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Hybrid PSO-GSA Technique for Environmental/ Economic Dispatch Problem

Muhammad Saleh, Fitri Imansyah, Usman A. Gani, Hardiansyah*
Department of Electrical Engineering, University of Tanjungpura
Jl. A. Yani Pontianak 78124, Indonesia

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, prohibited operating zones and valve point effect, are considered. The new algorithm is implemented to solve combined environmental economic dispatch (CEED) problem in power systems considering the power limits. The CEED is to minimize both the operating fuel cost and emission level simultaneously while satisfying the load demand and operational constraints. The effectiveness of the proposed algorithm has been tested on 10-unit system and the results were compared with other methods reported in recent literature. The simulation results show that the proposed algorithm outperforms previous optimization methods.

Keywords— Economic dispatch, emission dispatch, combined environmental economic dispatch, particle swarm optimization, gravitational search algorithm, valve-point effect.

I. INTRODUCTION

Modern power systems are very complex and include nonlinear characteristics. Economic dispatch (ED) is one of the most fundamental issues in power system operation and control for allocating generation among the committed units. The objective of the ED problem is to determine the amount of real power contributed by online thermal generators satisfying load demand at any time subject to unit and system constraints so as the total generation cost is minimized. Therefore, it is very important to solve the problem as quickly and precisely as possible [1, 2]. Therefore, recently most of the researchers made studies for finding the most suitable power values produced by the generators depending on fuel costs. In these studies, they produced successful results by using various optimization algorithms [3-5]. Despite the fact that the traditional ED can optimize generator fuel costs, it still cannot produce a solution for environmental pollution due to the excessive emission of fossil fuels.

Currently, a large part of energy production is done with thermal sources. Thermal power plant is one of the most important sources of carbon dioxide (CO_2), sulfur dioxide (SO_2) and nitrogen oxides (NO_x) which create atmospheric pollution [6]. Emission control has received increasing attention owing to increased concern over environmental pollution caused by fossil based generating units and the enforcement of environmental regulations in recent years [7]. Numerous studies have emphasized the importance of controlling pollution in electrical power systems [8].

Combined environmental economic dispatch (CEED) has been proposed in the field of power generation dispatch, which simultaneously minimizes both fuel cost and pollutant emissions. When the emission is minimized the fuel cost may be unacceptably high or when the fuel cost is minimized the emission may be high. A number of methods have been presented to solve CEED problems such as simplified recursive method [9], genetic algorithm [10-12], simulated annealing [13, 14], biogeography based optimization [15], differential evolution [16], particle swarm optimization [17, 18], and artificial bee colony algorithm [19, 20].

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 [21, 22]. 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 [23]. 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 [24].

In this paper, a novel and efficient approach is proposed to solve CEED problems using hybrid PSO-GSA technique. The performance of the proposed approach has been tested on 10-unit systems. Obtained simulation results demonstrate that the proposed method provides very remarkable results for solving the CEED problem. The results have been compared to those reported in the literature.

II. PROBLEM FORMULATIONS

The CEED problem targets to find the optimal combination of load dispatch of generating units and minimizes both fuel cost and emission while satisfying the total power demand. Therefore, CEED consists of two objective functions, which are economic and emission dispatches. Then these two functions are combined to solve the problem. The CEED problem can be formulated as follows [11]:

$$F_T = Min\ f\left(FC, EC\right) \tag{1}$$

where F_T is the total generation cost of the system, *FC* is the total fuel cost of generators and *EC* is the total emission of generators.

2.1. Minimization of Fuel Cost

Mathematically, the fuel cost of each generating unit, considering the valve-point effects, is defined as the sum of a quadratic function and a sinusoidal function [11]. Total fuel cost of a power generating station can be expressed as:

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

where P_i is the power generation of the *i*th unit; a_i, b_i, c_i, e_i, and f_i are fuel cost coefficients of the *i*th generating unit; and *N* is the number of generating units.

