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Soft Computing Techniques For Solving Economic Load Dispatch With Generator Constraints

Eko Sarwono[1], Hardiansyah[2]
[1]*Department of Mechanical Engineering, Universitas Muhammadiyah Pontianak, Indonesia*
[2]*Department of Electrical Engineering, University of Tanjungpura, Indonesia*
Corresponding Author: Hardiansyah

-ABSTRACT-
This paper proposes a novel and efficient hybrid algorithm based on combining particle swarm optimization (PSO) and gravitational search algorithm (GSA) techniques, called PSO-GSA. The core of this algorithm is to combine the ability of social thinking in PSO with the local search capability of GSA. Many practical constraints of generators, such as power loss, ramp rate limits, and prohibited operating zones are considered. The new algorithm is implemented to the economic load dispatch (ELD) problem so as to minimize the total generation cost when considering the equality and inequality constraints. In order to validate of the proposed algorithm, it is applied to two cases with six and fifteen generators, respectively. The results show that the proposed algorithms indeed produce more optimal solution in both cases when compared results of other optimization algorithms reported in literature.
Keywords *- Particle swarm optimization, gravitational search algorithm, economic load dispatch, ramp rate limits, prohibited operating zones*

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I. INTRODUCTION

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. Traditionally, 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.

Most of classical optimization techniques such as lambda iteration method, gradient method, Newton's method, linear programming, Interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. There are various practical limitations in power system operation and control such as ramp rate limits, prohibited operating zones, transmission losses, etc. Therefore, the practical ELD problem is represented as a non-convex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming (DP) method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the last 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], particle swarm optimization (PSO) [13]-[16], differential evolution (DE) [17], and gravitational search algorithm (GSA) [18].

PSO is a stochastic algorithm that can be applied to nonlinear optimization problems. PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling by Kennedy and Eberhart [11], [12]. 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 goal for them is to find the best outcome (global optimum) among all possible inputs. In order to do 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 ELD problems using a new hybrid PSO-GSA technique. The performance of the proposed approach has been demonstrated on two different test systems, i.e. 6-unit and 15-unit systems. Obtained simulation results demonstrate that the proposed method provides very remarkable results for solving the ELD problem. The results have been compared to those reported in the literature.

II. PROBLEM FORMULATION

The objective of ELD problem is minimizing total fuel cost in power system so that reach to the best generation between power plants and satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator as defined by (1) under a set of operating constraints.

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

where F_T indicates total fuel cost of generation in the 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 is the number of generators.

2.1. Active Power Balance Equation

The total generated power should be equal to the total load demand plus the total transmission loss.

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

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

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

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

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

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

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

2.3. Ramp Rate Limits

The ramp-up and ramp-down constraints can be written as follows,

$$P_i(t) - P_i(t-1) \le UR_i \qquad (5)$$

$$P_i(t-1) - P_i(t) \le DR_i \qquad (6)$$

where $P_i(t)$ and $P_i(t\text{-}1)$ are the present and previous power outputs, respectively. UR_i and DR_i are the ramp-up and ramp-down limits of the *i*-th generator (in units of MW/time period).

To consider the ramp rate limits and power output limits constraints at the same time, therefore, equations (4), (5) and (6) can be rewritten as follows:

$$\max\{P_i^{\min}, P_i(t-1) - DR_i\} \le P_i(t) \le \min\{P_i^{\max}, P_i(t-1) + UR_i\} \qquad (7)$$

2.4. Prohibited Operating Zones

The generating units with prohibited operating zones have discontinuous and nonlinear cost characteristics. This characteristic can be formulated in ELD problems as follows:

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{l} \\ P_{i,k-1}^{u} \le P_i \le P_{i,k}^{l}, \quad k = 2,3,\ldots,pz_i \\ P_{i,pz_i}^{u} \le P_i \le P_i^{\max}, \; i = 1,2,\ldots,n_{pz} \end{cases} \qquad (8)$$

where $P_{i,k}^{l}$ and $P_{i,k}^{u}$ are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. Here, pz_i is the number of prohibited zones of unit *i* and n_{pz} is the number of units which have prohibited operating zones.

