Simulated annealing optimization for multi-objective economic dispatch solution

Ismail ZIANE*, Farid BENHAMIDA, Amel GRAA

Irecom Laboratory, Department of Electrotechnics UDL University of Sidi Bel Abbes Sidi Bel Abbes, Algeria.
E-mails: ziane_ismail2005@yahoo.fr ; farid.benhamida@yahoo.fr; graa_amel@yahoo.fr
[*] Corresponding author, Phone: +213555835940

Abstract

This paper presents a multi-objective Simulated Annealing Optimization to solve a Dynamic Generation Dispatch problem. In this work, the problem is formulated as a multi-objective one with two competing functions, namely economic cost and emission functions, subject to different constraints. The inequality constraints considered are the generating unit capacity limits while the equality constraint is generation-demand balance. To show the advantages of the proposed algorithm, it has been applied for solving multi-objective EELD problems in a 3-generator system with NO_x and SO_2 emission. Results obtained with Simulated Annealing have been compared with other existing relevant approaches available in literatures. Experimental results show a proficiency of Simulated Annealing over other existing techniques in terms of robustness.

Keywords

Economic dispatch; Multi-objective optimization; Simulated annealing.

Introduction

The traditional economic dispatch is an optimization problem to find the most economical schedule of the generating units while satisfying load demands and load constraints.

The conventional economic dispatch (ED) cannot satisfy the environmental protection requirements, since it only considers minimizing the total fuel cost. The gaseous pollutants emitted by the power stations cause harmful effects with the human beings and the environment like the sulphur dioxide (SO_2), nitrogen oxide (NO_x), and the carbon dioxide (CO_2), etc. [1]. The optimization of production cost should not be the only objective but the reduction of emission must also be taken into account.

The ED problem can be handled as a multi-objective optimization problem that the objective functions are the total cost of electrical energy and the total emission function [2].

In general, multi-objective optimization problems are solved by reducing them to a scalar equivalent [3]. This is achieved by aggregating the objective functions into a single function [3].

Recently, multi-objective algorithms have also been used to solve the Dynamic Generation Dispatch problem. IBPVT approach [4], particle swarm optimization (PSO) [5], genetic algorithm (GA) [6], and linear programming [7]. New multi-objective stochastic search [8] has also been proposed to solve EED multi-objective problem by generating the Pareto optimal solution.

The objective of economic dispatch is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. On the other hand emission dispatch reduces the total emission from the system by an increase in the system operating cost.

Material and method

Economic dispatch and emission dispatch

The present formulation treats the EELD problem as a multi-objective mathematical programming problem which is concerned with the attempt to minimize each objective simultaneously. The equality and inequality constraints of the system must meanwhile, be satisfied. The following objectives and constraints are taken into account in the formulation of the EELD problem.

The economic dispatch problem can be modelled by:

$$\min F_T(P) = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

where F_T is the total fuel cost; $F_T(P_i)$ is the fuel cost of generating unit i; n is the no. of generator.

Fuel Cost Function: The fuel cost function of a generating unit is usually described by a quadratic function of power output P_i as:

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

where a_i ,b_i and c_i are the cost co-efficient of unit *i*.

Emission Equation: The Emission equation kg/hr of a generating unit is usually described by a quadratic function of power output P_i as:

$$E_{SO2i}(P_i) = d_{SO2i} P_i^2 + e_{SO2i} P_i + f_{SO2i} \tag{3}$$

where d_{SO2i}, e_{SO2i} and f_{SO2i} are the SO_2 emission co-efficient of unit *i*.

Similarly, the emission dispatch problem for NO_x can be defined as the following optimization problem

$$E_{NOxi}(P_i) = d_{NOxi} P_i^2 + e_{NOxi} P_i + f_{NOxi} \tag{4}$$

where d_{NOxi}, e_{NOxi} and f_{NOxi} are the NO_x emission co-efficient of unit *i*.