2.2. Minimization of Emission

The classical ED problem can be obtained by the amount of active power to be generated by the generating units at minimum fuel cost, but it is not considered as the amount of emissions released from the burning of fossil fuels. Total amount of emissions such as SO_2 or NO_X depends on the amount of power generated by until and it can be defined as the sum of quadratic and exponential functions and can be stated as [11]:

$$EC = \sum_{i=1}^{N}\left(\alpha_i P_i^2 + \beta_i P_i + \gamma_i + \eta_i \exp(\delta_i P_i)\right) \tag{3}$$

where α_i, β_i, γ_i, η_i and δ_i are emission coefficients of the *i*th generating unit.

2.3. Combined Environmental Economic Dispatch (CEED)

CEED is a multi-objective problem, which is a combination of both economic and environmental dispatches that individually make up different single problems. At this point, this multi-objective problem needs to be converted into single-objective form in order to fulfill optimization. The conversion process can be done by using the price penalty factor [11]. However, the single-objective CEED can be formulated as shown in equation (4):

$$F_T = (w_1 * FC + w_2 * h * EC) \tag{4}$$

under the following condition,

$$w_1 + w_2 = 1 \text{ and } w_1, w_2 \geq 0 \tag{5}$$

where w_1, w_2 are weight factor and *h* is the price penalty factor.

2.4. Problem Constraints

There are two constraints in the CEED problem which are power balance constraint and maximum and minimum limits of power generation output constraint.

Power balance constraint:

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{6}$$

$$P_L = \sum_{i}^{N}\sum_{j}^{N} B_{ij} P_i P_j \tag{7}$$

Generating capacity constraint:

$$P_{i\min} \leq P_i \leq P_{i\max} \tag{8}$$

where P_D is total demand of system (MW); P_L is total power loss; $P_{i\,min}$ and $P_{i\,max}$ are minimum and maximum generation of unit *i* (MW); and B_{ij} is coefficients of transmission loss.

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, adjusting its 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.

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

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{10}$$

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

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 concept of the searching mechanism of PSO using the modified velocity and position of individual *i* based on (9), (10) and (11) if the value of *w*, c_1, c_2, r_1, and r_2 are 1.

The process of implementing the PSO is as follows:

Step 1: Create an initial population of individual with random positions and velocity within the solution space.
Step 2: For each individual, calculate the value of the fitness function.
Step 3: Compare the fitness of each individual with each *Pbest*. If the current solution is better than its *Pbest*, then replace its *Pbest* by the current solution.
Step 4: Compare the fitness of all individual with *Gbes*t. If the fitness of any individual is better than *Gbest*, then replace *Gbest*.
Step 5: Update the velocity and position of all individual according to (9) and (10).
Step 6: Repeat steps 2-5 until a criterion is met.

3.2. Gravitational Search Algorithm (GSA)

Rashedi et al. proposed one of the newest heuristic algorithms, namely Gravitational Search Algorithm (GSA) in 2009. GSA is based on the physical law of gravity and the law of motion. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them [23]. GSA a set of agents called masses has been proposed to find the optimum solution by simulation of Newtonian laws of gravity and motion. In the GSA, consider a system with *m* masses in which position of the *i-th* mass is defined as follows:

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

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:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{13}$$

where M_i is the mass of the object *i*, M_j is the mass of the object *j*, *G(t)* is the gravitational constant at time *t*, R_{ij} *(t)* is the Euclidian distance between the two objects *i* and *j*, and ε is a small constant.

The total force acting on agent *i* in the dimension *d* is calculated as follows:

$$F_i^d(t) = \sum_{\substack{j=1 \\ j \neq i}}^{m} rand_j F_{ij}^d(t) \tag{14}$$

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

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

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{15}$$

Furthermore, the next velocity of an agent is a function of its current velocity added to its current acceleration. Therefore, the next position and the next velocity of an agent can be calculated as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad (16)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (17)$$

where $rand_i$ is a uniform random variable in the interval [0, 1].

