Emission Dispatch Problem with Cubic Function Considering Transmission Loss using Particle Swarm Optimization

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***Abstract*—In this research, authors have exploited particle swarm optimization (PSO) technique for solving the emission dispatch problem. Authors have used cubic function, instead of quadratic function, to solve emission dispatch problem to make the system more robust against nonlinearities of actual power generator. PSO with cubic function reveals better results by optimizing less emission of hazardous gases, transmission losses and showing robustness against nonlinearities than simplified direct search method (SDSM).**

***Index Terms*—Cubic Function; Emission Dispatch; Particle Swarm Optimization; Transmission Loss.**

I. INTRODUCTION

Fossil fuels are one of the major ingredients of power generation systems. World's almost two third of the power generation comes from fossil fuels [1]. These thermal plants are one of the main sources of releasing hazardous gases and particulates into the air like sulfur dioxide (SO_2), carbon dioxide (CO_2), nitrogen dioxide (NO_2), ozone (O_3) etc. Emission of these hazardous gases and particulates are one of the main environmental concerns nowadays. The large emission of CO_2 gas from different fossil fuels powered power generation system is contributing to the already existing global warming problem. Besides, burning coal in thermal plants can even cause to emit radioactive materials [2] and toxic heavy materials like arsenic, mercury etc. Sulfur and nitrogen dioxide contribute to smog and acid rain. It is thus very important to employ a model that minimizes the control of emissions from thermal power plants.

Many conventional and non-conventional techniques have been used to minimize economic emission dispatch problem [3-5]. These techniques can be divided into three types, such as classical techniques, intelligent techniques and hybrid techniques. Classical techniques like Newton Raphson method [3] and Lagrangian relaxation method [6] were used for solving emission dispatch with economic dispatch problem. Newton Raphson method was proved to be fast and accurate in solving the binding constraint equations, whereas Lagrangian relaxation method had the ability to easily accommodate different environmental constraints without major modification. However, these methods suffered from non-satisfactory results and take large computational time for nonlinear complex problems. Recently, many advanced metaheuristic methods like cuckoo search (CS) [7], bat algorithm (BA) [8], firefly algorithm (FA) [9], artificial bee colony (ABC) [10], genetic algorithm (GA) [11], particle swarm optimization (PSO) algorithms [12] have been exploited to solve emission problem. They have used quadratic function to solve emission problem with economic dispatch, but quadratic criterion function make the solution deviated from the optimality because it does not represent the actual response, on the other hand higher polynomial function gives actual response of generating units [13, 14].

In this research, cubic function has been used to represent emission dispatch problem. Hybrid methods [5, 15] have also been used to solve emission problem combined with economic dispatch problem with better global optimal results, but hybrid methods take greater computational time than stand-alone methods. In this research, authors have exploited PSO to solve emission dispatch problem considering transmission loss, power balance and generator limit constraints. PSO is a population-based evolutionary optimization technique [16]. The main advantages of PSO are simplicity, fast, reliable and ability to deliver accurate result consistently [17].

II. METHODOLOGY

There are various ways to formulate emission dispatch problem. Most of the previous researchers used quadratic function to formulate and solve the emission dispatch problem [7, 8]. But higher order polynomial function gives robustness against the nonlinearities of power generator and gives us actual response of thermal generating units [13]. For that reason, authors have used cubic function in particle swarm optimization (PSO) to represent emission dispatch problem. Authors compare the results found in this research with SDSM considering the same co-efficient values and generation unit limit. The goal of this research is to minimize the objective function i.e. emission dispatch problem function satisfying all other constraints. The emission dispatch problem can be formulated as:

$$E = \sum_{i=1}^{n} (a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i) \quad (1)$$

where E is total emission (kg/h). The a_i, b_i, c_i and d_i are emission coefficients of generating unit i. Additionally, P_i and n are the real power generation of the ith unit (in MW) and the total number of generation units, respectively.

Authors have considered total two constraints in this research. They can be formulated as below:

Power Balance Constraint: The total active power generation must be equal to the total real power demand plus transmission losses:

$$P = \sum_{i=1}^{n} P_i = P_D + P_L \quad (2)$$

where P, P_D and P_L are total active power generated (in MW), total power demand (in MW) and transmission loss (in MW) respectively. Transmission loss (P_L) can be defined with the help of Kron's loss formula [18] by:

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \quad (3)$$

where B_{ij} is a square matrix also known as loss coefficient of George's formula. B_{i0} is transmission loss constant of generating unit i. B_{00} is also a constant. Later two constants are also known as Kron's transmission loss constant. Here, transmission loss is also need to be minimized.