The emission dispatch problem for CO_2 can be defined as the following optimization problem

$$E_{CO2i}(P_i) = d_{CO2i} P_i^2 + e_{CO2i} P_i + f_{CO2i} \tag{5}$$

where d_{CO2i} , e_{CO2i} and f_{CO2i} are the CO_2 emission co-efficient of unit *i*.

Transmission losses: The transmission losses P_L can be found using B-coefficients

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} P_i P_i \tag{6}$$

where B_{ij} is the transmission line coefficients.

Power Balance Constraints: The total supply must be equal to power demand

$$\sum P_i = P_D + P_L \tag{7}$$

where P_D is the load demand.

Generator limit Constraints: The power generation of unit *i* should be between its minimum and maximum limits.

$$P_{i\,\min} \le P_i \le P_{i\,\max} \tag{8}$$

where $P_{i\,min}$ is the minimum generation limit of unit *i* and P_i max is the maximum generation limit of unit *i*.

Multi-objective dispatch model

The general structure of multi-objective generation and emission dispatch problem is expressed as- find:

$$\begin{aligned} P &= \left[P_1, P_2, \cdots, P_N\right]^T \\ \min F &= \left[F_{FC}, F_{SX}, F_{NX}, F_{CX}\right] \end{aligned} \tag{9}$$

Subject to:

$$\begin{aligned} h(P_i) &= 0 \\ g(P_i) &\le 0 \end{aligned} \tag{10}$$

The above mentioned multi- objective optimization problem can be converted to a single objective optimization problem by introducing price penalty factors as follows:

$$F_{Ti}(P_i) = F(P_i) + h_{SO2i}E_{SO2i}(P_i) + h_{NOXi}E_{NOxi}(P_i) + h_{CO2i}E_{CO2i}(P_i) \tag{11}$$

where h_{SO2}, h_{NOx} and h_{CO2} are price penalty factors for SO_2, NO_x, and CO_2, respectively, blending the emission costs with the normal fuel costs.

A simulated annealing algorithm for multi-objective dispatch model

The concept of simulated annealing was first introduced in the field of optimization in the early 1980's by Kirkpatrick and independently by Cerny [9]. Simulated annealing is a robust, general-purpose combinatorial optimization algorithm based on probabilistic methods which has been applied successfully too many areas such as VLSI circuit design, neural-networks, image processing, code design, capacitor placement in power systems, and economic load dispatch.

This method is based on slow cooling of a material at state fusion, which leads it to a solid state with low energy.

The same basic principle can be used in an optimization algorithm. The objective function to be minimized can be considered as the system energy, while different combinations of the optimization are the configurations of the system given its degrees of freedom.

Analogy to physical annealing

The name simulated annealing comes from an analogy between combinatorial optimization and the physical process of annealing. In physical annealing a solid is cooled very slowly, starting from a high temperature, in order to achieve a state of minimum internal energy. It is cooled slowly so that thermal equilibrium is achieved at each temperature. Thermal equilibrium can be characterized by the Boltzmann distribution.

$$P_T\{X = x\} = (e^{-E_X/k_B T}) / (\sum_i e^{-E_i/k_B T}) \tag{12}$$

where X is a random variable indicating the current state, E_x is the energy of state x, k_B is Boltzmann's constant, and T is temperature.

The evolution of the state of a solid in a heat bath toward thermal equilibrium can be efficiently simulated by a simple algorithm based on Monte Carlo techniques which was proposed by Metropolis [10] in 1953. The Metropolis algorithm takes the current state x, and generates a new state y by applying some small perturbation. The transition from state x to state y is then accepted with probability.

$$P_{accept}\{x, y\} = \begin{cases} 1, & if\ E_X - E_Y \le 0 \\ e^{-(E_x - E_y)/k_B T}, & if\ E - E > 0 \end{cases} \tag{13}$$

If accepted, y becomes the current state and the procedure is repeated. This acceptance rule is known as the Metropolis criterion. Given a particular combinatorial optimization problem let the solution x correspond to the current state of the solid, the cost function correspond to the energy of the current state, and the control parameter T correspond to the temperature of the solid. The simulated annealing algorithm consists simply of iterating the Metropolis algorithm for decreasing values of the artificial temperature parameter T.

