Economic Load Dispatch with Emission Constraints using Various PSO Algorithms

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Abstract:- This paper develops an efficient and clear insight view about the application of various PSO algorithms to the economic load dispatch problem with emission restrictions as the constraint. Solution acceleration techniques in the algorithm which enhance the speed and robustness of the algorithm are developed. The power and usefulness of the algorithm is demonstrated through its application to a test system.

Key-Words:- Economic dispatch, Combined Emission and economic dispatch (CEED),Particle swarm optimization(PSO), Dispersed particle swarm optimization(DPSO),New particle swarm optimization(NPSO).

1 Introduction

The definition of economic dispatch is given as "The operation of generation facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities." In traditional economic dispatch, the operating cost is reduced by proper allocation of the amount of power to be generated by different generating units. However the optimum economic dispatch may not be the best in terms of the environmental criteria. Recently many countries throughout the world have concentrated on the reduction of the amount of pollutants from fossil fuel power generating units. Apart from particulate pollutants, there are three gaseous pollutants namely carbon di-oxide, sulphur oxides and nitrogen oxides emitted from fossil fuel power plants.

The two primary power plant emissions from a dispatching perspective are sulphur oxides (SO_2) and nitrogen oxides (NOx). The economic dispatch and emission dispatch are considerably different. The economic dispatch reduces the total fuel cost (operating cost) of the system at an increased rate of NOx. On the other hand emission dispatch reduces the total emission from the system by an increase in the system operating cost. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (CEED).

The two primary power plant emissions from a dispatching perspective are sulphur oxides (SO_2) and nitrogen oxides (NOx). In the power plant, the sulfur enters the boiler as a part of the fuel. During the combustion process, some of the sulphur unites with oxygen from the fuel and combustion air to form SO_2. The remaining sulphur becomes a part of the bottom ash in the boiler. If stack gas clean up equipment is present, most of the SO_2 is removed. The remaining SO_2 exits the stack as an emission. Fuel blending, fuel switching and scrubbers are the primary methods for reducing the amount of SO_2 emitted. NOx emissions are more complex.

There are two sources of nitrogen that combine with oxygen from the fuel and the combustion air to produce NOx. The first source is nitrogen in the air that produces emission called thermal NOx. The second source is nitrogen in the fuel that produces emission called fuel NOx. The total NOx produced during combustion is the sum of the thermal NOx and fuel NOx. In coal, there is no apparent correlation between the amount of fuel-bound nitrogen and the fuel NOx produced.

The main purpose of the optimal generation dispatch problem has so far been confined to minimizing the total generation cost of the power system. However, in order to meet the environmental regulations enforced in recent years, emission control has become one of the important operational objectives.

2 Problem Formulation

2.1 Economic Dispatch

The economic load dispatching (ELD) problem is one of key problems in power system operation and planning. The ELD problem may be expressed by minimizing the fuel cost of generating units under some constraints. The fuel cost curve is approximated as a quadratic function of the active power output from the generating units.

The ELD problem can be defined as the following optimization problem,

Minimize $F_{cost} = \sum_{i=1}^{n}(\alpha_i P_i^2 + \beta_i P_i + \gamma_i)$ (2.1)

Where

F_{cost}: total fuel cost in the system ($/hr)

α_i, β_i, γ_i: fuel cost coefficients of the i th generating unit

N : number of thermal units

Subjected to

1. Power balance constraint $P_D + P_L = \sum P_i$ (2.2)

2. Generating capacity limits

$P_{imin} \leq P_i \leq P_{imax}$ (2.3)

Where

P_D = total system demand (MW)

P_L = total transmission network loss (MW

$P_{i\,min}$ = minimum power output limit of i^{th} generator (MW)

$P_{i\,max}$ = maximum power output limit of i^{th} generator (MW)

P_L can be calculated by

$P_L = \sum_{j=1}^{n}\sum_{i=1}^{n} P_i B_{ij} P_j$ (2.4)

Where B_{ij}'s are the elements of loss coefficient matrix B.

