

Combined Economic Emission Dispatch Solution using Simulated Annealing Algorithm

Hardiansyah¹, Junaidi², Yandri³

^{1,2,3}(Department of Electrical Engineering, University of Tanjungpura, Indonesia)

Abstract: This paper present a simulated annealing (SA) algorithm for solving the combined economic emission 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 philosophy involves the introduction of a new decision variable through a prudent mathematical transformation of the relation between the decision variable and the optimal generations. A novel best mechanism algorithm based on global optimization approaches is inspired by annealing process of thermodynamics. Numerical results for the standard IEEE 30-bus 6-generator test system have been presented to illustrate the performance and applicability of the proposed approach. The results obtained are compared to those reported in the recent literature. Those results show that the proposed algorithm provides effective and robust high-quality solution of the CEED problem.

Keywords: Economic dispatch, emission dispatch, combined economic emission dispatch, simulated annealing algorithm, global optimization.

I. Introduction

The principal objective of the economic dispatch (ED) problem is to find a set of active power delivered by the committed generators to satisfy the required demand subject to the unit technical limits at the lowest production cost. 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 (CO₂), sulfur dioxide (SO₂) 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. Numerous studies have emphasized the importance of controlling pollution in electrical power systems [7].

Combined economic and emission 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 genetic algorithm [8], artificial bee colony algorithm [9, 10], analytical solution [11, 12], particle swarm optimization [13, 14], and biogeography based optimization [15].

This paper proposes a SA algorithm to solve the CEED problem. The performance of the proposed algorithm is tested on the standard IEEE 30-bus 6-generator test system. Numerical results obtained by the proposed approach were compared with other optimization results reported in the recent literature.

II. Problem Formulations

The economic emission dispatch (EED) 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, EED consists of two objective functions, which are economic and emission dispatches. Then these two functions are combined to solve the problem. The EED problem can be formulated as follows [8]:

$$F_T = \text{Min } f(FC, EC) \quad (1)$$

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 Economic Dispatch (ED)

The ED problem targets to find the optimal combination of power generation by minimizing the total fuel cost of all generator units while satisfying the total demand. The ED problem can be formulated in a quadratic form as follows:

$$F_C = \sum_{i=1}^N (a_i P_i^2 + b_i P_i + c_i) \tag{2}$$

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

2.2 Emission Dispatch (ED)

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 SO₂ or NO_x depends on the amount of power generated by until and it can be defined as the sum of a quadratic function as follows:

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

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

2.3 Combined Economic Emission 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. However, the single-objective EED can be formulated as shown in equation (4) [8, 10]:

$$\text{Min } F_T = \sum_{i=1}^N ((a_i P_i^2 + b_i P_i + c_i) + h_i (\alpha_i P_i^2 + \beta_i P_i + \gamma_i)) \text{ (\$/h)} \tag{4}$$

where h_i is the price penalty factor, and is formulated as follows:

$$h_i = \frac{a_i P_{i\max}^2 + b_i P_{i\max} + c_i}{\alpha_i P_{i\max}^2 + \beta_i P_{i\max} + \gamma_i} \tag{5}$$

where $P_{i\max}$ is the maximum power generation of the i th unit in MW.

2.4 Problem Constraints

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

Power balance constraint:

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

$$P_L = \sum_i \sum_j B_{ij} P_i P_j \tag{7}$$

Generating capacity constraint:

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

where:

- P_D = Total demand of the system (MW)
- P_L = Total power loss (MW)
- $P_{i\min}$ = Minimum generation of unit i (MW)
- $P_{i\max}$ = Maximum generation of unit i (MW)
- B_{ij} = Coefficients of transmission losses.

The conditions for optimality can be obtained by using Lagrangian multipliers method and Kuhn Tucker conditions as follows [1]:

$$\text{Min } L = F_T - \left(\sum_i P_i - P_D - P_{Loss} \right), \quad i = 1, 2, \dots, N \tag{9}$$

Equation coordination of these functions can be obtained as

$$\frac{dL(P_i)}{dP_i} = 2(a_i + h_i\alpha_i)P_i + (b_i + h_i\beta_i) = \lambda \tag{10}$$

The above equation can be solved iteratively to EED impose on the boundary of the generation and power balance equation as a constraint.