Table 1. Simulated vs. physical annealing.

Optimization problem	Physical system
solution x	current state of the solid
cost or objective value f(x)	energy of current state
control parameter T	temperature
optimal solution xopt	ground state
simulated annealing	gradual cooling

Some of the analogies between the thermal process of physical annealing and the artificial process of simulated annealing in a combinatorial optimization problem are summarized in Table 1.

Control parameters of AS algorithm

The algorithm of simulated annealing consists of operating parameters [11], [12], which should be well set in order to achieve its best performance. These are briefly mentioned in the following.

Initial temperature

At beginning, initial temperature must be set at a higher value, in order to get more probability of acceptance for non-optimized solutions during the first stages of the algorithm. Too much higher selection of initial temperature makes an algorithm slow and computationally inefficient. On the other hand, very low initial temperature may not be capable of searching a minimum especially for multi model function. There is no particular way to find out proper initial temperature which is suitable for whole range of problems.

Final temperature

While working with SA algorithm generally the final temperature fall is set to zero degree Celsius. SA algorithm can take much longer time to execute the operation, if the decrement in the temperature is exponential in nature. Finally, the stopping criterion is selected, which can be either an appropriate low temperature or the value where the system get freeze at that temperature.

Temperature decrement

As initial and final temperatures have predefined values, it is essential to find the approach of transition from starting to its final temperature as the success of algorithm depends on it. The decrement of temperature at time "*t*" is

$$T(t) = \frac{d}{\log(t)} \quad (14)$$

where d is a positive constant.

The temperature decrement can also be implemented using

$$T(t+1) = \alpha T \quad (15)$$

where α, is a constant close to 1.

Iterations at each Temperature

To enhance efficiency of the algorithm, selection of proper number of iterations is another important factor. The realization of only iteration for each temperature and the fall in temperature should take place at a really slow rate which can be expressed as:

$$T(t) = \frac{t}{(1+\beta t)} \quad (15)$$

Generally, β have very small value.

Simulated annealing algorithm

The SA algorithm for dispatch problem is stepped as follows:

Step 1: Initialization of the values temperature T, parameter α and iterations number criterion. Find randomly, an initial feasible solution, which is assigned as the current solution Si and perform ELD in order to calculate the total cost, Fcost, with the preconditions (7) and (8) fulfilled.

Step 2: Set the iteration counter to $\mu = 1$.

Step 3: Find a neighboring solution S_j through a random perturbation of the counter one and calculate the new total cost F_{cost}

Step 4: If the new solution is better, we accept it, if it is worse, we calculate the deviation of cost $\Delta S = S_j - S_i$ and generate a random number uniformly distributed over $\Omega \in (0,1)$.

If $e^{-\frac{\Delta S}{t}} \geq \Omega \in (0,1)$

Accept the new solution S_j to replace S_i .

Step 5: If the stopping criterion is not satisfied, reduce temperature using parameter α: $T(t) = \alpha T$ and go to Step 2.

The proposed SA algorithm has been tested on a 3-generator system with NO_x and SO_2 emission. The software was implemented by the MATLAB language. For conducting the test, the initial temperature is fixed at 0.4°C, alpha is fixed at 0.5 and max tries is 10000. The final temperature is 1e-10°C.

Results and discussion

The generator cost coefficients, emission coefficients, generation limits, and loss coefficients of 3 units system are taken from [14]. The multi-objective EELD solution for the 3- unit system is solved using SA when system demand is 850 [MW].

Table 2. Best fuel cost.