The gravitational constant, *G*, is initialized at the beginning and will be decreased with time to control the search accuracy. In other words, *G* is a function of the initial value (G_0) and time *t*:

$$G(t) = G(G_0, t) \quad (18)$$

$$G(t) = G_0 e^{-\frac{t}{T}} \quad (19)$$

The masses of the agents are calculated using fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and moves more slowly. Supposing the equality of the gravitational and inertia mass, the values of masses is calculated using the map of fitness. The gravitational and inertial masses are updating by the following equations:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (20)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \quad (21)$$

where $fit_i(t)$ represents the fitness value of the agent *i* at time *t*, and the *best(t)* and *worst(t)* in the population respectively indicate the strongest and the weakest agent according to their fitness route. For a minimization problem:

$$best(t) = \min_{j \in [1,\ldots,m]} fit_j(t) \quad (22)$$

$$worst(t) = \max_{j \in [1,\ldots,m]} fit_j(t) \quad (23)$$

For a maximization problem:

$$best(t) = \max_{j \in [1,\ldots,m]} fit_j(t) \quad (24)$$

$$worst(t) = \min_{j \in [1,\ldots,m]} fit_j(t) \quad (25)$$

The GSA approach for optimization problem can be summarized as follows [23]:

Step 1: Search space identification,
Step 2: Generate initial population between minimum and maximum values,
Step 3: Fitness evaluation of agents,
Step 4: Update *G(t)*, *best(t)*, *worst(t)* and $M_i(t)$ *for* $i = 1,2,\ldots,m$,
Step 5: Calculation of the total force in different directions,
Step 6: Calculation of acceleration and velocity,
Step 7: Updating agents' position,
Step 8: Repeat step 3 to step 7 until the stop criteria is reached,
Step 9: Stop.

3.3. The Hybrid PSO-GSA

In this section, the hybridize PSO with GSA using low-level co-evolutionary heterogeneous hybrid. The hybrid is low-level because we combine the functionality of both algorithms. It is co-evolutionary because we do not use both algorithm one after another. In other words, they run in parallel. It is heterogeneous because there are two different algorithms that are involved to produce final results.

The basic idea of PSO-GSA method is to combine 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:

$$V_i(t+1) = w \times V_i(t) + c_1 \times rand_i \times a_i(t) + c_2 \times rand_i \times (gbest - X_i(t)) \quad (26)$$

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 position of the particles at each iteration updated as follow:

$$X_i(t+1) = X_i(t) + V_i(t) \quad (27)$$

The process of the proposed PSO-GSA algorithm can be summarized as the following steps:

Step 1: Get the data for the system,
Step 2: Generate initial population,
Step 3: Fitness evaluation of agents,
Step 4: Update *G(t)* and *gbest(t),*
Step 5: Calculation of the mass of the object, gravitational constant, the total force, and acceleration,
Step 6: Updating agents' velocity and position,
Step 7: Repeat step 3 to step 6 until the stop criteria is reached,
Step 8: Stop.

IV. SIMULATION RESULTS

The proposed techniques have been applied to a test power system consists of ten generators at 2000 MW power demand. Generation unit data has been taken from [25]. Simulations were performed in MATLAB R2010a environment on a PC with a 3 GHz processor. 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, for all case studies.

The cases considered are as follows:

1) Case I: Optimization of each of the two objectives individually.
2) Case II: Optimization of the fuel cost and gas emission simultaneously.

1) Case I:

In this case, the fuel cost and the gas emission are minimized separately as a single objective functions. Minimizing each objective function individually is executed by giving full weight to the function to be optimized and neglecting others. Table 1 presents the results of economic dispatch when the objective is minimizing just the fuel cost (w_1=1, w_2=0). The fuel cost and the gas emission output of 10 unit system for 2000 MW are 111263.9098 $/h and 4364.1590 lb/h respectively when the fuel cost is the optimized function. The power losses are 87.0147 MW.