Generator Limit Constraint: The real power generation of each power generating unit has its minimum and maximum value. The power generation should lie within this limit. This inequality can be formulated as below:

$$P_{i,min} \le P_i \le P_{i,max} \quad (4)$$

PSO technique, pioneered by Kennedy [19], was inspired by the movement pattern of bird flock or fish school. Figure 1 shows the simple flowchart of PSO. In PSO, a swarm comprises of a group particles. These particles are at first randomly created and set into motion through search space. The particles move around in a multidimensional search space to approach the optima. Each position of a particle represents a solution to the target problem. Each particle changes its position on the search space using its own experience and the experience of neighbouring particles by utilizing the best position encountered by itself and its neighbours. In this way, they move toward those with a better position and towards the optimum.

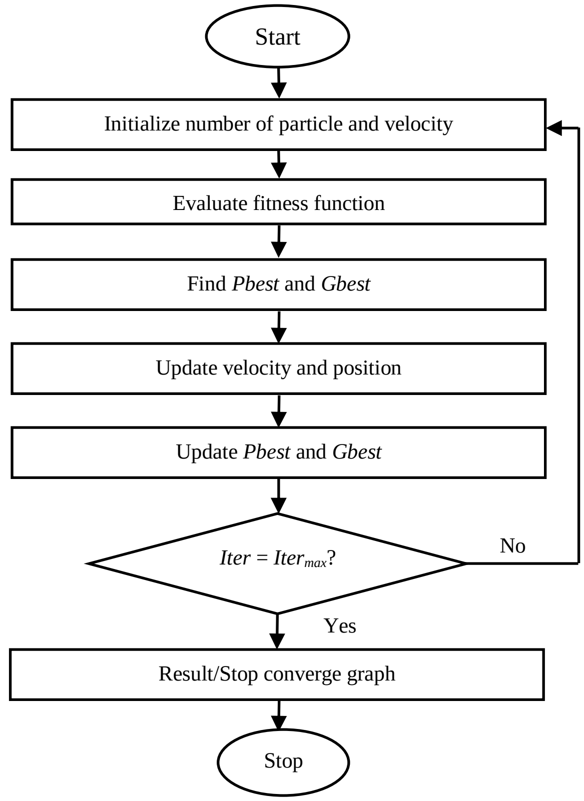

Figure 1: Flow chart of Particle Swarm Optimization

Initially, the variables are encoded and then decoded in the next step for transparency purposes in the test. Authors have only considered three units here (P_1, P_2 and P_3) and these constraints are compared with a different real power of the demand, P_D. The real power generations, P_i are evaluated and compared to test efficiency of the power systems to meet the losses and gains. In order to modify the position of each individual, calculation of velocity of each individual is important. Velocity update can be made using the following equation:

$$V_i^{k+1} = wV_i^k + c_1 rand_1 \times (Pbest_i^k - X_i^k) + c_2 rand_2 \times (Gbest^k - X_i^k) \quad (5)$$

where V_i velocity of individual i at iteration k, w weight parameter, c_1 and c_2 are acceleration constant, $rand_1$ and $rand_2$ are random numbers between 0 and 1, X_i^k is position of individual i at iteration k, $Pbest_i^k$ is the best position of individual i until iteration k and $Gbest^k$ is best position of the group until iteration k.

Again, individuals change their current positions by modifying velocity in (5) using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (6)$$

To continue updating velocity, calculation of certain parameters like w, c_1 and c_2 need to be determined in advance. The weighting function can be defined as below [20]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{Iter_{\max}} \times Iter \qquad (7)$$

The pseudo code of the PSO can be written as follows:

Algorithm 1. PSO algorithm.