2.2 Emission Dispatch

The solution of economic dispatch problem will give the amount of power to be generated by various generating units of a power system for a minimum total fuel cost.

But limitation on emission release is not considered by this problem. The emission of pollutants affects not only human beings, but it is harmful to other life forms. It also causes damage to materials and cause global warming. These effects may be interpreted as cost, as they degrade the environment in one or other form. The objective of emission dispatch is to minimize the total environmental degradation or the total pollutant emission due to the burning of fuels for production of power to meet the load demand.

The emission function can be expressed as the sum of all types of emissions as NO, SO_2, particulate materials and thermal radiation with suitable pricing for each pollutant emitted. The emission dispatch problem can be defined as the following optimization problem,

Minimize $E_{cost} = \sum_{i=1}^{n}(a_i P_i^2 + b_i P_i + c_i)$ (2.5)

Where

E_{cost} : total emission release (Kg/hr)

a_i, b_i , c_i : emission coefficients of the i^{th} generating unit

n : number of thermal units

Subject to demand constraint (2.2) and generating capacity limits (2.3).

2.3 Combined Economic and Emission Dispatch (CEED)

The economic dispatch and emission dispatch are considerably different. The economic dispatch reduces the total fuel cost (operating cost) of the system at an increased rate of NOx. On the other hand emission dispatch reduces the total emission from the system by an increase in the system operating cost. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (CEED).

The CEED problem can be formulated as,

Minimize f (F_{cost}, E_{cost}) (2.6)

Where

$F_{cost} = \sum_{i=1}^{n}(\alpha_i P_i^2 + \beta_i P_i + \gamma_i)$ $/hr

$E_{cost} = \sum_{i=1}^{n}(a_i P_i^2 + b_i P_i + c_i)$ kg/hr

Subject to demand constraint (2.2) and generating capacity limits (2.3).

The above mentioned multi-objective optimization problem can be converted to a single objective optimization problem by introducing a price penalty factor Pf as follows,

Minimize $f = F_{cost} + h\, E_{cost}$ (2.7)

Where h is price penalty factor, which blends the emission, cost with the normal fuel costs. After the introduction of the price penalty factor, the total operating cost of the system is the cost of fuel plus the implied cost of emission .This factor avoids the use of two classes of dispatching .The procedure to find out *h* is as follows.

1. The fuel cost of each generator is evaluated at its maximum output

$(\alpha_i P_{i\,max}^2 + \beta_i P_{i\,max} + \gamma_i)$ $/hr (2.8)

2. The emission release of each generator is evaluated at its maximum output,

$(a_i P_{i\,max}^2 + b_i P_{i\,max} + c_i)$ Kg/hr (2.9)

3. h for each generating unit is calculated

$h = (\alpha_i P_{i\,max}^2 + \beta_i P_{i\,max} + \gamma_i) / (a_i P_{i\,max}^2 + b_i P_{i\,max} + c_i)$ \$/Kg (2.10)

i= 1, 2, 3,….., n

4. h (i = 1 ,2, 3 …,n) are arranged in ascending order.

5. The maximum capacity of each unit, (P_{max}) is added one at a time, starting from the smallest h unit until $\sum P_{i\,max} \geq P_D$.

6. At this stage "h" associated with the last unit in the process is the price penalty factor h (\$/Kg) for the given load demand P_D.

Once the value of P_f is known, by minimizing the equation (2.7) subjected to the constraint equations (2.2) and (2.3.3), the optimal generation schedule can be obtained.

3 Particle Swarm Optimization

3.1 Basic concepts of Particle Swarm Optimization

As socio biologist E. O. Wilson has written, in reference to fish schooling, "In theory at least, individual members of the school can profit from the discoveries and previous experience of all other members of the school during the search for food. This advantage can become decisive, outweighing the disadvantages of competition for food items, whenever the resource is unpredictably distributed in patches"**.** This statement suggests that social sharing of information among consecrates offers an evolutionary advantage: this hypothesis was fundamental to the development of particle swarm optimization.

