Fully Informed Particle Swarm Optimization for Solving Economic Load Dispatch

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***Abstract*— The allocation of required load between the available generation units at minimum cost is known as Economic Load Dispatch (ELD). ELD is a non-linear constrained optimization problem having both equality and inequality constraints. In this paper Fully Informed Particle Swarm Optimization (FIPSO) is proposed to solve ELD problem minimizing fuel cost considering valve point effect. Obtained results are compared with the results obtained by classical Particle Swarm Optimization (PSO) and Flower Pollination Algorithm (FPA). The proposed approach outperform other approaches in terms of power losses and cost minimization.**

Keywords*— *Economic load dispatch, Fully Informed Particle Swarm Optimization, FIPSO, ELD, Valve Point Effect

I. Introduction

The operation planning of power system is characterized by having to maintain a high degree of economy and reliability [1]. To operate the power system, there are plenty of choices available for the engineers, but the most significant choice is Economic Dispatch. Power system should be operated under a high degree of economy for competition of deregulation [2]. Economic Dispatch is one of the major optimization problems in the operation and planning of power system. It is very difficult to solve these types of problems because of non-linear objective functions and larger number of constraints. The main objective of the economic dispatch is to allocate the power demand among the committed generators economically, while satisfying all operational and physical constraints. The total cost of power generation, particularly in fossil fuel plants is very high and economic dispatch helps in saving a significant amount of revenue [3]. Various studies have been undertaken on ELD till now, to seek for better solutions, as better solutions would result in considerable economic benefits.

Previously, a number of conventional methods are applied to solve the economic dispatch problems. These methods include Gradient method [4], lambda iteration method [5], Base-point and participation factor method [2], and Newton method [5]. These methods mainly rely on the assumptions that generators cost curves are monotonically increasing in nature [3]. But in practice, these assumptions are not valid because the input-output characteristics of modern generators have discontinuities and are non-linear due to ramp-rate limits [6], valve-point loading [7], prohibited zones [8], and multi-fuel options of generators. To meet the requirements of the above classical methods, an assumption of the characteristics have to be made and due to such approximation, we cannot get the full optimal solutions, which results in huge amount of revenue loss and inaccurate dispatches. Due to non-linear characteristics of these units, we have to find the solution techniques that have no restriction on the fuel cost curve [9].

Dynamic programming [5], proposed by Wood and Wollenberg, has no restriction on the nature of cost curves and can solve both convex and non-convex ELD problems. But this method suffers from the computational complexity, dimension problem with the increase in the size of the system. In the past decades, several computational optimization algorithms such as genetic algorithm [10] simulated annealing [11], tabu searches [12], ant colony optimization, differential evolution [13], and particle swarm optimization [14] have been developed and applied successfully to ELD problems. More interest has been focused on the applications of Artificial Intelligence technology for the solution of ELD problems. Yalceinoz and short [15] have proposed a new mapping technique for the Hopfield neural network to solve

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ELD problems for units with piece-wise quadratic fuel cost function and prohibited zone constraints. By adopting sigmoid function in this model, it suffers from very slow convergence.

Another approach for solving the ELD problems is to implement the Evolutionary algorithms techniques. These techniques are very effective for non-linear objective cost functions. Genetic Algorithm [16] and Simulated Annealing [17] have been applied successfully to solve the ELD problems. GA has a parallel search capability feature, which makes it faster than SA. The main drawback of the GA is its computational time increases with the increase in the size of the system. Moreover, GA has premature convergence, due to which it degrades the performance and searching capabilities and leads to greater probability of getting trapped in the local optimum [18]. Differential Evolution [13], invented by Price and Storm, mainly includes the three basic operations i.e. mutation, crossover, and solution, to reach an optimal solution. DE is much faster and produces better results while satisfying all the constraints. But, as system complexity and size increases, DE fails to map its unknown variables in a better way.