III. Simulated Annealing Algorithm

3.1. Overview

Simulated annealing is an optimization technique that simulates the physical annealing process in the field of combinatorial optimization. Annealing is the physical process of heating up a solid until it melts, followed by slow cooling it down by decreasing the temperature of the environment in steps. At each step, the temperature is maintained constant for a period of time sufficient for the solid to reach thermal equilibrium. At any temperature T , the thermal equilibrium state is characterized by the *Boltzmann distribution*. This distribution gives the probability of the solid being in a state i with energy E_i at temperature T as

$$P_i(T) = k \exp(-E_i/T) \tag{11}$$

where k is a constant.

Metropolis et al. [16] proposed a Monte Carlo method to simulate the process of reaching thermal equilibrium at a fixed value of the temperature T . In this method, a randomly generated perturbation of the current configuration of the solid is applied so that a trial configuration is obtained. Let E_c and E_t denote the energy level of the current and trial configurations, respectively. If $E_t < E_c$; then a lower energy level has been reached, and the trial configuration is accepted and becomes the current configuration. On the other hand, if $E_t \geq E_c$ the trial configuration is accepted as current configuration with probability proportional to $\exp(\Delta E/T)$, $\Delta E = E_t - E_c$. The process continues until the thermal equilibrium is achieved after a large number of perturbations, where the probability of a configuration approaches Boltzmann distribution [17, 18].

By gradually decreasing the temperature T and repeating Metropolis simulation, new lower energy levels become achievable. As T approaches zero least energy configurations will have a positive probability of occurring. The general algorithm of SA can be described in steps as follows:

- Step 1:** Set the initial value of C_{p0} and randomly generate an initial solution x_{initial} and calculate its objective function. Set this solution as the current solution as well as the best solution, i.e. $x_{\text{initial}} = x_{\text{current}} = x_{\text{best}}$
- Step 2:** Randomly generate an n_1 of trial solutions in the neighborhood of the current solution.
- Step 3:** Check the acceptance criterion of these trial solutions and calculate the acceptance ratio. If acceptance ratio is close to 1 go to Step 4; else set $C_{p0} = \alpha.C_{p0}$; $\alpha > 1$; and go back to Step 2.
- Step 4:** Set the chain counter $k = 0$.
- Step 5:** Generate a trial solution x_{trial} . If x_{trial} satisfies the acceptance criterion set $x_{\text{current}} = x_{\text{trial}}$, $J(x_{\text{current}}) = J(x_{\text{trial}})$ and go to Step 6; else go to Step 6.
- Step 6:** Check the equilibrium condition. If it is satisfied go to Step 7; else go to Step 5.
- Step 7:** Check the stopping criteria. If one of them is satisfied then stop; else set $k = k + 1$ and $C_p = \mu.C_p$; $\mu < 1$; and go back to Step 5.

3.2. Proposed SA

In all the existing SA algorithm based approaches for solving ELD problems, the real power generation of all generating units are considered as the decision variables that makes the size of the problem vary large, slow down the speed of these algorithms and hence not suitable for systems having larger number of generating units. In the proposed approach, the penalty factor λ of the classical λ - iteration is considered as the only decision variable irrespective of the number of generating units. The real power of all the generating plants are considered as the problem dependant variables and expressed as a function of λ . The real power generations are computed using (10) for each λ value obtained during the SA iterations.

The lower and upper limits of the decision variable- λ depend on the minimum and maximum power demands that the system can supply. The first step in obtaining these values is to compute the lower and upper incremental cost values by substituting the respective to real power limits in (10) for all the plants as

$$IC_i^{\min} = 2(a_i + h_i\alpha_i)P_i^{\min} + (b_i + h_i\beta_i) \tag{12}$$

$$IC_i^{\max} = 2(a_i + h_i\alpha_i)P_i^{\max} + (b_i + h_i\beta_i)$$

The next step is choosing the lowest and highest incremental cost value, obtained from (12), as the limits for λ .