	Tabu Search[13]	NSGA-II[14]	OBBO[15]	BBO[15]	BB_BC[16]	SA
P_1	435.69	436.366	435.1981	435.1966	434.5152	435.1972
P_2	298.828	298.187	299.9697	299.9723	300.7308	299.9632
P_3	131.28	131.228	130.6604	130.6600	130.6044	130.6684
Losses(MW)	15.798	15.781	15.8282	15.8289	15.8505	15.8288
Fuel cost ($/h)	8344.598	8344.606	8344.5875	8344.5927	8344.5952	8344. 5927
SO_2 Emission (ton/h)	9.02146	9.02083	9.021948	9.02195	9.02261	9.0220
NO_2 Emission (ton/h)	0.09863	0.09860	0.098686	0.098686	0.09871	0.0987

Table 2 shows the distribution of load among generators as system demand for minimum cost of generation and the obtained results by SA are compared with Tabu Search, NSGA-II, OBBO, BBO, and BB_BC.

Table 3. Best SO_2 emission.

	Tabu Search[13]	NSGA-II[14]	OBBO[15]	BBO[15]	BB_BC[16]	SA
P_1	549.247	541.308	552.1113	552.1111	552.7414	552.1083
P_2	234.582	223.249	219.4441	219.4441	219.0790	219.4484
P_3	81.893	99.919	92.9597	92.96053	92.6958	92.9592
Losses(MW)	15.722	14.476	14.5151	14.5158	14.5164	14.5159
Fuel cost ($/h)	8403.485	8387.518	8396.4616	8396.4665	8397.023	8396.4800
SO_2 Emission (ton/h)	**8.974**	**8.96655**	**8.965931**	**8.965937**	**8.965936**	**8.9659**
NO_2 Emission (ton/h)	0.09740	0.09637	0.096817	0.096817	0.09684	0.0968

Table 4. Best NO_x emission.

	Tabu Search[13]	NSGA-II[14]	OBBO[15]	BBO[15]	BB_BC[16]	SA
P_1	502.914	505.81	508.5800	508.5813	508.291	508.5594
P_2	254.294	252.951	250.4423	250.4433	250.600	250.4430
P_3	108.592	106.023	105.7228	105.7212	105.854	105.7433
Losses(MW)	15.8	14.784	14.7451	14.7459	14.747	14.7457
Fuel cost ($/h)	8371.143	8363.627	8365.1088	8365.1146	8364.953	8365.1022
SO_2 Emission (ton/h)	8.874	8.96655	8.973662	8.973667	8.965936	8.9737
NO_X Emission (ton/h)	**0.0958**	**0.09593**	**0.095923**	**0.095923**	**0.09592**	**0.0959**

Issue 25, July-December 2014
p. 43-56

Table 5. Best compromise solution emission.

	NSGA-II[14]	OBBO[15]	OBBO [15]	BB_BC[16]	SA
P_1	496.328	507.11971	507.11954	442.893	442.1752
P_2	260.426	251.64200	251.64262	305.503	305.8545
P_3	108.144	106.00030	106.00042	117.546	117.9238
Losses(MW)	14.898	14.76251	14.76258	15.94	15.9535
Fuel cost ($/h)	8358.896	8364.30627	8364.31126	8345.813	8345.7469
SO_2 Emission (ton/h)	8.97870	8.974195	8.974201	9.01602	9.0166
NO_X Emission (ton/h)	0.09599	0.0959248	0.0959248	0.09776	0.0978
Total cost ($/h)	**31234.99029**	**31226.40958**	**31226.41898**	**25035.140**	**25035.1214**

The obtained results for minimum emission of SO_2 are presented in Table 3, and the obtained results for minimum emission of NO_x are presented in Table 4. The best compromise solution for the precedent methods are presented in Table 5.

The best fuel cost is obtained by SA (8344. 5927 $/h). The best SO_2 emission output is 8.9659 ton/h. The best NO_x emission output is 0.0959 ton/h. The best compromise solution is 25035.1214 $/h. The same test system was taken to solve the dynamic generation dispatch problem using the proposed SA method. The power demands for the 5 time intervals are given in Table 6.

Table 6. Best compromise solution.