The PSO first introduced by Kennedy and Eberhart [19] is a very powerful approach for solving non-linear optimization problems. PSO is rapidly gaining acceptance for solving the Economic dispatch problems [20-23] and a variety of power system problems [24-27], due to its simplicity, easy to implement, fast convergence and high quality of solutions. It has been observed in the recent research that the classical PSO approach undergoes premature convergence, particularly for non-linear optimization problems having multiple minima [28, 29]. A remarkable limitation of PSO algorithm is due to the fact that each member of the swarm changes its velocity considering the influence of only two specific solutions: the best previous success of each individual member of the swarm and the best previous success of the whole swarm.

Fully Informed Particle Swarm Optimization (FIPSO) pioneered by Mendes et.al [30] proposed a modification in the classical PSO in the sense that, in each iteration of the algorithm, every particle of the swarm gathers information from all or many of its informing neighbors rather than one or two of its best members. This leads to a more informed swarm resulting in better convergence and an improved minimized cost function.

In this paper, FIPSO is applied to solve the ELD problems considering valve-point effect. The proposed algorithm is applied to determine optimal loading of generators in power system. Simulation results for small and large scale power system considering the valve-point effect are implemented to indicate the robustness of FIPSO.

II. ECONOMIC LOAD DISPATCH

The fundamental objective of Economic dispatch is to minimize the total cost of generation, over an appropriate time, while satisfying the overall constraints. Mainly, there are two types of ELD problems: convex and non-convex. The convex ELD problem assumes quadratic cost function along with system power demands and operational limit constraints. But, when we include the practical operating conditions, the basic ELD problems becomes non-convex optimization problems and consider generator non-linearities such as valve-point loading effect, prohibited operating zones, ramp rate limits and multi-fuel options.

A. *Objective function of ELD*

Fuel costs are usually represented as-

$$F(P) = a + b * P + c * P^2 \tag{1}$$

Minimize

$$F_t = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N} a_i + b_i * P_i + c_i * P_i^2 \tag{2}$$

Where, F_t is called the total cost of generation ($/hr)
F_i is the fuel cost function of generator i ($/hr)
P_i is the real power output of generator (MW)
N is the number of generators
a_i b_i c_i are the fuel cost coefficients of generators i
The minimization is performed subject to the equality that the total generation must be equal to the total demand including losses.

$$\sum_{i=1}^{N} P_i = P_L + P_D \tag{3}$$

Where, P_D is the total load in the system (MW)

P_L is the total network loss (MW) that can be calculated by B matrix loss formula.

Based on the minimum and maximum power limits of generators the inequality constraints is-

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{4}$$

The total transmission loss using kron's formula is given by-

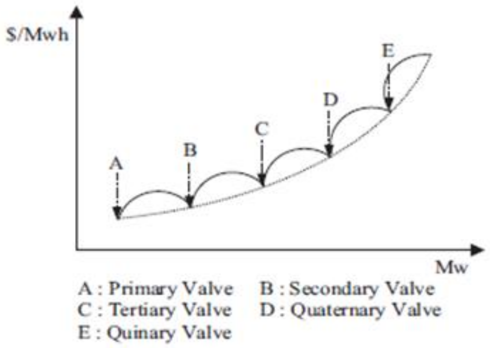
$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} (P_i * B_{ij} * P_j) + \sum_{i=1}^{N} B_{oi} * P_i + B_{oo} \tag{5}$$

B. *Effect of valve point on fuel cost objective*

To be more practical, the valve-point effect is taken into account in the cost function of generators. The deviation in the fuel cost due to valve-point with the change in generation value P_i is shown in fig-1. By including this effect, the objective function becomes more complex and is given as the sum of quadratic and sinusoidal function.

$$F_t = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N}(a_i + b_i * P_i + c_i * P_i^2 + e_i * \sin(f_i * (P_i^{min} - P_i))) \tag{6}$$

Fig. 1. Valve Point Effect



III. FULLY INFORMED PARTICLE SWARM OPTIMIZATION (FIPSO)

A. Introduction

Initially, the behavior of PSO algorithm was developed assuming that each member of the swarm changes its velocity in the consecutive iteration of the algorithm, considering the influence of only two specific solutions: the best previous success of each individual particle and the best previous success of the whole swarm. Fully Informed Particle Swarm Optimization (FIPSO) introduced by Mendes, Kennedy and Neves [30] proposed a modification in this approach. In the traditional PSO, a particle having k neighbors selects its source of influence as one* of them and neglects the influence of others. However, in fully informed particle swarm neighborhood, all neighbors in each iteration are considered as the source of influence. Thus FIPSO provides an optimization algorithm with a diverse neighborhood influence.

