A NEW APPROACH TO ECONOMIC POWER DISPATCH USING PARTICLE SWARM OPTIMIZATION WITH ADAPTIVE INERTIA WEIGHT

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ABSTRACT

This paper presents a new particle swarm optimization based on nature inspired dynamic inertia weight (PSO-NIDIW) for solving economic power dispatch problems. NIDIW which mimics the social behavior of humans is proposed to cogently balance the global exploration and local exploitation abilities for PSO. In each iteration during the run, each particle can select appropriate weight according to its situation. The performance of the PSO algorithm is improved by this fine strategy of naturally adjusting dynamic inertia weight. The economic load dispatch (ELD) is formulated as a nonlinear constrained optimization problem with equality and inequality constraints. The results obtained by the PSO-NIDIW are analyzed statistically in terms of solution quality and computation efficiency with genetic algorithm (GA) and PSO for various power systems. The statistical analyses disclose that PSO-NIDIW is an ultimate method to solve economic power load dispatch problems as it provides higher solution quality in comparison with other optimization algorithms.

Keywords: *Particle Swarm Optimization, Dynamic Inertia Weight, Economic Load Dispatch*.

I. INTRODUCTION

The main aim of economic load dispatch (ELD) is to minimize the total generation cost of generation units, while satisfying several equality and inequality constraints. Due to the physical limitations of generators, generating units have prohibited operating zones (POZs). The optimum dispatch of power generating units leads to saving of substantial amount of power and money.

An extensive category of classical and artificial intelligence methods has been applied to solve the ELD problems. The Classical and gradient based methods include linear programming, λ-iteration method [1], gradient method [2], branch and bound [3], quadratic programming [4]. The ELD problem becomes discontinuous one due to the presence of POZs and multiple fuels [5]. As gradient methods are applicable for smooth and continuous functions, it is difficult to solve the ELD problems. Modified gradient methods such as dimensional steepest decline method [5] and Big-M method [6] have been developed. But these methods involve additional computation to account the modifications. The dynamic programming method can be used to generate global solutions for the nonlinear and discrete cost curves of the generation units [7]. Nevertheless, dynamic programming has the drawback of curse of dimensionality that worsens for large scale problems and results in higher computation time.

The heuristic optimization techniques (HOTs) can be classified into several categories like evolutionary algorithms, swarm intelligence techniques and immune algorithms. Swarm intelligence techniques are inspired by the flocking behavior of birds, bees and bats. The HOTs include genetic algorithm (GA) [8,9], Evolutionary Programming (EP) [10], Particle Swarm Optimization (PSO) and its variants [11-15], neural networks [16,17], Differential Evolution (DE) [18] Firefly Algorithm (FA) [19], Bat Algorithm [20], Differential Search algorithm [21], and Artificial BeeColony Algorithm (ABC) [22] have been applied to solve the ELD problem.

The recent advancement in HOTs is to amend the existing algorithms by dynamically adapting the parameters which enhance the performance of the algorithm to improve diversity and avoid premature convergence [23-26]. In this research article, a new particle swarm optimization with nature inspired inertia weight (PSO-NIDIW) is developed to solve the ELD problem of power systems. In PSO-NIDIW, the inertia weight is naturally adapted on the basis of the improvement in the best fitness of the particles as the search process progresses. The NIDIW controls the exploitation and exploration ability of the PSO algorithm. Two test systems have been solved by PSO-NIDIW to demonstrate its performance. The PSO-NIDIW is easy to implement and exhibits promising results.

The rest of the paper is organized as follows. Section 2 describes the ELD problem formulation, Section 3 introduces the PSO-NIDIW algorithm, and Section 4 explains its application to the ELD problem. Section 5 presents the results of the PSO-NIDIW applied to two test systems, and Section 6 concludes the paper.

II. PROBLEM FORMULATION OF ELD PROBLEM

The objective of ELD problem is to find an optimal power generation schedule while minimizing fuel cost and also satisfying various power system operating constraints.

A. Objective function

The ELD problem is formulated as follows:

$$\text{Minimize } F = \sum_{i=1}^{ng} F_i(P_i) \tag{1}$$

The total fuel cost of the generators is defined by:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i \tag{2}$$

Where, F_i total fuel cost of the generators

a_i, b_i, c_i cost coefficients of generator i.

B. Problem Constraints

1) Power balance constraints

The total power output of the generators must be equal to the sum of power demands and total transmission losses and is given by:

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

The transmission losses are expressed as

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i} P_i + B_{00} \tag{4}$$

Where, P_D power demand

P_L transmission losses

B_{ij} line loss coefficients

1)Generator capacity constraints

The output power of each unit needs to be restricted with inequality constraints between lower and upper bounds. This constraint is represented by

$$P_{i,min} \le P_i \le P_{i,max} \tag{5}$$

Where, $P_{i,min}$, $P_{i,max}$ minimum and maximum generation of uniti.