Load	550	600	700	800	850
P_1	307.1310	329.3138	374.0705	419.3406	442.1703
P_2	160.3247	184.6185	233.1539	281.6376	305.8578
P_3	88.6302	93.4363	103.1426	112.9674	117.9255
Losses(MW)	6.0859	7.3686	10.3669	13.9456	15.9536
Fuel cost ($/h)	5581.4799	6028.7064	6939.2480	7871.4463	8345.7467
SO_2 Emission (kg/h)	6.0071	6.4941	7.4855	8.5004	9.0166
NO_X Emission (kg/h)	0.0880	0.0882	0.0902	0.0947	0.0978
Total cost ($/h)	**18760.5958**	**19660.5278**	**21633.8869**	**23841.8787**	**25035.1214**

Table 7. Comparison of best compromise solution and best fuel cost.

Time interval	P_D	Best compromise solution			Best fuel cost			Percent change (%)		
		Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission
1	**550**	5581.4799	6.0071	0.0880	5575.7533	6.0283	0.0889	0.1026	-0.3529	-1.0227
2	**600**	6028.7064	6.4941	0.0882	6024.9087	6.514	0.0889	0.0630	-0.3064	-0.7937
3	**700**	6939.248	7.4855	0.0902	6937.9036	7.5012	0.0909	0.0194	-0.2097	-0.7761
4	**800**	7871.4463	8.5004	0.0947	7870.6929	8.5097	0.0954	0.0096	-0.1094	-0.7392
5	**850**	8345.7467	9.0166	0.0978	8344.5927	9.0219	0.0987	0.0138	-0.0588	-0.9202

Table 8. Comparison of best compromise solution and best SO_2 emission.

Time interval	P_D	Best compromise solution			Best SO_2 emission			Percent change (%)		
		Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission
1	**550**	5581.4799	6.0071	0.0880	5621.4302	5.9771	0.0925	-0.7158	0.4994	-5.1136
2	**600**	6028.7064	6.4941	0.0882	6073.1566	6.4619	0.0922	-0.7373	0.4958	-4.5351
3	**700**	6939.248	7.4855	0.0902	6987.6191	7.4476	0.0922	-0.6971	0.5063	-2.2173
4	**800**	7871.4463	8.5004	0.0947	7921.8504	8.4545	0.0947	-0.6403	0.5400	0.0000
5	**850**	8345.7467	9.0166	0.0978	8396.4286	8.9659	0.0968	-0.6073	0.5623	1.0225

Table 9. Comparison of best compromise solution and best NO_x emission.

Time Interval	P_D	Best compromise solution			Best NO_x emission			Percent change (%)		
		Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission	Fuel cost	SO_2 emission	NO_x emission
1	550	5581.4799	6.0071	0.0880	5583.1452	6.0061	0.0880	-0.0298	0.0166	0.0000
2	600	6028.7064	6.4941	0.0882	6033.0901	6.4862	0.0881	-0.0727	0.1216	0.1134
3	700	6939.248	7.4855	0.0902	6949.3417	7.4638	0.0897	-0.1455	0.2899	0.5543
4	800	7871.4463	8.5004	0.0947	7887.6146	8.4645	0.0933	-0.2054	0.4223	1.4784
5	850	8345.7467	9.0166	0.0978	8365.1352	8.9737	0.0959	-0.2323	0.4758	1.9427