3.2 Concept of Swarm

The term ***swarm*** has a basis in the literature. In particular, the authors use the term in accordance with a paper by Millonas, who developed his models for applications in artificial life, and articulated five basic principles of swarm intelligence.

→First is the proximity principle: the population should be able to *carry* out simple space and time computations.

→Second is the quality principle: the population should be able to respond to quality factors in the environment.

→Third is the principle of diverse response: the population should not commit its activities along excessively narrow channels.

→Fourth is the principle of stability: the population should not change its mode of behavior every time the environment changes.

→Fifth is the principle of adaptability: the population must be able to change behavior mode when it's worth the computational price.

Note that principles four and five are the opposite sides of the same coin. The term ***particle*** was selected as a compromise. While it could be argued that the population members are mass-less and volume-less, and thus could be called "points," it is felt that velocities and accelerations are more appropriately applied to particles, even if each is defined to have arbitrarily small mass and volume.

PSO is basically developed through simulation of bird flocking in two dimensional spaces. The position of each agent is represented by XY axis position and the velocity is expressed by V (the velocity of X axis) and V (the velocity of Y axis). Modification of the agent position is realized by the position and velocity information. Bird flocking optimizes a certain objective function. Each agent knows its best value, so far "P_{best}" and its XY position. Moreover, each agent knows the best value so far in the group "G_{best}" among "P_{bests}". Namely each agent tries to modify its position using the following information

i. The distance between current position and "P_{best}"

ii. The distance between current position and "G_{best}"

iii. This modification can be represented by the concept of velocity.

Velocity of each agent can be modified by the following equation:

$$V_{ij}^{(iter+1)} = w * V_{ij}^{(iter)} + c_1 * rand_1 * (Pbest_{ij} - P_j^{(iter)} + c_2 * rand_2 (gbest_i - P_{ij}^{(iter)}) \quad (3.a)$$

Where

w inertia weight factor

c_1, c_2 are the acceleration constants

$rand_1$, $rand_2$ are uniform random values in the range [0,1]

$V_{ij}^{(iter)}$ velocity of j^{th} dimension in i^{th} particle,

$V_j^{min} \leq V_j^{iter} \leq V_j^{max}$

$P_{ij}^{(iter)}$ current position of the j^{th} dimension in i^{th} particle at iteration iter.

The right hand side of equation consists of three terms (vectors). The first term is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent. Without the second and third terms, the agent will keep on flying in the same direction it hits the boundary. Namely it is corresponds to a kind of inertia and tries to explore new areas. Therefore, the first term can realize the diversification in the search procedure. On the other hand, without the first term, the velocity of the flying agent is only determined by using its current position and its best solutions in search history. Namely the agents will try to converge to their "P_{best}" and or "G_{best}" and, therefore the terms correspond to identification in the search procedure. The following weighting function is usually used in eq.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \quad (3.1)$$

where

w_{max} and w_{min} are both random numbers called initial weight and final weight respectively

$iter_{max}$ the maximum iteration number
iter the current iteration number

The model using equation is called "inertia weights approach". Using the above equation the diversification characteristic is gradually decreased and a certain velocity, which gradually moves the current searching point close to "P_{best}" and "G_{best}", can be calculated. The current position (searching point in the solution space) can be modified using the following eq,

$$P_{ij}^{(iter+1)} = P_{ij}^{iter} + V_{ij}^{(iter+1)} \quad (3.2)$$

3.1.2 Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is one of the evolutionary optimization methods inspired by nature which include evolutionary strategy (ES), evolutionary programming (EP), genetic algorithm (GA), and genetic programming (GP). PSO is distinctly different from other evolutionary-type methods in that it does not use the filtering operation (such as crossover and/or mutation) and the members of the entire population are maintained through the search procedure. In PSO algorithm, each member is called "particle", and each particle flies around in the multi-dimensional search space with a velocity, which is constantly updated by the particle's own experience and the experience of the particle's neighbors.