3) Ramp rate constraints

The actual operating range of all the generating units is limited by the ramp-rate constraint and is given as follows:

$$P_i - P_i^0 \le UR_i \tag{6}$$

Where, P_i, P_i^0 current and previous power output of i^{th} unit respectively

UR_i,DR_i up and down ramp limits of i^{th} unit respectively

4) Prohibited operating zone

Prohibited operating zones in the input–output curve of generator are due to steam valve operation or vibration in its shaft bearing. For units with prohibited operating zones, there are additional constraints on the unit operating range:

$$P_{i,min} \le P_i \le P_1$$

$$P_{i,k-1}^{U} \le P_i \le P_{i,k}^{L} \qquad k = 2, \ldots nz$$
$$P_{i,nz}^{U} \le P_i \le P_{i,max}$$

Where, k index of prohibited zone
nz number of prohibited zones of unit i
$P_{i,k}^{L}$, $P_{i,k}^{U}$ lower and upper limits of kth prohibited zone of generator i

II. REVIEW OF PSO AND PSO-NIDIW

A. Particle swarm optimization

PSO is a population-based optimization paradigm which models the social behavior of birds flocking or fish schooling for food. It works with a population of potential solutions rather than with a single individual and the solutions are flown through hyperspace and are accelerated towards better or more optimum solutions. Its paradigm is implemented in simple form of computer codes and computationally inexpensive in terms of both memory requirements and speed. The higher dimensional space calculations of the PSO concept are performed over a series of time steps. The population is responding to the quality factors of the previous best individual values and the previous best group values. This approach can be used to solve many of the same kinds of problems as GA, and does not suffer from some of GAs difficulties. It has also been found to be vigorous in solving non-linear, non-differential and high-dimensional problems.

PSO consists of a swarm of particles moving in the D-dimensional space of possible problem solutions. Each particle embeds the relevant information regarding the D decision variables and is associated with a fitness that provides an indication of its performance in the objective space. Each particle i has a position $X_i = [X_{i,1}, X_{i,2} \ldots X_{i,D}]$ and a flight velocity $V_i = [V_{i,1}, V_{i,2} \ldots V_{i,D}]$. Moreover, a swarm contains each particle i own best position $pbest_i = (pbest_{i,1}, pbest_{i,2}, \ldots, pbest_{i,D})$ found so far and a global best particle position gbest = ($gbest_i$, $gbest_i$, ……., $gbest_D$) found among all the particles in the swarm so far.In essence, the trajectory of each particle is updated according to its own flying experience as well as to that of the best particle in the swarm.

The standard PSO algorithm can be described as

$$V_{i,d}^{k+1} = W \times V_{i,d}^{k} + C_1 \times rand_1 \times (pbest_{i,d}^{k} - X_{i,d}^{k}) + C_2 \times rand_2 \times (gbest_d^{k} - X_{i,d}^{k} \quad (7)$$

$$X_{i,d}^{k+1} = X_{i,d}^{k} + V_{i,d}^{k+1} \quad i= 1, 2\ldots, n;\ d= 1, 2\ldots, D \quad (8)$$

Where W is a inertia weighting factor; C_1 is a cognition acceleration factor; C_2 is a social acceleration factor; $rand_1$ and $rand_2$ are two random numbers uniformly distributed between 0 and 1; $V_{i,d\,k}$ is the velocity of particle i at iteration k; $X_{i,d\,k}$ is the dth dimension position of particle i at iteration k; $pbest_{i,d}^{k}$ is the dth dimension of the own best position of particle i until iteration k; $gbest_d^{k}$ is the dth dimension of the best particle in the swarm at iteration k.

The time varying weighting function was introduced in as per which W is given by

$$W= W_{max} - (W_{max} - W_{min}) \times t / t_{max} \quad (9)$$

Where W_{max} and W_{min} initial and final weight respectively,
t and t_{max} current and maximum iteration numbers.

The model using Eq. (9) is called 'inertia weights approach (IWA)'. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. Thus, the parameter W regulates the trade-off between the global and the local exploration abilities of the swarm. A large inertia weight facilitates exploration, while a small one tends to facilitate exploitation.

B. Particle swarm optimizer with nature inspired dynamic inertia weight (PSO-NIDIW)

In this paper, a greedy approach is used to self-adopt the inertia weight factor in PSO algorithm [23]. The inertia weight is updated at each iteration rendering to the improvement in the best fitness. This approach mimics the human behavior that "a success of one's act increases one's self-possession, while a failure decreases it". In this adaptation strategy, the inertia weight should be increased for better fit particles and vice versa. When the algorithm starts with larger inertia weight values, the strong exploration behavior is achieved among the swarms. In contrast, smaller inertia weight at the final generation of the algorithm leads the swarms to search better solution in the smaller region. The inertia weight is taken as a function of generation number and is updated as follows:

$$W(t+1) = 0.9 \qquad if\ t = 0$$
$$= F(t-1) - F(t) \qquad if\ t > 0$$

Where $W(t+1)$ inertia weight at (t +1)th iteration

$F(t)$ objective value at tth iteration.