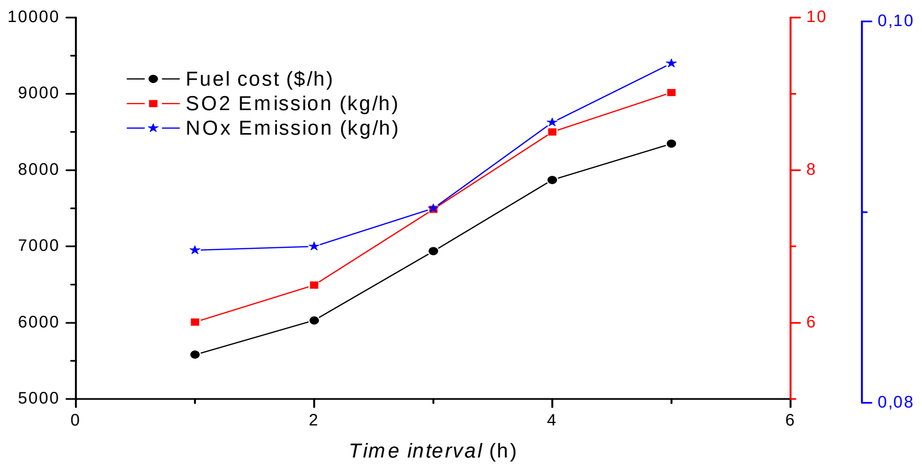

Figure 1. *Best compromise solution for fuel cost, SO_2 and NO_x emission for the 5 time intervals.*

In Figure 1, the black axis presents the fuel cost, the blue axis presents the NO_x emission and the red axis presents the SO_2 emission for the 5 time intervals. The Table 7 presents a percent change between the best compromise solution and the best fuel cost for the 5 time intervals. We note that the results from the best compromise solution give the best NO_x and SO_2 emission. The Tables 8 and 9 present a percent change between the best compromise solution and the best SO_2 emission, the best compromise solution and the best NO_x emission, for the 5 time interval.

In Figure 1, the load demand augmentation makes increasing in the fuel cost and the gas emission outputs (SO_2 and NO_x). In Figure 2, the best compromise solution can give a better minimum NO_x emission output than the best fuel cost and the best SO_2 emission solutions.

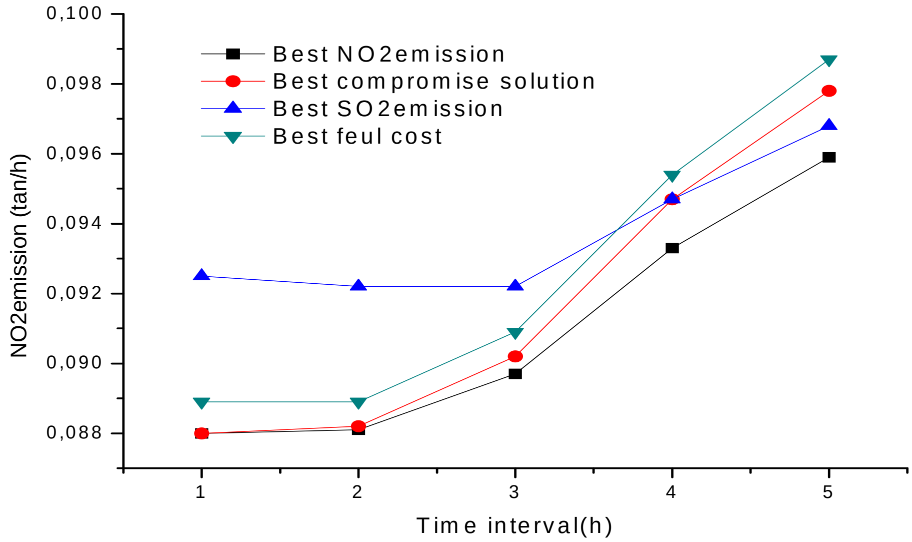

Figure 2. *NO_x emission for the 4 solution cases (best fuel cost, best SO_2 emission, best NO_x emission and best compromise solution).*

In contrast, from an environmental perspective, minimizing the harmful impacts of the gaseous emission is an imperative objective. These two conflicting objectives in particular are considered in both the single and multi-objective optimization of power system operation treated in this work. In general, optimization methods are classified into two main categories; deterministic and heuristic. In this thesis, one of the recently introduced heuristic optimization methods, SA, has been discussed, developed and employed to treat the considered economic and environmental optimization problems of power system operation. Various types of optimization functions were considered including single and multi-objective. The dynamic generation dispatch problem has been solved considering the transmission power losses. By these simulated results, SA method provides superior result than previously reported methods.

