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Optimum Static Load Dispatch using Simulated Annealing Algorithm considering Transmission Losses

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Abstract— *This paper presents Simulated Annealing (SA) algorithm for optimization inspired by the process of annealing in thermodynamics for the determination of the global or near global optimum dispatch solution. The proposed approach is found to provide optimal results while working with the load balance constraint and the operating limit constraints of the generators. Transmission losses are incorporated in the algorithm through the use of the B matrix loss formula. In order to prove the robustness of the algorithm it is investigated on two different standard test cases consisting of 3 unit and 6 unit test systems. The proposed method has been compared with other existing relevant approaches like Artificial Bee Colony(ABC) algorithm, Genetic Algorithm (GA), Particle Swarm Optimization(PSO) and also with classical optimization technique i.e., lambda iteration method. Experimental results support to justify superiority of the approach over other reported techniques in terms of fast convergence, robustness and most significantly its optimal search behavior.*
Keywords—Thermodynamics, Simulated Annealing, Economic load dispatch, B matrix, Algorithms.

I. INTRODUCTION

Economic operation is very important for a power system to get profits on the capital invested. Operational economics involving power generation and delivery can be sub divided into two parts: minimization of power production cost, called economic load dispatch and minimization of transmission losses. Thus in general, Economic dispatch is the method of determining the most efficient, low-cost and reliable operation of a power system by dispatching the available electricity generation resources to supply the load on the system. The primary objective of economic dispatch is to minimize the total cost of generation while respecting the operational constraints of the available generation resources.

Various classical optimization techniques were used to solve the ELD problem, for example: lambda iteration approach, gradient method, linear programming method and Newton's method (Wood *et al.*1996). Lambda iteration method, the most common one has been applied to solve ELD problems. But for its effective implementation, the formulations have to be continuous. Linear programming methods is fast and reliable but the main weakness is they are associated with the piecewise linear cost approximation (Park *et al.*1993). Dynamic programming (DP) method is one of the approaches to solve the non-linear and discontinuous ED problem, but it suffers from the problem of "curse of dimensionality" or local optimality.

In recent times, different heuristic approaches have been proved to be effective with promising performance. These include genetic algorithm (GA), particle swarm optimization (PSO), Artificial Bee Colony (ABC) and Simulated Annealing (SA) are some of the, those which have been successfully applied to solve the ELD problem.

A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. Genetic algorithms belong to the larger class of evolutionary algorithms (EA). The GA procedure is based on the principle of survival of the fittest. The algorithm identifies the individuals with the optimizing fitness values, and those with lower fitness will naturally get discarded from the population. But there is no absolute assurance that a genetic algorithm will find a global optimum. Also the genetic algorithm cannot assure constant optimization response times. These unfortunate genetic algorithm properties limit the genetic algorithms use in optimization problems.

Particle Swarm Optimization (PSO) is motivated by social behaviour of organisms such as bird flocking and fish schooling. The PSO is an optimization tool, which provides a population-based search procedure. A PSO system combines local search methods with global search methods, but no guaranteed convergence even to local minimum. It has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs.

Simulated Annealing (SA) has been proved to be effective and quite robust in solving the optimization problems. SA can provide near global solutions and can also handle effectively the discrete control variables. SA does not stick into local optima because SA begins with many initial points and search for the most optimum in parallel. SA considers only the pay-off information of objective function regardless whether it is differentiable or continuous. Consequently, the most realistic cost characteristic of power plants can be formulated.

This paper present SA approach for optimization has been used to get to the bottom of economic load dispatch problems. Simulated Annealing (SA) is a stochastic optimization technique which is based on the process of annealing in Thermodynamics proposed by Kirkpatrick [10]. Mathematical model of simulated annealing describes how the molecules of liquidated metal move freely with respect to each other and by gradually cooling (thermodynamic process of annealing) thermal mobility are lost. The atoms start to get arranged and finally form crystals, having the minimum energy which depends on the cooling rate. The proposed method is found to give optimal results while working with constraints in the ELD.

This paper provides a brief explanation and mathematical formulation of ELD problems in Section 2. The concept of Simulated Annealing (SA) is discussed in Section 3. Section 4 provides the implementation process of the algorithm used in the test system. The parameter settings for the test system to evaluate the performance of SA and the simulation studies are discussed in Section 5. Finally, Section 6 presents the conclusions.