When using this greedy approach, the oscillations in inertia weight are larger at initial generations of swarms which help the swarm in sustaining the diversity and resulting in good exploration. Thus, the particles fly through the entire search space quickly. Towards the final generation, the inertia weight oscillations become smaller which facilitate fine tuning of the solution. When the inertia weight is zero for many successive iterations, the cognitive and social components stuck with the suboptimum solutions and also decelerates the search process. If the swarm trapped for consecutive iterations, some inertia is given to increase the diversity. Thus, the inertia factor is modified as follows

$$W(t+1) = 0.9 \qquad if\ t = 0\ (10)$$
$$= F(t-1) - F(t) \qquad if\ t > 0$$
$$= W_{\max} - (W_{\max} - W_{\min}) \times \frac{t}{t_{\max}} \qquad if\ W = 0$$

III. SOLUTION OF ELD PROBLEMS WITH PSO-NIDIW

The process of the PSO-NIDIW algorithm for solving ELD problems can be summarized as follows:

Step 1: Initialization of the swarm

Since the decision variables are real power generationsfor the ELD problems, they are used to form the swarm. The real power output of all generators is represented as the particle's positions in the swarm. Each element of the swarm is initialized by a uniform probability distribution function in the range [0 – 1] and located between the upper and the lower operating limits of the generators.

Step 2: Evaluation of velocity

The velocities of the particles are generated randomly in the range [$-V_j^{max}$,V_j^{max}]

Step 3: Defining the evaluation function

The constrained optimization problem uses the concept of penalty function to handle constraints. The penalty function method employs fitness functions in proportion to the magnitude of the constraint violation. The penalty parameters are selected carefully to distinguish between feasible and infeasible solution. The evaluation function is defined as follows

$$f(P_i) = \sum_{i=1}^{ng} F_i(P_i) + \alpha \left[\sum_{i=1}^{ng} P_i - P_D - P_L \right]^2 + \beta \left[\sum_{i=1}^{ng} P_i(violation) \right]^2 \ (11)$$

Where α and β are penalty factors for real power balance and POZ constraints, and P_i(violation) is an indicator of falling into the POZ.

Step 4: Initialization of pbest and gbest

The fitness values obtained by Eq. (11) for the initial particles of the swarm are set as the initial pbest values of the particles. The best value among all the pbest values is ascertained as gbest.

Step 5: Updating of NIDIW factor

The nature inspired dynamic inertia weight factor is calculated using Eq. (10)

Step 6: Updating of particles velocity

In the PSO-NIDIW, new velocities for all the dimensions in each particle are updated using Eq. (7).

Step 7: Updating of particles' position

The new position of the particles is updated using Eq. (8) and then pbest and gbest valuesare updated.

Step 7: Stopping criteria

Check the termination condition. If the maximum iteration number is reached, then the IPSO is terminated and output the optimal results. Otherwise, the procedure is repeated from Step 4.

IV. TEST RESULTS AND ANALYSIS

To test the effectiveness of the PSO-NIDIW approach, two different test systems have been solved. The results obtained are compared with the GA and PSO. To compare the performance of the PSO-NIDIW approach, 50 independent trial runs are made and the results of the maximum, minimum and mean fuel costs are tabulated for each test system. The number of particles in the swarm is 40 and the maximum number of iterations is 100 for the two test systems. The programs are implemented in MATLAB.

A. Case study I: 6-unit system

This is a small system comprising six generators and satisfying a load demand of 1263 MW, and includes transmission loss, POZ and ramp rate limits. The system data of this test case is presented in Table 1. Table 3 depicts the optimal generation schedule and total generation cost obtained by GA, PSO and PSO-NIDIW approaches. It is found from the Table that the proposed PSO-NIDIW approach provides lesser fuel cost than the other approaches.

