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Hybrid PSO-GSA for Economic Load Dispatch with Valve-Point Effects

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ABSTRACT: This paper developed a new method to solve the economic load dispatch (ELD) considering the valve-point effects in power systems. The method is based on a hybrid particle swarm optimization and gravitational search algorithm (hybrid PSO-GSA) techniques. The fundamentally of this algorithm is to combine the ability of social thinking in PSO with the local search capability of GSA. The hybrid PSO-GSA technique is applied to a thirteen unit test system to illustrate the effectiveness of the proposed algorithm. The results show that the proposed algorithms certainly produce more optimal solution when compared results of other optimization algorithms reported in literature.

KEYWORDS: Particle swarm optimization, gravitational search algorithm, economic load dispatch, valve-point effects.

I. INTRODUCTION

The economic load dispatch (ELD) problem is one of the fundamental issues in power system operation and control. The ELD problem finds the optimum allocation of load among the committed generating units subject to satisfaction of power balance and capacity constraints, such that the total cost of operation is kept at a minimum. Various methods and investigations are being carried out until date in order to produce a significant saving in the operational cost. Generally, fuel cost function of a generator is represented by single quadratic function. But a quadratic function is not able to show the practical behavior of generator. The ELD problem is a non-convex and nonlinear optimization problem. Due to ELD complex and nonlinear characteristics, it is hard to solve the problem using classical optimization methods such as gradient method, lambda iteration method, Newton's method, linear programming, Interior point method and dynamic programming [1, 2].

Over the past few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed for ELD problem such as genetic algorithm (GA) [3], improved tabu search (TS) [4], simulated annealing (SA) [5], neural network (NN) [6], evolutionary programming (EP) [7]-[9], biogeography-based optimization (BBO) [10], differential evolution (DE) [11], gravitational search algorithm (GSA) [12], and particle swarm optimization (PSO) [13]-[16].

PSO is a stochastic algorithm which can be applied to a nonlinear optimization problem. PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling by Kennedy and Eberhart [17], [18]. The main difficulty classic PSO is its sensitivity to the choice of parameters and they also premature convergence, which might occur when the particle and group best solutions are trapped into local minimums during the search process. One of the recently improved heuristic algorithms is the gravitational search algorithm (GSA) based on the Newton's law of gravity and mass interactions. GSA has been verified high quality performance in solving different optimization problems in the literature [19]. The same objective for them is to find the best outcome (global optimum) among all possible inputs. For undertake this, a heuristic algorithm should be equipped with two major characteristics to ensure finding global optimum. These two main characteristics are exploration and exploitation [20].

In this paper, a novel and efficient approach is proposed to solve the ELD problems using a new hybrid PSO-GSA technique. The performance of the proposed approach has been demonstrated on 13-unit test system. Obtained

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simulation results demonstrate that the proposed method provides very remarkable results for solving the ELD problem. The results have been compared with other optimization reported in the literature.

II. PROBLEM FORMULATION

The main objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for each unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be explained as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i\right) \quad (1)$$

where F_T is total fuel cost of generation in power system ($/hr), a_i, b_i, and c_i are the cost coefficient of the *i*-th generator, P_i is the power generated by the *i*-th unit and n indicates the number of generators.

2.1. Active Power Balance Equation

For the balance of power, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total transmission loss.

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \quad (2)$$

where P_D is the total load demand and P_{Loss} is total transmission loss. The transmission losses P_{Loss} can be calculated by using B matrix technique and is defined by (3) as,

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \quad (3)$$

where B_{ij} is coefficient of transmission losses and the B_{0i} and B_{00} is matrix for loss in transmission which are constant under certain assumed conditions.

2.2. Minimum and Maximum Power Limits

The output power of each generator should lie between minimum and maximum limits, so that

$$P_i^{\min} \le P_i \le P_i^{\max} \quad \text{for } i = 1,2,\cdots,n \quad (4)$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum outputs of the *i*-th generator, respectively.

2.3. Valve Point Effects

The fuel cost function with the valve-point effects of the thermal generating unit are taken into consideration in the ELD problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoidal component as follows [14]:

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i + \left|e_i \times \sin\left(f_i \times \left(P_i^{\min} - P_i\right)\right)\right|\right) \quad (5)$$

where F_T is total fuel cost of generation in ($/hr) including valve point loading, e_i, f_i are fuel cost coefficients of the *i*-th generating unit reflecting valve-point effects.