3.1.3 Simple PSO algorithm

Initialize parameters
Initialize population -1
Evaluate
Do {
Find particle best -2
Find global best
Update velocity -3
Update position -4
Evaluate
} While (Termination)

Step 1: Initialization: The initial particles are chosen randomly and would attempt to cover the entire parameter space uniformly. Uniform probability distribution for all random variables is assumed, that is:

$$X_i = X_{i\,min} + \rho_i\,(X_{i\,max} - X_{i\,min}) \qquad i=1..\,.\,N_p \quad (3.3)$$

Where ρ_i € [0, 1] is a random number. The initial process produces N_p individuals of X_i randomly. Similarly, initial velocities are also chosen randomly and would attempt to cover the entire parameter space uniformly.

$$V_i = V_{i\,min} + \rho_i (V_{i\,max} - V_{i\,min}) \qquad i=1...N_p \quad (3.4)$$

$X_{i\ min}$, $X_{i\ max}$ minimum and maximum limits of X_i which are initialized at start .

$V_{i\,min}$, $V_{i\,max}$ are calculated as follows:

$$V_{min} = (X_{min} - X_{max})/n; \quad (3.5)$$

$$V_{min} = -V_{max} \quad (3.6)$$

Where n is percentage change for the population can be taken as 10

Step 2: Finding bests: The fitness values of the population are found and population with best fitness is named as Particle best and best fitness among these particle best is taken as Global best. These Particle best and global best are updated for every iteration after obtaining the new population by adding velocities. The fitness value of each individual is compared and the best individual among the two is chosen.

Step 3: Updating Velocities: To modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage. In this velocity updating process, the values of parameters such as , ω,c1,c2 should be determined in advance.

Here, the weighting function is defined as follows:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \quad (3.7)$$

where

w_{max} and w_{min} are both random numbers called initial weight and final weight respectively

$iter_{max}$ the maximum iteration number iter the current iteration number

$$V_{ij}^{(iter+1)} = w * V_{ij}^{(iter)} + c_1 * rand_1 * (Pbest_{ij} - P_{ij}^{(iter)}) + c_2 * rand_2(gbest_i - P_{ij}^{(iter)}) \quad (3.8)$$

Where

w = inertia weight factor

c_1, c_2 = are the acceleration constants

$rand_1$, $rand_2$ = are uniform random values in the range [0, 1]

$V_{ij}^{(iter)}$ = velocity of j^{th} dimension in i^{th} particle,

$V_j^{min} \leq V_j^{iter} \leq V_j^{max}$

$P_{ij}^{(iter)}$ = current position of the j^{th} dimension in i^{th} particle at iteration iter.

Step 4: Updating Position*:* Position of each individual is modified by adding the velocity of each individual. The resulting position of individual is not always guaranteed to satisfy the constraints due to over/under velocity. If any element of an individual violates its inequality constraint due to over/under speed then the position of the individual is fixed to its maximum/minimum operating point.

$$P_{ij}^{(iter+1)} = P_{ij}^{iter} + V_{ij}^{(iter+1)}$$

Finally the G_{best} is the best solution.

Step –5: Stop criterion: The search procedure can be stopped when the current iteration number reaches the predetermined maximum iteration number. The last "g_{best}" can be output as a solution.

3.2 Dispersed Particle Swarm Optimization

As a population-based evolutionary technique, in PSO each individual (called particle) searches the multi-dimensional domain space with position and velocity information, and preserve the best position found by itself.

$$V_{ij}^{(iter+1)} = w * V_{ij}^{(iter)} + c_1 * rand_1 * (Pbest_{ij} - P_{ij}^{(iter)}) + c_2 * rand_2(gbest_i - P_{ij}^{(iter)}) \quad ......(3.2.1)$$

Where

w inertia weight factor

c_1, c_2 are the acceleration constants

$rand_1$, $rand_2$ are uniform random values in the range [0,1]

$V_{ij}^{(iter)}$ velocity of j^{th} dimension in i^{th} particle,

$V_j^{min} \leq V_j^{iter} \leq V_j^{max}$

$P_{ij}^{(iter)}$ current position of the j^{th} dimension in i^{th} particle at iteration iter.

