide in search, GA will only evaluates the objective function or most fit strings. In short, GA's searching strategy is by highest probability of finding improved performance.

F. Particle Swarm Optimization (PSO)

Particle Swarm Optimization is a population based stochastic search algorithm which is introduced by Kennedy and Eberhart in 1995. The idea of this algorithm is generated from the social behavior of bird flocks and fish schooling. Initially, this optimization technique only solves the nonlinear continuous optimization problems. Then, improvement on this optimization was made to solve global optimal solution of complex problems of engineering and sciences. The attractive feature of PSO is its simplicity [5]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with 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 neighbours of the particle. This location is called *lbest*. When a particle takes all the population as its topological neighbours, the best value is a global best and is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations.

IV. METHODOLOGY

The test system having six thermal units is considered for this simulation. The data of the plant is given in the table 1 and table 2. The optimization techniques are applied for the demand 500 MW, 700 MW and 1000MW. Then the results are compared.

TABLE I FUEL COST DATA AND GENERATING CAPACITY LIMIT FOR SIX UNIT OF GENERATING PLANTS

Unit	a_i	b_i	c_i	P_{min}	P_{max}
1	0.15247	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.3965	1049.9977	35	225
4	0.03546	38.30553	1243.5311	35	210
5	0.02111	36.32782	1658.569	130	325
6	0.01799	38.27041	1356.6592	125	315

TABLE 2 LOSS COEFFICIENT, B DATA FOR THE MATRIX nXn WHERE N IS TOTAL GENERATING UNITS

0.14	0.17	0.15	0.19	0.26	0.22
0.17	0.60	0.13	0.16	0.15	0.20
0.15	0.13	0.65	0.17	0.24	0.19
0.19	0.16	0.17	0.71	0.30	0.25
0.26	0.15	0.24	0.30	0.69	0.32
0.22	0.20	0.19	0.25	0.32	0.85

V. SIMULATION RESULTS & DISCUSSION

The simulation results for QP, SA, DE, ABC, GA and PSO are tabulated in the Table 3 where the real power generation by each generator unit for the given demand and the total cost are described.

TABLE 3 TOTAL POWER GENERATING FOR EACH UNIT AND TOTAL COST FOR VARIOUS TYPE OF OPTIMIZATION TECHNIQUES

Method	**P_D(MW)**	**P_1(MW)**	**P_2(MW)**	**P_3(MW)**	**P_4(MW)**	**P_5(MW)**	**P_6(MW)**	**P_{loss} (MW)**	**(RM/hr)**
QP	500	20.1935	10.0000	72.4221	82.7976	174.8621	149.5480	9.8232	28276.0
DE		20.1935	10.0000	72.4221	82.7976	174.8620	149.5481	9.8232	27440.2
SA		20.1908	10.0000	72.4206	82.7999	174.8566	149.5554	9.8233	27440.2
ABC		20.1920	10.0000	72.4186	82.7972	174.8666	149.5490	9.8233	27440.2
GA		25.3197	10.9481	63.3659	91.6016	150.1575	168.4263	9.8190	27474.1
PSO		20.1894	10.0000	72.3537	82.8233	174.8882	149.5694	9.8242	27440.2
QP	700	29.3827	10.0000	118.6855	118.4592	230.4109	212.3595	19.2979	38627.0
DE		29.3828	10.0000	118.6860	118.4593	230.4111	212.3589	19.2980	36907.0
SA		29.3814	10.0001	118.6834	118.4584	230.4150	212.4599	19.2981	36907.1
ABC		29.3837	10.0000	118.6894	118.4620	230.4133	212.3495	19.2979	36907.1
GA		30.6498	16.4640	131.1318	116.0797	215.8734	208.5903	18.7890	36925.1
PSO		29.3896	10.0000	118.6907	118.4798	230.2659	212.4715	19.2977	36907.1
QP	1000	42.9173	27.6496	186.1303	170.2407	310.2789	301.9752	39.1920	56082.0
DE		42.9174	27.6498	186.1321	170.2413	310.2799	301.9724	39.1929	52349.2
SA		42.9157	27.6484	186.1336	170.2399	310.2839	301.9716	39.1930	52349.2
ABC		42.9173	27.6496	186.1353	170.2409	310.2781	301.9717	39.1928	52349.2
GA		43.7480	27.7782	169.3992	161.9487	322.0224	315.0000	39.8969	52367.4

PSO		42.9139	27.6443	186.1231	170.2497	310.2518	302.0106	39.1936	52349.2

For the case where the demand is 500 MW, Quadratic Programming (QP) have far deviated total cost compared with other optimization techniques then followed by Genetic Algorithm. Other techniques have same total cost in simulation result which is 27440.20 RM/MW hr with minimum total transmission loss 9.8232 MW. For the lower power demand, it is clear that Differential Evolution Programming have better result in term of fuel cost and transmission loss compared with other techniques.

For the case where the demand is 700MW, the highest fuel cost simulation result still by quadratic programming. Although genetic algorithm have smallest transmission loss but the fuel cost is not efficient enough if compared with other techniques. Differential Evolution Programming has lowest fuel cost which is 36907.0 RM/MW hr with acceptable transmission loss which is 19.2980 MW. Whereas, Particle Swarm Optimization has acceptable fuel cost of 36907.1 RM/MW hr with lowest transmission loss which is 19.2977MW.

For higher power demand which was tested with 1000MW, Genetic Algorithm which have lower transmission loss previously shows the transmission loss increased to the highest at higher power demand. This proved Genetic Algorithm is not stable enough to solve economic dispatch problem. ABC, PSO, SA and DE have the lowest fuel cost which is 52349.2 RM/MW hr. In term of transmission loss, Artificial Bee Colony has the lowest power loss 39.1928MW then followed by Differential Evolution 39.1929MW with acceptable fuel cost.

Quadratic Programming (QP) and Genetic Algorithm (GA) can be said not efficient enough to solve economic dispatch problem due the approximation method used in these both techniques. Hence, the fuel cost are much more deviated compared with others. Simulated Annealing (SA), Artificial Bee Colony (ABC), Differential Evolution (DE) and Particle Swarm Optimization (PSO) have almost similar result in term of fuel cost and transmission loss and suitable to further implementation for economic dispatch.

Based on the simulated result for power demand of 500MW, 700MW and 1000MW, Differential Evolution method has most stable result on total fuel cost and transmission loss for that three cases compared with other techniques.

VI. Conclusion

The various optimization techniques have been applied to economic problem in this paper. All the techniques which are consists of QP, DE, SA, ABC, GA and PSO has been compared each other using six unit generating system with three different power demand. The result obtained shows that Differential Evolution technique have most constant result compared with other techniques in terms of minimizing total fuel cost and lower transmission loss.

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