Conclusions

In this paper, Simulated Annealing Optimization (SA) has been proposed. In order to prove the effectiveness of the algorithm it is applied to EELD problem with three generating units. The results obtained by proposed method were compared with Tabu Search, NSGA-II, OBBO, BBO, and BB_BC. The best fuel cost is obtained by SA (8344. 5927 $/h). The best SO_2 emission output is 8.9659 ton/h. The best NO_x emission output is 0.0959 ton/h. The best compromise solution can create compatibility between production costs and the environment.

The comparison shows that the Simulated Annealing performs better than above mentioned methods. SA has superior features, including quality of solution, stable convergence characteristics and better computational efficiency. Therefore, this result shows that SA optimization is a promising technique for solving complicated problems in power system.

References

1. Younes M., Khodja F., Kherfene R. L., *Economic and emission dispatch problems using a new hybrid algorithm*, International Conference on Environment, Energy, Ecosystems and Development, 2013, p. 119-126.
2. Mojarrad H. D., Niknam T., Meymand H. Z. and Hassan Rastegar, *A novel multi-objective modified honey bee mating optimization algorithm for economic/emission dispatch*, Electrical engineering (ICEE), 2011 19th Iranian Conference On, 2011.
3. Jubril A. M., Komolafe O. A., Alawode K. O., *Solving multi -objective economic dispatch problem via semidefinite programming*, IEEE Transactions on Power Systems, 2013, 28(3), p. 2056-2064.
4. Chen P. H., Chen H. C., Wu F. J., Chen L. M., Liu A., *Environmental protection power dispatch for modern power system*, International Journal of Environmental Science and Development, 2013, 4(5), p.501-508.
5. AlRashidi M. R., El-Hawary M. E., *Economic dispatch with environmental considerations using particle swarm optimization*, Power Engineering, Large Engineering Systems Conference, 2006.

6. Abido M. A., *Multiobjective evolutionary algorithms for electric power dispatch problem*, Evolutionary Computation, IEEE Transactions, 2006, 10(3), p. 315-329.

7. Farag A., Al-Baiyat S., Cheng T. C., *Economic load dispatch multiobjective optimization procedures using linear programming techniques*, IEEE Transactions on Power Systems, 1995, 10(2), p. 731-738.

8. Das D. B., Patvardhan C., *New multi-objective stochastic search technique for economic load dispatch*, IEE Proc.-Gener. Trmsm. Distrib., 1998, 145(6), p. 747-752.

9. Kirkpatrick S., Gelatt Jr C. D., Vecchi M. P., *Optimization by simulated annealing*, Science, 1983, 220, p. 671-680.

10. Metropolis N., Rosenbluth A., Rosenbluth M., Teller A., and Teller E., *Equation of state calculations by fast computing machines*, Journal of chemical physics, 1953, 21, p. 1087-1092.

11. Kolahan F., Abachizadeh M., *Optimizing turning parameters for cylindrical parts using simulated annealing method*, World academy of science, Engineering and technology, 2008, 22, p.436-439.

12. Vishwakarma K. K., Dubey H M., *Simulated annealing based optimization for solving large scale economic load dispatch problems*, International journal of engineering research & technology (IJERT), 2012, 1(3).

13. Roa-Sepulveda C. A., Salazar-Nova E. R., Gracia-Caroca E., Knight U. G., Coonick A., *Environmental economic dispatch via hopfield neural network and tabu search*, UPEC', 1996, p. 1001-1004.

14. Ah King R. T. F., Rughooputh H. C. S., *Elitist multiobjective evolutionary algorithm for environmental/economic dispatch*, Congress on evolutionary computation, 2003, 2, p. 1108-14.

15. Pranab A B., Chattopadhyay K., *Oppositional Biogeography-Based Optimization for Multi-objective Economic Emission Load Dispatch*, Annual IEEE India Conference (INDICON), 2010.

16. Labbi Y., Ben Attous D., *Combined Economic and Emission Dispatch Using Big Bang–Big Crunch Optimization Algorithm*, ICEN'2010 – International Conference on Electrical Networks, 2010.