To control excessive roaming outside the search space

$$V_{ij}^{(iter+1)} \leq V_{max} \quad (3.2.2)$$

Where

V_{max} is the velocity threshold with statistic analysis, Y. Peng proved that the performance of PSO was mainly affected by social coefficient. All of these settings are all particle-independent, in other words, centralized control—the same value among the swarm in each generation. In this manner, the swarm tends to search around the historical best position of the swarm G_{best}. Then, some useful information inside the personal historical best position P_{best} may lose, then decrease the search efficiency. To overcome this shortcoming, a dispersed control manner is introduced, in which each particle selects its social coefficient value to decide the search direction: P_{best} or G_{best} for standard particle swarm optimization, each particle maintains the same flying (or swimming) rules which means in the conventional PSO the social co efficient was centralized, as in all the particles have the same coefficient. Generally, the centralized social coefficient setting makes the particles converge onto one position G_{best}. Thus, some useful information among P_{best} is neglected.

At each iteration, the social coefficient c_2, an important parameter affecting the performance, is the same within the whole swarm of standard PSO, thus the differences among particles are omitted. Since the complex swarm behaviors can emerge the adaptation, a more precise model, incorporated with the differences, can provide a deeper insight of swarm intelligence, and the corresponding algorithm may be more effective and efficient. Inspired with this method, we propose a new dispersed social coefficient setting.

In order to compensate for the above disadvantages we define a new parameter called as

$$Grade_u(t) = \frac{f_{worst}(t) - f(x_u(t))}{f_{worst}(t) - f_{best}(t)} \quad ...(3.2.3)$$

Where

$f_{worst}(t)$ and $f_{best}(t)$ are the corresponding worst and best positions at time t. If the swarm converges at point where $f_{worst} = f_{best}$ then, $Grade_u(t) = 1$

$Grade_u(t)$ is an information index to represent the differences of particle u at time t, according to its fitness value of the current position. The better the particle is, the larger $Grade_u(t)$ is, and vice versa.

3.2.1 Social Coefficient Settings

The social co efficient setting is being modified to as follows

$$c_{2,j}(t) = c_{low} + (c_{up} - c_{low})Grade_j(t) \quad (3.2.4)$$

Where

c_{low} and c_{up} are two predefined constants and $c_{2,j}(t)$ represents the social coefficient of particle j at time t.

3.2.2 Mutation Strategy

In order to prevent pre mature convergence due to the introduction of $Grade_u(t)$ a mutation strategy is introduced to enhance the ability of escaping from the local optima. This mutation strategy is designed as follows. At each time, particle j is uniformly random selected within the whole swarm, as well as the dimensionality k is also uniformly random selected, then, the $v_{jk}(t)$ is changed as follows.

$v_{jk}(t) = 0.5 \times x\max \times r1$, if $r2 < 0.5$,
$-0.5 \times x\max \times r1$, otherwise (3.2.5)

Where r1 and r2 are random numbers generated with uniform distribution from [0,1]

3.2.3 The Details Of The Steps Of DPSO

Step 1. Initializing the position and velocity vectors of the swarm, and determining the historical best position G_{best} and P_{best} $(j = 1, 2, \ldots, n)$;

Step 2. Calculating the dispersed social coefficient according to formula (3.2.3) and (3.2.4);

Step 3. Updating the position and velocity vectors with formula (3.2.1) and (3.2.2) whereas the social coefficient $c2$ is replaced by $c_{2,j}(t)$;

Step 4. Updating the historical best position G_{best} and P_{best} $(j = 1, 2, \ldots, n)$;

Step 5. Making mutation strategy;

Step 6. If the stopping criteria is applied, then the output is the fitness value of G_{best}; otherwise, **goto** Step 2.

3.3 New Particle Swarm Optimization

In PSO, each particle moves in the search space with a velocity according to its own previous best solution and its group's previous best solution. The dimension of the search space can be any positive integer. The original PSO described above is basically developed for continuous optimization problem. However, lots of practical engineering problems are formulated as combinational optimization problem.