For each particle
Initialize particle
END

Do
For each particle
Calculate fitness value
If the fitness value is better than the best fitness value (PBest) in history
Set current value as the new PBest
End

Choose the particle with the best fitness value of all the particles as the GBest
For each particle
Calculate particle velocity using equation (5)
Update particle position using equation (6)
End
While maximum iterations or minimum error criteria is not attained

Particle forms are changed and updated followed up by a particle decoding of the particle generations. If the conditions are met, results will be gathered to reflect the effectiveness of the proposed method. If there are further doubts on the constraints or so as if the results do not meet certain criteria in the given method, the particles will eventually be evaluated again and further evaluated to test for effectiveness.

III. Simulation Results and Analysis

Particle swarm optimization algorithm is exploited here in this paper for emission dispatch problem with three units. The algorithm is implemented in MATLAB R2015a and executed with Intel® Core™ i5-3470 CPU @ 3.20 GHz (4 CPUs), ~3.2GHz and 4GB RAM personal computer. Table 1 shows the parameter settings used in this research for cubic function of emission dispatch problem. The values of acceleration constant 1 & 2 and final & initial weighting vector have been taken from the work of Y. Shi and C. Eberhart [21]. They had proved that when initial inertia, w_{max} is equal to 0.9, all the 30 runs find the global optimum [21]. In this paper, authors consider total 30 number of runs.

Table 2 shows the coefficients values, maximum and minimum value of each power generating unit and coefficients and constants values of transmission loss. Authors have considered reasonable transmission loss coefficients matrix in this research to satisfy the transmission capacity constraints. To compare with SDS method [13], authors have used the same value for minimum/maximum limit of power generating unit, emission and loss coefficients. The selection of parameters in PSO should be done carefully as it is sometimes quite sensitive to certain parameters. Before choosing the parameters, authors run the algorithm for several sets of parameters. From those simulation data, authors can conclude that larger population size gives better result. But at the same time bigger population size increases the computational time.

Table 1
Settings of parameters for PSO

Parameters	Values
Population Size	500
Maximum number of steps	100
Acceleration constant 1, c_1	2
Acceleration constant 2, c_2	2
Initial inertia weight, w_{max}	0.9
Final inertia weight, w_{min}	0.4
Maximum Iteration	1000
Number of Runs	30

Table 2
Test system data for emission dispatch problem

Unit No.	1	2	3
Generator Data			
a_i (kg/MW^{3}h)	2.2×10^{-6}	3.3×10^{-6}	2.3×10^{-6}
bi (kg/MW^{2}h)	0.00419	0.00683	0.00461
c_i (kg/MWh)	0.32767	-0.54551	-0.51116
di (kg/h)	13.85932	40.2699	42.89553
$P_{i,min}$ (MW)	50	75	200
$P_{i,max}$ (MW)	175	200	375
B coefficients			
1	0.06760	0.00953	-0.00507
2	0.00953	0.05210	0.00901
3	-0.00507	0.00910	0.02940
B_0	-0.00766	-0.000342	0.001890
B_{00} = 4.037 MW			

PSO shows good convergence for emission dispatch problem with cubic function (Fig. 2). In the figure 2, y axis is for Gbest value that stands for total emission and x axis represents epoch or number of iteration. Simulation data shows that the PSO often converges to its best value of the particles to achieve the best position. Authors have shown the maximum, average and minimum value (table 2) of the test runs for total emission, generation of power in each unit, transmission loss and computational time.

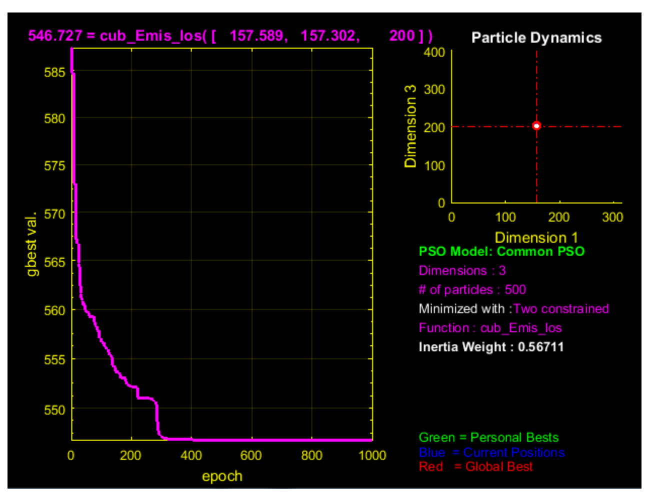

Figure 2: Convergence curve of the PSO for emission dispatch considering transmission loss

Table 3
Fitness evaluation of PSO

	Total Emission, *E* (Kg/h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Transmission Loss, P_L (MW)	Time (sec)
Max.	548.32	160.68	167.70	200	10.91	1.92
Avg.	547.10	154.03	160.8	200	10.8	1.8
Min.	546.73	147.02	154.26	200	10.69	1.72

From the simulation result, authors can conclude (from Table 3) that the stability and reliability (from Fig. 3 & 4) of PSO in solving emission dispatch problem with cubic function is verified and proved.