III. META-HEURISTIC OPTIMIZATION

3.1. Overview of Particle Swarm Optimization (PSO)

The particle swarm optimization (PSO) algorithm is introduced by Kennedy and Eberhart based on the social behavior metaphor. In PSO a potential solution for a problem is considered as a bird without quality and volume, which is called a particle, flying through a *D*-dimensional space by adjusting the position in search space according to its own experience and its neighbors. In PSO, the *i*-th particle is represented by its position vector x_i in the *D*-dimensional space

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and its velocity vector v_i. In each time step t, the particles calculate their new velocity then update their position according to equations (6) and (7) respectively.

$$v_i^{t+1} = w \times v_i^t + c_1 \times r_1 \times \left(pbest_i - x_i^t\right) + c_2 \times r_2 \times \left(gbest - x_i^t\right) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

$$w = w_{\max} - \left(\frac{(w_{\max} - w_{\min}}{Iter_{\max}}\right) \times Iter \tag{8}$$

where v_i^t is velocity of particle i at iteration t, w is inertia factor, c_1 and c_2 are accelerating factor, r_1 and r_2 are positive random number between 0 and 1, $pbest_i$ is the best position of particle i, $gbest$ is the best position of the group, w_{max} and w_{min} are maximum and minimum of inertia factor, $Iter_{max}$ is maximum iteration, n is number of particles.

The PSO begin with randomly placing the particles in a problem space. In each iteration, the velocities of particles are calculated using (6). After defining the velocities, position of masses can be calculated as (7). The process of changing particles' position will continue until the stop criteria is reached.

3.2. Gravitational Search Algorithm (GSA)

Gravitational Search Algorithm (GSA) is a novel heuristic optimization technique which has been proposed by E. Rashedi et al in 2009 [19]. The basic physical theory which GSA is inspired from the Newton's theory. This algorithm, which is based on the Newtonian physical law of gravity and law of motion, has great potential to be a breakthrough optimization method. In the GSA, consider a system with N agent (mass) in which position of the i-th mass is defined as follows:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i = 1,2,\ldots,m \tag{9}$$

where x_i^d is position of the i-th mass in the d-th dimension and n is dimension of the search space. At the specific time t a gravitational force from mass j acts on mass i, and is defined as follows:

$$F_{ij}^d(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{10}$$

where $G(t)$ is the gravitational constant at time t, $M_i(t)$ and $M_j(t)$ are the masses of the objects i and j, and ε is a small constant, and $R_{ij}(t)$ is the Euclidean distance between the two objects i and j objects described as follows:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \tag{11}$$

The masses of the agents are calculated as follows by comparison of fitness:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{12}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \tag{13}$$

where $fit_i(t)$ represents the fitness value of the agent i at time t, $best(t)$ is maximum fitness values of all agents and $worst(t)$ is the minimum fitness.

Randomly initialized gravitational constant $G(t)$ is decreased according to the time as follows:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \tag{14}$$

where α and G_0 are descending cooefficient and initial value respectively, t is current iteration, and T is maximum number of iterations.

The total force that acts on agent i in the dimension d is described as follows:

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$$F_i^d(t) = \sum_{\substack{j=1 \\ j \neq i}}^{m} rand_j F_{ij}^d(t) \qquad (15)$$

where $rand_j$ is a random number interval [0, 1].

According to the law of motion, the acceleration of the agent *i*, at time *t*, in the *d* dimension, $a_i^d(t)$ is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \qquad (16)$$

Then, the searching strategy can be described by the next velocity and next position of an agent. The next velocity function is the sum of the current velocity and its current acceleration. The current acceleration is described as the initial acceleration calculated from (16). The initial position is calculated from (9) and the initial speed is determined by producing a zero matrix, which has a dim x *N* dimension (dim: dimension of problem, *N*: number of agents). Also, the next position function is the sum of the current position and the next velocity of that agent. These functions are shown as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \qquad (17)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (18)$$

were $rand_i$ is a random number interval [0, 1], $v_i^d(t)$ is the velocity and $x_i^d(t)$ is the position of an agent at time *t* in the *d* dimension.

While solving an optimization problem with GSA, at the beginning of the algorithm, every agent is located at a certain point of the search space, which represents a solution to the problem at every unit of time. Next, according to (17) and (18), masses are evaluated and their next positions are calculated. Then, gravitational constant *G*, masses *M*, and acceleration α are calculated through (12)–(14) and (16) and updated at every time cycle. The search process is stopped after a certain amount of time.

3.3. The Hybrid PSO-GSA

A hybrid PSO-GSA approach is an integrated approach between PSO and GSA which combines the ability of social thinking (*gbest*) in PSO with the local search capability of GSA. In order to combine these algorithms, the updated velocity of agent *i* can be calculated as follows [20]:

$$V_i(t+1) = w \times V_i(t) + c_1 \times rand_i \times a_i(t) + c_2 \times rand_i \times \left(gbest - X_i(t)\right) \qquad (19)$$

where V_i(t) is the velocity of agent *i* at iteration *t*, c_j is a weighting factor, *w* is a weighting function, *rand* is a random number between 0 and 1, a_i(t) is the acceleration of agent *i* at iteration *t*, and *gbest* is the best solution so far.