New PSO is a new variation in the classical PSO by splitting the cognitive component of the classical PSO into two different components. The first component can be called good experience component. That is, the bird has a memory about its previously visited best position. This component is exactly the same as the cognitive component of the basic PSO. The second component is given the name bad experience component. The bad experience component helps the particle to remember its previously visited worst position. To calculate the new velocity, the bad experience of the particle is also taken into consideration.

This gives the new model of the PSO as below. The new velocity update equation is given by

$$V_{ij}^{(iter+1)} = w * V_{ij}^{(iter)} + c_{1g} * rand_1 * \left(P_{best\,ij}^{(iter)} - P_{ij}^{(iter)}\right) + c_{1b} * rand_2 * \left(P_{ij}^{(iter)} - P_{worst\,ij}^{(iter)}\right) + c_2 * rand_3 (G_{best}^{(iter)} - P_{ij}^{(iter)}) \quad \ldots\ldots(3.3.1)$$

Where

i = (1,2,……….n) n is number of decision variables.

j = (1,2,…………m) m is the number of particles in the swarm

iter = iteration count

$V_{ij}^{(iter+1)}$ = dimension of the velocity of particle at iteration

$P_{ij}^{(iter)}$ = dimension of the position of particle at iteration

W = inertia weight

c_1, c_2 = acceleration coefficients

$P_{best\,ij}^{(iter)}$ = dimension i of the own best position of particle j until iteration;

$G_{best}^{(iter)}$ = dimension i of the best particle in the swarm at iteration;

c_{1g} = acceleration coefficient, which accelerates the particle toward its best position;

c_{1b} = acceleration coefficient, which accelerates the particle from its worst position $rand_1$, $rand_2$ and $rand_3$ = three separately generated uniformly distributed random numbers in the range [0, 1].

$$P_{ij}^{(iter+1)} = P_{ij}^{iter} + V_{ij}^{(iter+1)} \quad \ldots(4.3.2)$$

The positions are updated using equation (4.3.2)

The inclusion of the worst experience component in the behavior of the particle gives additional exploration capacity to the swarm. By using the bad experience component, the bird (particle) can bypass its previous worst position and always try to occupy a better position.

4. Application Example

In order to show the effectiveness of the various PSO algorithms proposed in this paper, the optimization results for a six unit test system are presented here. For implementation of PSO, population size of 10 and maximum number of iterations of 100 are taken All the related programs are written in MATLAB software package, and they are executed using P-IV computer @1.5GHz.The results are compared with those of GA.The results for pure economic dispatch for a demand of 500 MW are presented in Table 1,and the results for pure emission dispatch for a demand of 700 MW are presented in Table 2.From the results it is clear that PSO gives global optimum solution with less computation time ,than the other techniques .It is also observed that the losses are also minimum. Table 3 presents dispatch results for economic and emission dispatch.

Table 1. CEED Results For 500 Mw System

	PSO	DPSO	NPSO
Fuel Cost ($/hr)	2.7613 $*10^4$	2.7616 $*10^4$	2.7640 $*10^4$
Emission (Kg/hr)	263.0109	262.9595	262.6220
Total Cost ($/Kg)	3.9159 $*10^4$	3.9151 $*10^4$	3.9168 $*10^4$
Losses(P_L) (MW)	8.9331	8.9293	8.8848
Standard Deviation	19.0106	18.1118	60.2486
Mean	3.9208 $*10^4$	3.9168 $*10^4$	3.9188 $*10^4$
P_1(MW)	33.1966	33.3990	34.5469
P_2(MW)	26.9218	27.1529	28.1660
P_3(MW)	89.9363	89.5262	90.4942
P_4(MW)	90.4776	90.6532	91.4414
P_5(MW)	135.7146	135.6969	130.000
P_6(MW)	132.7834	132.5011	134.2356
Time(sec)	0.26500	0.29700	0.26600