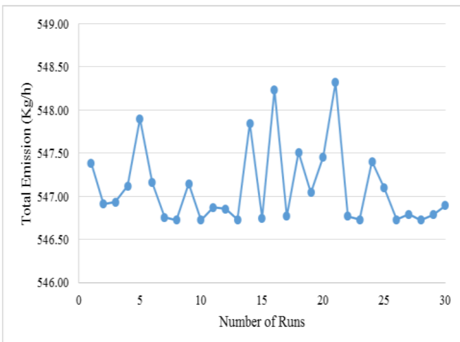

Figure 3: Total emission (Kg/h) vs number of runs curve for emission dispatch using PSO

The deviation from the average result is small and the computational time is also concentrated into a small zone. The generated power output of P_1, P_2 and P_3 are calculated randomly to meet the total power demand with system constraints. At the end of this section, authors have shown (Table 4) that PSO outperforms SDSM in optimizing best solution i.e. reduce the amount of emission for emission dispatch problem using cubic function.

Table 4
Comparison of final result between SDSM and PSO

	SDSM [13]	PSO
P_1 (MW)	65	154.03
P_2 (MW)	92	160.8
P_3 (MW)	355.71	200
E (kg/h)	646.06	547.10
P_L (MW)	12.71	10.8

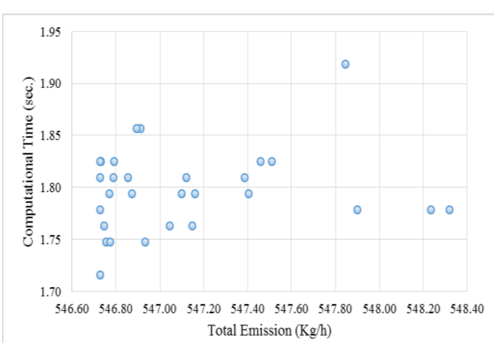

Figure 4: Computational time vs total emission (Kg/h) curve for emission dispatch using PSO

PSO has also been able to minimize transmission loss than SDSM. Although, SDSM has considered less complex equation for calculating transmission losses.

IV. Discussion

In this research, authors have considered 3-unit system for emission dispatch problem. The results from the simulation data confirm that PSO performs better in terms of convergence, near global optimal solution, stability, reliability, robustness and computational time. One of the problems with PSO is selecting the parameters, especially the maximum iteration and population size. In this research, authors have run the algorithm for different parameter settings e.g. with different iteration and population size. From the obtained data, authors have selected the suitable number of iteration and population size. To avoid exhaustive experiment on selecting other parameters, authors have selected the acceleration constant, weighting vector and constant value of transmission loss from the well-known literature [20].

V. Conclusion

In this paper, authors have successfully exploited PSO method to solve the emission dispatch problem using cubic function considering transmission losses and generator limit constraints. This method is applied to 3-unit system and its results affirm its high performance in solving the emission dispatch problem by demonstrating its superior features, near global optimal solution, stable convergence characteristic, and less computational time. Comparing with classical method like SDSM, authors have shown that PSO is better than classical method. Cubic function of emission dispatch problem works well in reducing the nonlinearities of power generator and gives us actual response of thermal generating units. Total 30 trials have been considered as a fair test of robustness of the proposed method. Authors have found the results for the test systems which confirm that the proposed method is highly robust in solving the emission dispatch problems. To the best of knowledge, no previous work has been done on single objective emission dispatch problem with cubic function considering transmission loss using PSO. Authors next work is to implement quantum PSO, Bat, Cuckoo Search (CS) and Teaching and Learning Based Optimization (TLBO) technique for emission dispatch problem using cubic function and compare between them. Authors will also exploit these techniques for multiobjective combined economic emission dispatch problems using cubic equation.

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