Table 1. System data for 6-units

Unit(i)	P_i^{max}	P_i^{min}	a_i	b_i	c_i	P^{UR}	P^{DR}	P_i^{prev}	POZs
1	100	500	240	7.0	0.0070	80	120	440	[210,240],[350,380]
2	50	200	200	10.0	0.0095	50	90	170	[90,110],[140,160]
3	80	300	220	8.5	0.0090	65	100	200	[150,170],[210,240]
4	50	150	200	11.0	0.0090	50	90	150	[80,90],[110,120]
5	50	200	220	10.5	0.0080	50	90	190	[90,110],[140,150]
6	50	120	190	12.0	0.0075	50	90	110	[75,85],[100,105]

Table 2.System data for 15-units

Unit(i)	P_i^{max}	P_i^{min}	a_i	b_i	c_i	P^{UR}	P^{DR}	P_i^{prev}	POZs
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185,225],[305,335],[420,450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.4	0.000205	80	120	90	[180,200],[305,335],[390,420]
6	135	460	630	10.1	0.000301	80	120	400	[230,255],[365,395],[430,455]
7	135	465	548	9.80	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	
12	20	80	230	9.90	0.005513	80	80	40	[30,40],[55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 3. Best solution for 6-unit system

Unit (MW)	GA	PSO	PSO-NIDIW
P_1	474.8066	447.4970	434.4340
P_2	178.6363	173.3221	173.4276
P_3	262.2089	263.4745	274.2358
P_4	134.2826	139.0594	128.4132
P_5	151.9039	165.4761	179.5051
P_6	74.1812	87.1280	85.7725
P_L	13.0217	12.9584	12.9572
Minimum cost ($/hr)	15,459	15,450	15,449

Table 4. Results obtained by various methods for 6-unit system

Compared items	GA	PSO	PSO-NIDIW
Max. cost	15524	15492	15490
Min. cost	15,459	15,450	15,449
Mean cost	15469	15454	15449
CPU time (sec)	41.89	14.89	15.73

Moreover, the statistical results of the minimum, maximum and mean fuel cost obtained by various approaches are compared. From Table 4, it is evident that the proposed PSO-NIDIW approach outperforms the other approaches.

B. Case study II: 15-unit system

This is a slightly larger test system, and consists of the 15 generating units. The transmission losses and prohibited operating zone are considered. The total load demand of the system is 2630 MW. The generator coefficients, capacity limits ramp rate limits and prohibited zones are given in Table 4. The optimal generation schedule, cost and power loss obtained by the proposed PSO-NIDIW approach are compared with GA and PSO approaches in Table 5. Furthermore, the statistical results of 50 independent trials for the 15-unit system are tabulated in Table 6. The comparative results clearly show that the proposed PSO-NIDIW approach is proficient of producing higher quality solution than the other evolutionary methods.

Table 5. Best solution for 15-unit system

Unit (MW)	GA	PSO	PSO-NIDIW
P_1	415.31	439.12	454.99
P_2	359.72	407.97	380
P_3	104.42	119.63	129.99
P_4	74.98	129.99	130
P_5	380.28	151.07	169.568
P_6	426.79	459.99	460
P_7	341.32	425.56	429.98
P_8	124.79	98.56	78.1358
P_9	133.14	113.49	52.374
P_{10}	89.26	101.11	157.564
P_{11}	60.06	33.91	79.92
P_{12}	50.0	79.96	79.906
P_{13}	38.77	25.0	25.633
P_{14}	41.94	41.41	16.539
P_{15}	22.64	35.61	15.3854
P_L	38.2782	32.4306	31.964
Minimum cost ($/hr)	33113	32858	32760

Table 6. Results obtained by various methods for 15-unit system

Compared items	GA	PSO	PSO-NIDIW
Max. cost	33337	33331	33322
Min. cost	33113	32858	32760
Mean cost	33228	33039	33028
CPU time (sec)	49.31	26.59	28.34

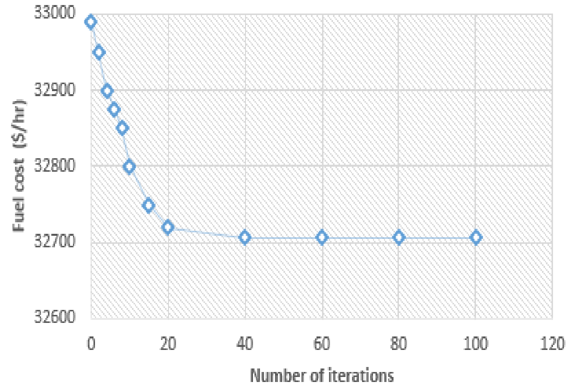

Figure1. Convergence behavior of PSO-NIDIW for 15-unit system

C. Convergence characteristics

Figure. 1 shows that the PSO-NIDIW approach has good convergence property, thus resulting in good evaluation value and low generation cost.

V. CONCLUSION

In this paper, nature inspired dynamic inertia weight based PSO algorithm (PSO-NIDIW) for solving the economic load dispatch (ELD) has been investigated. The PSO-NIDIW approach has been tested on two test systems and the obtained results are compared with GA and PSO approaches. The statistical analyses show that the proposed PSO-NIDIW approach improves the performance of PSO algorithm significantly in terms of solution quality, convergence speed and computational effort. The PSO-NIDIW approach can be extended to solve other optimization problems in the area of power systems. Comparative study of adaptive strategies to other HOTs could also be a good research area for future work.

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