Fig 1. Convergence Graph for 500 MW

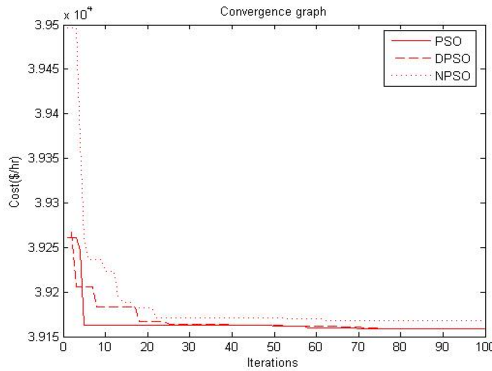

Table 2.CEED Results for 700 MW system

	PSO	DPSO	NPSO
Fuel Cost ($/hr)	3.7500 $*10^4$	3.7509 $*10^4$	3.7504 $*10^4$
Emission (Kg/hr)	439.6350	439.4550	439.5522
Total Cost ($/Kg)	5.719 $*10^4$	5.7191 $*10^4$	5.7190 $*10^4$
Losses(P_L) (MW)	17.0558	17.0596	17.0481
Standard Deviation	164.4414	148.9934	276.0508
Mean	5.7233 $*10^4$	5.7229 $*10^4$	5.7285 $*10^4$
P_1(MW)	62.0205	63.4199	62.1411
P_2(MW)	61.6289	60.9385	61.8393
P_3(MW)	120.0048	120.4518	120.3419
P_4(MW)	119.6732	119.1541	119.1079
P_5(MW)	178.1598	177.1551	178.2963
P_6(MW)	175.5687	175.9402	175.3215
Time(sec)	0.18700	0.21872	0.21900

Fig 2. Convergence Graph for 700 MW

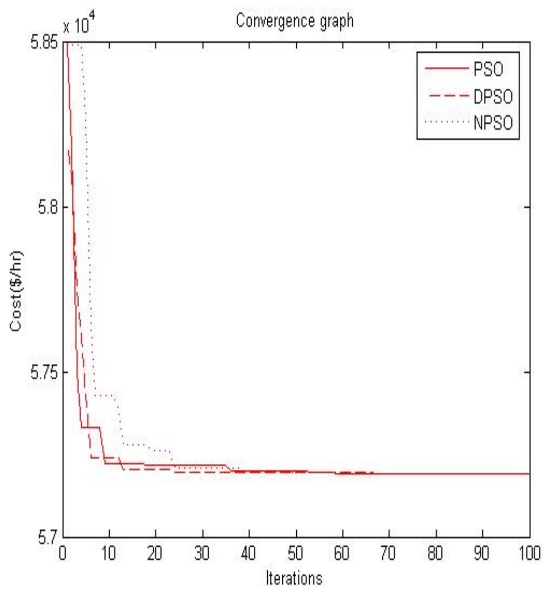

Fig 3. Convergence Graph for 900 MW

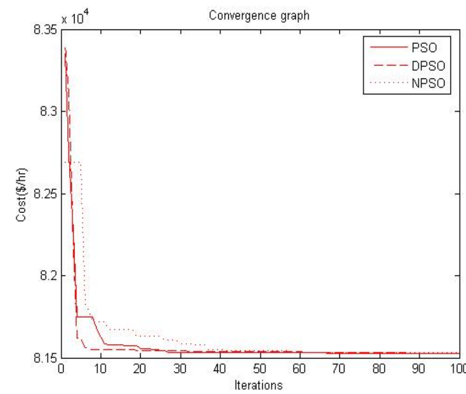

Table 2.CEED Results for 900 MW system

	PSO	DPSO	NPSO
Fuel Cost($/hr)	$4.8349*10^4$	$4.8371*10^4$	$4.8358*10^4$
Emission (Kg/hr)	693.8198	693.3819	693.8518
Total Cost ($/Kg)	$8.1529*10^4$	$8.1529*10^4$	$8.1532*10^4$
Losses(P_L) (MW)	28.0092	27.9816	27.8856
Standard Deviation	230.0807	248.8587	250.8676
Mean	$8.1587*10^4$	$8.1580*10^4$	$8.1630*10^4$
P_1(MW)	92.2106	92.4181	90.8027
P_2(MW)	98.4220	99.3425	100.0541
P_3(MW)	150.1833	149.9898	153.8375
P_4(MW)	148.6662	148.4845	148.0631
P_5(MW)	220.2796	220.2218	220.7988
P_6(MW)	218.2474	217.5250	214.3293
Time(sec)	0.1880	0.1875	0.2340