Performance of FIPSO is usually characterized by the size of ‘informing’ neighborhood, which depends on the topological structure of the population [31]. It is observed that FIPSO with a low degree of connectivity shows better performance than that with a fully connected topology. A thorough study of convergence of FIPSO is done in [32]. The observation of the authors suggests that for topologies with high degree of connectivity, the swarm particles explore a region close to the centroid of the swarm. This may generate positive results for some specific functions, however, for some functions there is a possibility of getting trapped in local minima. Fortunately, the present algorithm is successfully applied for engineering problems like power system optimization [33] and has shown promising results.

B. Fully Informed Swarm Algorithm

Let us first introduce the notations used in the algorithm. n denotes the number of particles used in solving the optimization problem (5), (6). Each particle is represented by a set of D-dimensional vector within the iteration *i* represented by $x_1(i)$, $x_2(i)\dots$ $x_n(i)$. $x_m(i)^*$ denotes the best position found by swarm particle m before iteration i and the corresponding cost function value is denoted by f $(x_m(i)^*)$. Also let $x(i)^*$ represents the best solution obtained by the algorithm in its first i iteration and the corresponding cost function value is denoted by f $(x(i)^*)$.

The position of the particle $x_m(i)$ is updated in each iteration by moving it along the velocity vector $v_m(i)$ with the dimension d = 1,2,….D. Using above notations the velocity equation used in the algorithm is given as follows:

$$v_{md}(i+1) = \chi\left[v_{md}(i) + \frac{1}{K_m}\sum_{t=1}^{K_m} U(0,\varphi)(x_{S_m(t)i}(k)^* - x_{md}(i))\right] \quad (7)$$

Where parameter χ is known as constriction factor with typical value of 0.729. U(0,r) denotes uniformly distributed random number in the range (0,r). Symbol φ represents acceleration coefficient, typically having a value 4.1. K_m represents the degree of connectivity of mth particle typically having values between 3 and 5, that is, the number of neighbors from which the particle is collecting information. Finally, the function that returns the index of t-th nearest neighbor is represented by $S_m(t)$. Using above notations and assumptions the pseudo code for the implementation of FIPSO algorithm is provided below:

IV. ALGORITHM FOR FULLY INFORMED PARTICLE SWARM OPTIMIZATION

i ← 1 {iteration initialization}
for m = 1 to n
Generate Solution (x_m (i))
Initialize Velocity (v_m (0))
f (x_m (0)) ← ∞
end for
{main loop}
repeat
{evaluation and updation of best solutions}
for m = 1 to n
f (x_m (i)) ← Evaluate cost function (x_m (i))
if f (x_m (i)) < f (x_m (i − 1)) then
x_m (i) _ ← x_m (i)
else
x_m (i) _ ← x_m (i − 1)
end if
if f (x_m (i)) < f (x (i)) then
x (i) _ ← x_m (i)
else
x (i) _ ← x (i − 1)
end if
end for
for m = 1 to n
for n = 1 to D
g_{md} (i) ← 0
for all K_m nearest neighbors of m with index q
g_{md} (i) ← g_{md} (i) + (U (0, φ)(x_{qd}(k) − x_{md} (i))
end for
v_{md} (i) ← χ *[v_{md} (i − 1) + 1/Km*g_{md} (i)]
x_{md} (i + 1) ← x_{md} (i) + v_{md} (i)
end for

```
end for
stop condition ← Check stop condition
i ← i + 1
until stop condition = false
return f(x (i)*), x(i)*, i
```

V. RESULTS AND DISCUSSIONS

FIPSO is employed to solve the ELD problems with and without considering the valve-point effect, applied to 3-bus and 10-bus system to assure its optimization efficiency, where its objective function is limited by various constraints like output limits of generators and transmission losses. The performance of the FIPSO is compared with classical particle swarm optimization and flower pollination optimization algorithm. Simulations were done in MATLAB environment.