$$\lambda^{\min} = \min(IC_1^{\min}, IC_2^{\min}, \dots, IC_N^{\min}) \tag{13}$$

$$\lambda^{\max} = \max(IC_1^{\max}, IC_2^{\max}, \dots, IC_N^{\max})$$

The SA searches for the optimal solution by minimizing a cost function. In the proposed formulation, the net fuel cost of all the generating plant is considered as the cost function. However, a penalty term is

included in the cost function to handle the explicit power balance constraint. The penalty term increases the cost function for infeasible solutions. The cost function is therefore built as a blend of fuel cost function and the power balance constraint through the use of a penalty factor as

$$\text{Minimize } F_T = \sum_{i=1}^N F_i(P_i) + \lambda \left[\sum_{i=1}^N P_i - P_D - P_{Loss} \right] \quad (14)$$

The number of decision variables in this formulation is always one, whereas the existing SA based approaches require the generation of all the plants as the variables. This reduction in decision variables will reduce the overall computational burden and improves the convergence rate. The algorithm of the proposed SA for solving the CEED problem is outlined.

1. Read the input data of the CEED problem
2. Set $k = 0$
3. Choose initial temperature T_i , cooling coefficient α , number of iterations for each temperature N_i and maximum number of iterations N_{max} .
4. Choose a random start point λ_0 within the specified range
5. Repeat the following:
 - a. Select a random point λ_k from the neighbourhood of λ_0 within the specified range
 - b. Solve (10) for P_i while imposing the limits given by (8)
 - c. Calculate F_T^k using (14)
 - d. If $F_T^k < F_T^0$ then accept the trial solution by setting $\lambda_0 = \lambda_k$
 Else select a random number \mathfrak{R} in the range $[0, 1]$
 If $P(T) > \mathfrak{R}$, then $\lambda_0 = \lambda_k$, otherwise discard the trial point
 - e. Check convergence by comparing the number of iterations k with N_{max}
 If converged, stop and print the CEED corresponding to the λ_0 . Otherwise, set $k = k + 1$
6. Reduce the temperature by the factor α and go to step 5.

IV. Simulation Results And Discussion

In the study of experiment, SA algorithm is tested over standard IEEE 30-bus 6-generator test system as shown in Figure 1. The parameters of all thermal units are presented in Table I, followed by B -loss coefficient [8, 10, 12].

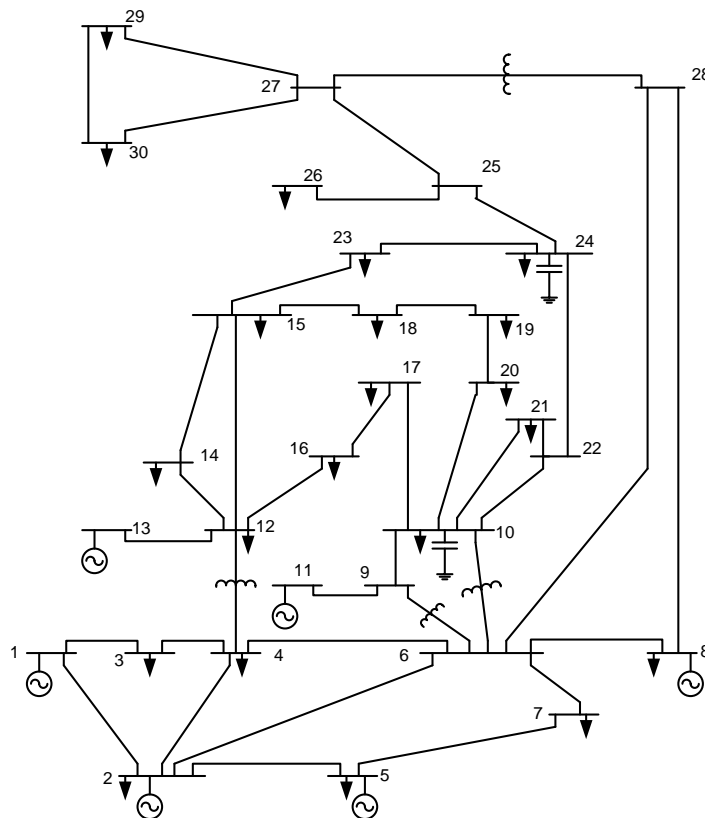


Figure 1 Single-line diagram of IEEE 30-bus test system [10]

The proposed technique is applied for CEED problem with load demands 500 MW, 700 MW, and 900 MW, respectively and it is compared with FCGA and NSGA-II [19]. Minimum fuel cost solution for CEED problem with all load demands are considered respectively in Table II, Table III, and Table IV. Minimum NO_x emission effect solution for CEED problem with all load demands are considered respectively in Table V, Table VI, and Table VII. The best compromise solution for CEED problem with all load demands are considered respectively in Table VIII, Table IX, and Table X.