The updating position of the particles at each iteration as follows:

$$X_i(t+1) = X_i(t) + V_i(t) \qquad (20)$$

In hybrid PSO-GSA, at the beginning of the algorithm, all agents are randomly initialized. Each mass (agent) is considered as a candidate solution. After initialization, Gravitational force, gravitational constant, and resultant forces among agents are calculated using (10), (14), and (15) respectively. After that, the acceleration of particles are defined as (16) and updated at every time cycle. After calculating the accelerations and with updating the best solution so far, the velocities of all agents can be calculated using (19). Finally, the positions of agents are defined as (20). The search process is stopped after a certain amount of time.

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IV. SIMULATION RESULTS

In order to validate the robustness of the proposed technique, a 13-unit system was tested. The generators data are shown in Table 1 [8]. In this sample system consisting of thirteen generators with valve-point effects and have a total load demands of 1800 MW and 2520 MW, respectively. The PSO-GSA parameters used for the simulation are adopted as follow: $c_1 = 0.5$, $c_2 = 1.5$, $w = \text{rand}[0, 1]$, $\alpha = 20$ and $G_0 = 100$. The population size N and maximum iteration number T are set to 30 and 100, respectively.

The results obtained by proposed methods are compared with other optimization algorithms as presented in Table 2 and Table 3 for load demands of 1800 MW and 2520 MW, respectively. In Table 2, generation outputs and corresponding cost obtained by the proposed method are compared with those of NN-EPSO, EP-EPSO, and GSA [12, 21]. The proposed algorithm provides a better solution (total generation cost of 17517.0118 $/hr) than other methods while satisfying the system constraints. In Table 3, generation outputs and corresponding cost obtained by the proposed method are compared with those of GA-SA, PSO-SQP, and GSA [12, 21]. The proposed algorithm provides a better solution (total generation cost of 24019.8924 $/hr) than other methods while satisfying the system constraints. We have also observed that the solutions using hybrid PSO-GSA algorithm always are satisfied with the equality and inequality constraints.

Table 1 Generating units capacity and coefficients

Unit	P_{min} (MW)	P_{max} (MW)	a	b	c	e	f
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Table 2 Comparison between several methods (P_D = 1800 MW)

Unit power output	NN-EPSO [21]	EP-EPSO [21]	GSA [12]	PSO-GSA
P1 (MW)	490.0000	505.4731	628.3185	425.0980
P2 (MW)	189.0000	254.1686	149.5996	182.5087
P3 (MW)	214.0000	253.8022	222.7492	133.5717
P4 (MW)	160.0000	99.8350	109.8666	162.4450
P5 (MW)	90.0000	99.3296	109.8665	153.9582
P6 (MW)	120.0000	99.3035	109.8665	113.9438
P7 (MW)	103.0000	99.7772	109.8665	133.8305
P8 (MW)	88.0000	99.0317	60.0000	104.7926
P9 (MW)	104.0000	99.2788	109.8666	85.6033
P10 (MW)	13.0000	40.0000	40.0000	66.7367
P11 (MW)	58.0000	40.0000	40.0000	60.8971
P12 (MW)	66.0000	55.0000	55.0000	77.3235
P13 (MW)	55.0000	55.0000	55.0000	99.2915
Total output power (MW)	1800	1800	1800	1800
Total generation cost ($/h)	18442.5931	17932.4766	17960.3684	**17517.0118**

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Table 3 Comparison between several methods (P_D = 2520 MW)

Unit power output	GA-SA [21]	PSO-SQP [21]	GSA [12]	PSO-GSA
P1 (MW)	628.23	628.3205	628.3185	590.3875
P2 (MW)	299.22	299.0524	299.1993	322.2105
P3 (MW)	299.17	298.9681	294.5730	319.4067
P4 (MW)	159.12	159.4680	159.7331	170.7089
P5 (MW)	159.95	159.1429	159.7331	136.4957
P6 (MW)	158.85	159.2724	159.7331	157.6274
P7 (MW)	157.26	159.5371	159.5371	128.8908
P8 (MW)	159.93	158.8522	159.7331	131.4204
P9 (MW)	159.86	159.7845	159.7331	158.3310
P10 (MW)	110.78	110.9618	77.3999	117.6114
P11 (MW)	75.00	75.0000	77.3999	92.3914
P12 (MW)	60.00	60.0000	92.3999	75.2367
P13 (MW)	92.62	91.6401	92.3999	119.2817
Total output power (MW)	2520	2520	2520	2520
Total generation cost ($/h)	24275.71	24261.05	24164.2514	**24019.8924**

V. CONCLUSION

In this paper, hybrid PSO-GSA technique has been successfully applied to solve the ELD problem of generating units with considering the valve-point effects. The proposed technique has provided the global solution in 13-unit test systems and the better solution than the previous studies reported in literature. Also, the equality and inequality constraints treatment methods have always provided the best solutions satisfying the constraints.

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