III. META-HEURISTIC OPTIMIZATION

3.1. Overview of Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is an evolutionary computation technique developed 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 and its velocity vector v_i. In each time step *t*, the particles calculate their new velocity then update their position according to equations (9) and (10) respectively.

$$v_i^{t+1} = w \times v_i^t + c_1 \times r_1 \times \left(pbest_i - x_i^t\right) + c_2 \times r_2 \times \left(gbest - x_i^t\right) \quad (9)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (10)$$

$$w = w_{\max} - \left(\frac{(w_{\max} - w_{\min}}{Iter_{\max}}\right) \times Iter \quad (11)$$

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 (9). After defining the velocities, position of masses can be calculated as (10). 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:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i = 1,2,\ldots,m \quad (12)$$

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:

$$F_{ij}^d(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \quad (13)$$

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:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \quad (14)$$

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

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (15)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \quad (16)$$

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:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \quad (17)$$

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:

$$F_i^d(t) = \sum_{\substack{j=1 \\ j \neq i}}^{m} rand_j F_{ij}^d(t) \tag{18}$$

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:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{19}$$

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 (19). The initial position is calculated from (12) 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:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{20}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{21}$$

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 (20) and (21), masses are evaluated and their next positions are calculated. Then, gravitational constant *G*, masses *M*, and acceleration *α* are calculated through (15)–(17) and (19) and updated at every time cycle. The search process is stopped after a certain amount of time.

3.3. The Hybrid PSO-GSA

The hybrid PSO-GSA technique 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]:

$$V_i(t+1) = w \times V_i(t) + c_1 \times rand_i \times a_i(t) + c_2 \times rand_i \times \left(gbest - X_i(t)\right) \tag{22}$$

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:

$$X_i(t+1) = X_i(t) + V_i(t) \tag{23}$$

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 (13), (17), and (18) respectively. After that, the acceleration of particles are defined as (19) 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 (22). Finally, the positions of agents are defined as (23). The search process is stopped after a certain amount of time.

IV. SIMULATION RESULTS

In order to confirm effectiveness and feasibility of the proposed technique for solving ELD problem, two different power systems were tested: 6-unit and 15-unit systems considering power loss, ramp rate limits and prohibited operating zones.

4.1. Test Case 1: 6-unit system

The system consists of six thermal generating units. The total load demand on the system is 1263 MW. The parameters of all thermal units are presented in Table 1 and Table 2 [13], respectively.

Table 1: Cost coefficients and unit operating limits

Unit	$P_i^{\min}$ (MW)	$P_i^{\max}$ (MW)	a_i (\$/MW^{2}h)	b_i (\$/MWh)	c_i (\$/h)
1	100	500	0.0070	7.0	240
2	50	200	0.0095	10.0	200
3	80	300	0.0090	8.5	220
4	50	150	0.0090	11.0	200
5	50	200	0.0080	10.5	220
6	50	120	0.0075	12.0	190

Table 2: Ramp rate limits and prohibited operating zones

Unit	P_i^0 (MW)	UR_i (MW/h)	DR_i (MW/h)	Prohibited operating zones (MW)
1	440	80	120	[210, 240] [350, 380]
2	170	50	90	[90, 110] [140, 160]
3	200	65	100	[150, 170] [210, 240]
4	150	50	90	[80, 90] [110, 120]
5	190	50	90	[90, 110] [140, 150]
6	110	50	90	[75, 85] [100, 105]

The transmission losses are calculated by *B* matrix loss formula which for 6-unit system is given as:

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 1.0e^{-3} * [-0.3908 \ -0.1297 \ 0.7047 \ 0.0591 \ 0.2161 \ -0.6635]$$

$$B_{00} = 0.0056$$

The obtained results for the 6-unit system using the proposed method are given in Table 3 and the results are compared with other methods reported in literature, including GA, PSO and IDP [21], RGA and GA-PSO [22]. It can be observed that the proposed method can get total generation cost of 15,443 (\$/h) and power losses of 12.3877 (MW), which is the best solution among all the methods. Note that the outputs of the generators are all within the generator's permissible output limit.