Table I Generator capacity limits, fuel cost and emission coefficients for IEEE 30-bus test system

Unit	P_i^{\min} (MW)	P_i^{\max} (MW)	a_i (\$/MW ²)	b_i (\$/MW)	c_i (\$)	α_i (\$/MW ²)	β_i (\$/MW)	γ_i (\$)
1	10	125	0.15240	38.53973	756.79886	0.00419	0.32767	13.85932
2	10	150	0.10587	46.15916	451.32513	0.00419	0.32767	13.85932
3	35	225	0.02803	40.39655	1049.9977	0.00683	-0.54551	40.26690
4	35	210	0.03546	38.30553	1243.5311	0.00683	-0.54551	40.26690
5	130	325	0.02111	36.32782	1658.5596	0.00461	-0.51116	42.89553
6	125	315	0.01799	38.27041	1356.6592	0.00461	-0.51116	42.89553

$$B_{ij} = \begin{bmatrix} 0.002022 & -0.000286 & -0.000534 & -0.000565 & -0.000454 & -0.000103 \\ -0.000286 & 0.003243 & 0.000016 & -0.000307 & -0.000422 & -0.000147 \\ -0.000534 & 0.000016 & 0.002085 & 0.000831 & 0.000023 & -0.000270 \\ -0.000565 & -0.000307 & 0.000831 & 0.001129 & 0.000113 & -0.000295 \\ -0.000454 & -0.000422 & 0.000023 & 0.000113 & 0.000460 & -0.000153 \\ -0.000103 & -0.000147 & -0.000270 & -0.000295 & -0.000153 & 0.000898 \end{bmatrix}$$

Table II Best fuel cost for 6-generator system ($P_D = 500$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	49.47	50.836	52.1024
P2 (MW)	29.40	31.806	29.0471
P3 (MW)	35.31	35.12	40.0000
P4 (MW)	70.42	73.44	68.0901
P5 (MW)	199.03	191.988	191.4150
P6 (MW)	135.22	135.019	136.4637
Fuel cost (\$/h)	28150.80	28150.834	28086.9456
Emission (kg/h)	314.53	309.04	306.3324
Power losses (MW)	18.86	18.208	17.1183
Total Capacity (MW)	518.86	518.208	517.1183

Table III Best fuel cost for 6-generator system ($P_D = 700$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	72.14	76.179	76.0897
P2 (MW)	50.02	51.81	49.0586
P3 (MW)	46.47	49.82	45.3525
P4 (MW)	99.33	103.407	102.7347
P5 (MW)	264.60	267.984	266.3914
P6 (MW)	203.58	184.734	191.3422
Fuel cost (\$/h)	38384.09	38370.746	38207.5910
Emission (kg/h)	543.48	534.924	532.6970
Power losses (MW)	36.15	33.934	30.9692
Total Capacity (MW)	736.14	733.934	730.9692

Table IV Best fuel cost for 6-generator system ($P_D = 900$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	101.11	102.963	103.4811
P2 (MW)	67.64	74.235	70.1005
P3 (MW)	50.39	66.003	60.6818
P4 (MW)	158.80	140.316	139.5618
P5 (MW)	324.08	324.888	325.0000
P6 (MW)	256.56	248.416	251.7912
Fuel cost (\$/h)	49655.40	49620.824	49297.9331
Emission (kg/h)	877.61	849.326	845.6922
Power losses (MW)	58.58	56.822	50.6162
Total Capacity (MW)	958.57	956.822	950.662