A. Case Study 1

This case studies a 3-unit generating system considering the valve-point effect. The generator cost coefficients, generator limits and transmission loss coefficients are taken from [34]. Table I and II summarizes the results of solving the objective function without and with considering the valve-point effect using the FIPSO and its results are compared with classical PSO and FPA. FIPSO indicate superior results in terms of total costs and power loss compared with other algorithms.

B. Case Study 2

This case involves a ten-unit generating system with valve-point effects. The fuel cost coefficients, generator limits and transmission loss coefficients are taken from [34]. Table III and IV summarizes the results of solving the objective function without and with considering the valve-point effect using the FIPSO and its results are compared with classical PSO and FPA. FIPSO indicates superior results in terms of total costs and power loss compared with the other algorithms.

TABLE I. BEST POWER OUTPUT FOR THREE-GENERATOR SYSTEM WITHOUT VALVE-POINT (PD=400)

Unit power output	**PSO**	**FPA**	**FIPSO**
P1 (MW)	83.1045	112.9067	81.5829
P3 (MW)	173.8271	159.6983	152.3735
P3 (MW)	150.6334	134.6855	173.6293
Total power output (MW)	407.5660	407.3445	407.5858
PLoss (MW)	7.5661	7.3445	7.2124
Total generation cost ($/hr)	20812.687	20520.051	20489.91

TABLE II. BEST POWER OUTPUT FOR THREE-GENERATOR SYSTEM WITH VALVE-POINT (PD=400)

Unit power output	**PSO**	**FPA**	**FIPSO**
P1 (MW)	80.8129	116.8201	81.3968
P2 (MW)	174.8619	157.8289	152.4731
P3(MW)	151.9215	132.6762	173.7165
Total power output (MW)	407.5963	407.3532	407.5865
PLoss (MW)	7.5963	7.3532	7.2891
Total generation cost ($/hr)	20873.0107	20575.5061	20514.7555

TABLE III. BEST POWER OUTPUT OF TEN-GENERATOR SYSTEM WITHOUT VALVE-POINT (PD=2000)

Best power output (MW)	**PSO**	**FPA**	**FIPSO**
P1 (MW)	25	42.7961	43.4138
P2 (MW)	50	69.1839	50
P3 (MW)	90	112.4637	90
P4 (MW)	100	115.6787	100
P5 (MW)	130	91.7610	130
P6 (MW)	210	95.1867	210
P7 (MW)	270	298.7932	270
P8 (MW)	310	331.2977	310
P9 (MW)	440	470	440
P10 (MW)	458.7904	459.0629	440
Total power output (MW)	2083.7904	2086.21	2095
PLoss (MW)	83.7901	86.2179	83.7503
Total generation cost ($/hr)	114485.7892	111621.9878	111521.3252

TABLE IV. BEST POWER OUTPUT OF TEN-GENERATOR SYSTEM WITH VALVE-POINT (PD=2000)

Best power output (MW)	**PSO**	**FPA**	**FIPSO**

P1 (MW)	55	51.4293	55
P2 (MW)	40	75.4193	80
P3 (MW)	80.1062	108.2635	118.0650
P4 (MW)	90	119.4277	90
P5 (MW)	120	78.0836	200
P6 (MW)	200	78.2707	120
P7 (MW)	260	299.9981	303
P8 (MW)	300	336.0492	257
P9 (MW)	470	469.9996	300
P10 (MW)	470	469.9999	430
Total power output (MW)	2085.16	2086.94	2085.0650
PLoss (MW)	85.1602	86.9409	83.065
Total generation cost ($/hr)	113872.8	111420.6086	111350.40

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