Table 3: Comparison of the best results of each methods (P_D = 1263 MW)

Unit	GA	PSO	IDP	RGA	GA-PSO	PSO-GSA
P1 (MW)	474.8066	447.4970	450.9555	420.2342	431.5408	447.3077
P2 (MW)	178.6363	173.3221	173.0184	199.4412	184.272	173.2182
P3 (MW)	262.2089	263.0594	263.6370	263.7234	259.7322	263.2595
P4 (MW)	134.2826	139.0594	138.0655	120.0030	138.8306	138.9686
P5 (MW)	151.9039	165.4761	164.9937	167.2319	168.6130	165.3604
P6 (MW)	74.1812	87.1280	85.3094	105.1250	92.4211	87.3293
Total power output (MW)	1276.0217	1275.9584	1275.9794	1275.7588	1275.4093	1275.4437
Total generation cost (\$/h)	15,459	15,450	15,450	15,461.3	15,446.1	15,443
Power losses (MW)	13.0217	12.9584	12.9794	12.7588	12.4093	12.3877

4.2. Test Case 2: 15-unit system

This system consists of 15 generating units and the input data of 15-generator system are given in Tables 4 and 5 [13], [23]. Transmission loss B-coefficients are taken from [23]. In order to validate the proposed method, it is tested with 15-unit system having non-convex solution spaces, and the load demand is 2630 MW.

The best solution obtained from proposed method and other optimization algorithms are compared in Table 6 for load demands of 2630 MW. In Table 6, generation outputs and corresponding fuel cost and losses obtained by the proposed method are compared with those of GA, PSO and MPSO [23]. The proposed method provide better solution (total generation cost of 32,579 \$/h and power losses of 28.2968 MW) than other methods while satisfying the system constraints. We have also observed that the solutions by proposed method always are satisfied with the equality and inequality constraints.

Table 4: Generating unit capacity and coefficients (15-units)

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^{2}h)	b_i ($/MWh)	c_i ($/h)
1	150	455	0.000299	10.1	671
2	150	455	0.000183	10.2	574
3	20	130	0.001126	8.8	374
4	20	130	0.001126	8.8	374
5	150	470	0.000205	10.4	461
6	135	460	0.000301	10.1	630
7	135	465	0.000364	9.8	548
8	60	300	0.000338	11.2	227
9	25	162	0.000807	11.2	173
10	25	160	0.001203	10.7	175
11	20	80	0.003586	10.2	186
12	20	80	0.005513	9.9	230
13	25	85	0.000371	13.1	225
14	15	55	0.001929	12.1	309
15	15	55	0.004447	12.4	323

Table 5: Ramp rate limits and prohibited operating zones

Unit	P_i^0 (MW)	UR_i (MW/h)	DR_i (MW/h)	Prohibited operating zones (MW)
1	400	80	120	
2	300	80	120	[185, 225] [305, 335] [420, 450]
3	105	130	130	
4	100	130	130	
5	90	80	120	[180, 200] [305, 335] [390, 420]
6	400	80	120	[230, 255] [365, 395] [430, 455]
7	150	80	120	
8	95	65	100	
9	105	60	100	
10	110	60	100	
11	60	80	80	
12	40	80	80	[30, 40] [55, 65]
13	30	80	80	
14	20	55	55	
14	20	55	55	

Table 6: Best solution of 15-unit systems (P_D = 2630 MW)

Unit	GA	PSO	MPSO	PSO-GSA
P1 (MW)	415.3108	439.1162	455.0000	455.0000
P2 (MW)	359.7206	407.9729	390.8112	455.0000
P3 (MW)	104.4250	407.9729	112.7000	130.0000
P4 (MW)	74.9853	129.9925	124.3310	130.0000
P5 (MW)	380.2844	151.0681	356.6001	230.4315
P6 (MW)	426.7902	459.9978	443.3111	460.0000
P7 (MW)	341.3164	425.5601	433.1601	465.0000
P8 (MW)	124.7876	98.5699	91.1211	60.0000
P9 (MW)	133.1445	113.4936	66.0001	25.0000
P10 (MW)	89.2567	101.1142	30.2511	36.4530
P11 (MW)	60.0572	33.9116	24.1401	74.8058
P12 (MW)	49.9998	79.9583	51.6001	80.0000
P13 (MW)	38.7713	25.0042	45.0300	25.0000
P14 (MW)	41.4140	41.4140	23.3000	15.0000
P15 (MW)	22.6445	36.6140	15.0000	15.0000
Total power output (MW)	2668.2782	2662.4306	2662.4306	2656.0964
Power losses (MW)	38.2782	32.4306	32.4306	26.0964
Total generation cost ($/h)	33,113	32,858	32,780	32,547

V. CONCLUSION

In this paper, a new hybrid PSO-GSA technique has been applied to solve the ELD problem of generating units considering ramp rate limits, prohibited operation zones and transmission losses. The proposed technique has provided the global solution in the 6-unit and 15-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 solutions satisfying the constraints.

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