Table V Best emission effects for 6-generator system ($P_D = 500$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	81.08	56.931	58.064
P2 (MW)	13.93	41.542	43.721
P3 (MW)	66.37	73.896	75.725
P4 (MW)	85.58	84.931	83.975
P5 (MW)	141.70	136.502	133.454
P6 (MW)	135.93	131.328	128.777
Fuel cost (\$/h)	28756.71	28641.078	28626.520
Emission (kg/h)	286.59	275.544	274.254
Power losses (MW)	24.61	25.129	23.717
Total Capacity (MW)	524.61	525.129	523.717

Table VI Best emission effects for 6-generator system ($P_D = 700$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	120.16	103.078	105.329
P2 (MW)	21.36	73.505	76.408
P3 (MW)	62.09	91.556	92.920
P4 (MW)	128.05	110.787	109.834
P5 (MW)	209.65	187.869	183.192
P6 (MW)	201.12	174.289	170.013
Fuel cost (\$/h)	39455.00	39473.433	39433.477
Emission (kg/h)	516.55	467.388	462.716
Power losses (MW)	42.44	41.083	37.699
Total Capacity (MW)	742.44	741.083	737.699

Table VII Best emission effects for 6-generator system ($P_D = 900$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	133.31	124.998	124.989
P2 (MW)	110.00	109.893	88.322
P3 (MW)	100.38	111.081	123.954
P4 (MW)	119.27	141.961	134.833
P5 (MW)	250.79	254.36	274.647
P6 (MW)	251.25	226.578	215.480
Fuel cost (\$/h)	53299.64	51254.195	50517.633
Emission (kg/h)	785.64	760.052	751.274
Power losses (MW)	65.00	68.87	62.226
Total Capacity (MW)	965.00	968.87	962.226

Table VIII Best compromise solution for 6-generator system ($P_D = 500$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	65.23	54.048	54.720
P2 (MW)	24.29	34.250	32.597
P3 (MW)	40.44	54.497	49.227
P4 (MW)	74.22	80.413	77.730
P5 (MW)	187.75	161.874	166.342
P6 (MW)	125.48	135.426	137.214
Fuel cost (\$/h)	28231.06	28291.119	28164.743
Emission (kg/h)	304.90	284.362	282.402
Power losses (MW)	17.41	20.508	17.142
Total Capacity (MW)	517.41	520.508	517.142

Table IX Best compromise solution for 6-generator system ($P_D = 700$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	80.16	86.286	84.150
P2 (MW)	53.71	60.288	55.655
P3 (MW)	40.93	73.064	66.005
P4 (MW)	116.23	109.036	107.266
P5 (MW)	251.20	223.448	230.931
P6 (MW)	190.62	184.111	187.647
Fuel cost (\$/h)	38408.82	38671.813	38371.892
Emission (kg/h)	527.46	484.931	476.537
Power losses (MW)	32.85	36.234	31.656
Total Capacity (MW)	732.85	736.234	731.656

Table X Best compromise solution for 6-generator system ($P_D = 900$ MW)

Unit Output	FCGA	NSGA-II	SA
P1 (MW)	111.40	120.052	115.276
P2 (MW)	69.33	85.203	78.809
P3 (MW)	59.43	89.565	81.388
P4 (MW)	143.26	140.278	137.345
P5 (MW)	319.40	288.614	298.677
P6 (MW)	252.11	233.687	238.178
Fuel cost (\$/h)	49674.28	50126.059	49553.835
Emission (kg/h)	850.29	784.696	772.456
Power losses (MW)	54.92	57.405	49.676
Total Capacity (MW)	954.92	957.405	949.676

Summary of the results in Table II to Table X for the best completion of SA method compared with NSGA-II in order to reduce fuel costs, emissions, and power losses are shown in Table XI. After comparing the simulation results with the others method, it is obviously seen that proposed SA algorithm give more powerful results than other algorithms.