Table 2, presents the results of economic emission dispatch when the objective is minimizing just the gas emission (w_1=0, w_2=1). The fuel cost and the gas emission output of 10 unit system for 2000 MW are 116230.2729 $/h and 3837.3189 lb/h respectively when the gas emission is the optimized function. The power losses are 81.5398 MW.

Table 1 Comparison of the best fuel cost results of each methods (P_D = 2000 MW)

Unit Output	ABC_PSO [25]	DE [16]	SA [14]	**PSO-GSA**
P1 (MW)	55	55	54.9999	54.9999
P2 (MW)	80	79.89	80	80
P3 (MW)	106.93	106.8253	107.6263	103.8418
P4 (MW)	100.5668	102.8307	102.5948	102.0008
P5 (MW)	81.49	82.2418	80.7015	80.9345
P6 (MW)	83.011	80.4352	81.1210	85.2378
P7 (MW)	300	300	300	300
P8 (MW)	340	340	340	340
P9 (MW)	470	470	470	469.9999
P10 (MW)	470	469.8975	470	470
Losses (MW)	87.0344	-	87.0434	**87.0147**
Fuel cost ($/h)	111500	111500	111498.6581	**111263.9098**
Emission (lb/h)	4571.2	4581	4584.8366	**4364.1590**

2) Case II:

In this case, the problem as multi-objective; two objectives are minimized simultaneously (the fuel cost and the gas emission objectives) by using the weighted factors w_1 = 0.5 and w_2 = 0.5. The multi-objective optimization problem can be converted to a single objective optimization problem by introducing weighted factors. Table 3, presents the results of combined environmental economic dispatch when the objective is minimizing both fuel cost and the gas emission. The fuel cost and the gas emission output of 10 unit system for 2000 MW are 113409.8128 $/h and 4117.1231 lb/h respectively. The power losses are 83.7851 MW.

Table 2 Comparison of the best emission results of each methods (P_D = 2000 MW)

Unit Output	ABC_PSO [25]	DE [16]	SA [14]	**PSO-GSA**
P1 (MW)	55	55	54.9999	55
P2 (MW)	80	80	80	80
P3 (MW)	81.9604	80.5924	76.6331	81.8053
P4 (MW)	78.8216	81.0233	79.4332	82.1708
P5 (MW)	160	160	160	160
P6 (MW)	240	240	240	240
P7 (MW)	300	292.7434	287.9285	288.3336
P8 (MW)	292.78	299.1214	301.4146	303.3357
P9 (MW)	401.8478	394.5147	412.4386	397.3793
P10 (MW)	391.2096	398.6383	388.9348	393.5152
Losses (MW)	81.5879	-	81.7827	**81.5398**
Fuel cost ($/h)	116420	116400	116386	**116230.2729**
Emission (lb/h)	3932.3	3923.4	3935.9769	**3837.3189**

Table 3 Comparison of CEED results of each methods (P_D = 2000 MW)

Unit Output	ABC_PSO [25]	DE [16]	NSGA-II [16]	**PSO-GSA**
P1 (MW)	55	54.9487	51.9515	55
P2 (MW)	80	74.5821	67.2584	79.9716
P3 (MW)	81.14	79.4294	73.6879	86.5561
P4 (MW)	84.216	80.6875	91.3554	83.4382
P5 (MW)	138.3377	136.8551	134.0522	142.6408
P6 (MW)	167.5086	172.6393	174.9504	160.3467
P7 (MW)	296.8338	283.8233	289.435	298.3295
P8 (MW)	311.5824	316.3407	314.0556	323.9501
P9 (MW)	420.3363	448.5923	455.6978	426.4291
P10 (MW)	449.1598	436.4287	431.8054	427.1231
Losses (MW)	84.1736	-	-	**83.7851**
Fuel cost ($/h)	113420	113480	113540	**113409.8128**
Emission (lb/h)	4120.1	4124.9	4130.2	**4117.2719**

V. CONCLUSIONS

In this paper, a new hybrid PSO-GSA technique has been applied to solve CEED problem of generating units considering the valve-point effects and transmission losses. The proposed technique has provided the global solution in the 10-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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