Table 4. Comparison Table for 500 MW

	GA	PSO	DPSO	NPSO
Total Cost ($/hr)	39258.030	$3.9159*10^4$	$2.7616*10^4$	$2.7640*10^4$
Fuel Cost ($\hr)	27638.300	$2.7613*10^4$	$2.7616*10^4$	$2.764*10^4$
Emission Cost ($/hr)	263.47	263.0109	262.9595	262.62
Losses (MW)	10.172	8.9331	8.9293	8.8848

Table 5. Comparison Table for 700 MW

	GA	PSO	DPSO	NPSO
Total Cost($/hr)	57346.19	$3.9159*10^4$	$2.7616*10^4$	$2.7640*10^4$
Fuel Cost($/hr)	37640.370	3.7500*10	3.7509*	$3.7504*10^4$
Emission Cost($/hr)	439.979	439.6350	439.455	439.552
Losses(MW)	18.521	17.0558	17.0596	17.0481

Table 6. Comparison Table for 900 MW

	GA	PSO	DPSO	NPSO
Total Cost($/hr)	81764.45	8.1529*1	8.1529 $*10^4$	8.1532 $*10^4$
Fuel Cost($/hr)	48567.75	4.8349*1	4.8371*1	4.8358*1
Emission Cost($/hr)	694.169	693.8198	693.3819	693.8518
Losses (MW)	29.725	28.0092	27.9816	27.8856

5. Conclusion

This paper introduces a new approach based on Particle Swarm Optimization (PSO) optimization to study the power system economic dispatch with Emission, which is formulated as a constrained optimization problem. The proposed method has been applied to one test case. When compared with Evolution with a Genetic Algorithm (GA), the analysis results have demonstrated that PSO outperforms the other methods in terms of a better optimal solution and significant reduction of computing times. However, the much improved speed of computation allows for additional searches to be made to increase the confidence in the solution. Overall, the PSO algorithms have been shown to be very helpful in studying optimization problems in power systems.

5.1 Data Required

Table 5.1 Fuel cost Equations (Rs/hr)

F1 = 0.15247 * P_1^2 + 38.53973 * P1 + 756.79886
F2 = 0.10587 * P_2^2 + 46.15916 * P2 + 451.32513
F3 = 0.02803 * P_3^2 + 40.39655 * P3 + 1049.9977
F4 = 0.03556 * P_4^2 + 38.30553 * P4 + 1234.5311
F5 = 0.02111 * P_5^2 + 36.32782 * P5 + 1658.5696
F6 = 0.01799 * P_6^2 + 38.27041 * P6 + 1356.6592

Table 5.2 Loss Co Efficients

B coefficients= * 10^{-4}

1.40	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

Table 5.3 Emission Equations

E1 = 0.00419 * P_1^2 + 0.32767 * P1 + 13.85932
E2 = 0.00419 * P_2^2 + 0.32767 * P2 + 13.85932
E3 = 0.00683 * P_3^2 - 0.54551 * P3 + 40.26690
E4 = 0.00683 * P_4^2 - 0.54551 * P4 + 40.26690
E5 = 0.00461 * P_5^2 - 0.51116 * P5 + 42.89553
E6 = 0.00461 * P_6^2 - 0.51116 * P6 + 42.89553

Table 5.4 Generator limits

Generator	P_1	P_2	P_3	P_4	P_5	P_6
Min Limit	10	10	35	35	130	125
Max Limit	125	150	225	210	325	315

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