Table XI Summary of SA VS NSGA-II for 6-generator system

	LOAD (MW)		
	500	700	900
Best fuel cost			
Fuel cost (\$/h)	63.888	163.155	322.890
Emission (kg/h)	2.707	2.227	3.633
Power losses (MW)	1.089	2.964	6.205
Best emission			
Fuel cost (\$/h)	14.557	39.955	736.561
Emission (kg/h)	1.289	4.671	8.777
Power losses (MW)	1.411	3.384	6.644
Best compromise			
Fuel cost (\$/h)	126.376	299.920	572.223
Emission (kg/h)	1.959	8.393	12.239
Power losses (MW)	3.365	4.577	7.728

V. Conclusion

In this paper, a SA algorithm has been proposed and successfully applied to solve the CEED problem. Simulation results show that the SA approach provides effective and robust high-quality solution. Moreover, the results obtained using SA are either better or comparable to those obtained using other techniques reported in the literature.

References

- [1] A.J Wood, and B.F. Wollenberg, *Power Generation Operation and Control* (New York: John Wiley and Sons, 1984).
- [2] Hadi Saadat, *Power System Analysis* (New Delhi: Tata McGraw Hill Publishing Company, 2002).
- [3] S.Y. Lim, M. Montakhab, and H. Nouri, Economic dispatch of power system using particle swarm optimization with constriction factor, *International Journal of Innovations in Energy Systems and Power*, 4(2), 2009, 29-34.
- [4] Z. L. Gaing, Particle swarm optimization to solving the economic dispatch considering the generator constraints, *IEEE Transactions on Power Systems*, 18(3), 2003, 1187-1195.
- [5] D. C. Walters, and G. B. Sheble, Genetic algorithm solution of economic dispatch with valve point loading, *IEEE Transactions on Power Systems*, 8(3), 1993, 1325-1332.
- [6] T. Ratniyomchai, A. Oonsivilai, P. Pao-La-Or, and T. Kulworawanichpong, Particle swarm optimization for solving combined economic and emission dispatch problems, *5th IASME/WSEAS Int. Conf. Energy Environ.*, 2010, 211-216.
- [7] N. Cetinkaya, Optimization algorithm for combined economic and emission dispatch with security constraints, *Int. Conf. Comp. Sci. Appl. ICCSA*, 2009, 150-153.
- [8] U. Güvenç, Combined economic emission dispatch solution using genetic algorithm based on similarity crossover, *Sci. Res. Essay*, 5(17), 2010, 2451-2456.
- [9] S. Hemamalini, and S. P. Simon, Economic/emission load dispatch using artificial bee colony algorithm, *Int. Conf. Cont., Comm. Power Eng.*, 2010, 338-343.
- [10] Y. Sonmez, Multi-objective environmental/economic dispatch solution with penalty factor using artificial bee colony algorithm, *Sci. Res. Essay*, 6(13), 2011, 2824-2831.
- [11] C. Palanichamy, and N. S. Babu, Analytical solution for combined economic and emissions dispatch, *Electr. Power Syst. Res.*, 78, 2008, 1129-1137.
- [12] R. Balamurugan, and S. Subramanian, A simplified recursive approach to combined economic emission dispatch, *Electr. Power Comp. Syst.*, 36(1), 2008, 17-27.
- [13] Y. M. Chen, and W. S. Wang, A particle swarm approach to solve environmental/economic dispatch problem, *International Journal of Industrial Engineering Computations*, 1, 2010, 157-172.
- [14] Anurag Gupta, K. K. Swarnkar, and K. Wadhvani, Combined economic emission dispatch problem using particle swarm optimization, *International Journal of Computer Applications*, 49(6), 2012, 1-6.
- [15] P. K. Roy, S. P. Ghoshal, and S. S. Thakur, Combined economic and emission dispatch problems using biogeography-based optimization, *Electrical Engineering*, 92(4), 2010, 173-184.

- [16] N. Metropolis, A.W. Rosenbluth, M. N. Rosenbluth, A. H. Teller, and E. Teller, Equations of State Calculations by Fast Computing Machines, *J. Chem. Phys.*, 21, 1953, 1087-1092.
- [17] S. Kirkpatrick, C. D. Gelatt Jr, and M. P. Vecchi, Optimization by Simulated Annealing, *Science*, 220, 1983, 671–680.
- [18] E. Aarts, and J. Korst, *Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing*, (New York: Wiley, 1989).
- [19] HCS Rughooputh, and RTFA King, Environmental/economic dispatch of thermal units using an elitist multi-objective evolutionary algorithm, *IEEE Int. Conf. Ind. Tech.*, 2003, 48-53.