II. ECONOMIC LOAD DISPATCH PROBLEM FORMULATION

In a power system, the unit commitment problem has various sub-problems varying from linear programming problems to complex non-linear problems. The concerned problem, i.e., Economic Load Dispatch (ELD) problem is one of the different non-linear programming sub-problems of unit commitment. The ELD problem is about minimizing the fuel cost of generating units for a specific period of operation so as to accomplish optimal generation dispatch among operating units and in return satisfying the system load demand considering generator operational constraints. The objective function corresponding to the production cost can be approximated to be a quadratic function of the active power outputs from the generating units. Symbolically, it is represented as

Minimize $$F_T = \sum_{i=1}^{N} F_i(P_{Gi}) \qquad (1)$$

Where $$\sum F_i(P_{Gi}) = \sum a_i + b_i P_i + c_i P_{Gi^2} \qquad i=1,2....N \qquad (2)$$

is the expression for cost function corresponding to i^{th} generating unit and a_i, b_i and c_i are its cost coefficients. P_i is the real power output (MW) of i^{th} generator corresponding to time period t. NG is the number of online generating units to be dispatched. This constrained ELD problem is subjected to a variety of constraints depending upon assumptions and practical implications. These include power balance constraints to take into account; these constraints are discussed as under

Constraint 1: Generation capacity constraint

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad (3)$$

Constraint 2: Power balance constraint

The total power generation must cover the total demand P_D and the real power loss in transmission lines P_L. This relation can be expressed as:

$$P_{Gi} = P_D + P_L \qquad (4)$$

Here a reduction is applied to model transmission losses as a function of the generators output through Kron's loss coefficients. The Kron's loss formula can be expressed as follows:

$$P_L = \sum\sum P_{Gi}$$

$$P_L = \sum\sum P_{Gi} B_{ij} P_{Gj} + \sum B_{oi} P_{Gi} + B_{oo} \qquad i=1,2.....N \quad j=1,2.....N \qquad (5)$$

where B_{ij}, B_{oi}, B_{oo} are the transmission network power loss B-coefficients, which are assumed to be constant, and reasonable accuracy can be achieved when the actual operating conditions are close to the base case where the B-coefficients were derived. In the summary, the objective of economic power dispatch optimization is to minimize F_T subject to the constraints (3) and (4).

III. SIMULATED ANNEALING

Simulated Annealing (SA) algorithm is a nature inspired method which is adapted from process of gradual cooling of metal in nature. In the metallurgical annealing process, a solid is melted at high temperature until all molecules can move about freely and then a cooling process is performed until thermal mobility is lost. The perfect crystal is the one in which all atoms are arranged in a low level pattern, so crystal reaches the minimum energy. It is basically a stochastic optimization technique which is based on the principles of statistical engineering. The search for global minima of a multidimensional function is quite a complex problem especially when a big number of local minima correspond to the respective function. The main purpose of the optimization is to prevent hemming about to local minima. The originality of the SA method lies in the application of a mechanism that guarantees the avoidance of local minima. Following its introduction from [8], simulated annealing is mainly applied to large-scale combinatorial optimization problems.

a. The Process of Annealing in Thermodynamics:

At high temperature, the metal is in liquid stage. The molecules of liquidated metal move freely with respect to each other, via gradual cooling (thermodynamic process of annealing) thermal mobility is lost. The atoms start to get arranged and finally form crystals, having the minimum energy which depends on the cooling rate. If the temperature is reduced at a very fast rate, the crystalline state transforms to an amorphous structure, a meta-stable state that corresponds to a local minimum of energy [9]. Annealing process of metal influences SA algorithm. If the system is at a thermal balance for given temperature *T*, then the probability $P_T(s)$ that it has a configuration depends on the energy of the corresponding configuration *E(s)*, and is subject to the Boltzmann distribution

$$P_T(s) = \frac{e^{-E(s)/kT}}{\sum_W e^{-E(w)/kT}} \quad (6)$$

Where, *k* is the Boltzmann constant and the sum Σ_W includes all possible states *W*. Metropolises [11] were the first to suggest a method for calculating a distribution of a system of elementary particles (molecules) at the thermal balance state. Let the system has a configuration *g*, which corresponds to energy *E(g)*. When one of the molecules of the system is displaced from its starting position, a new state *σ* occurs which corresponds to energy *E(σ)*. The new configuration is compared with the old one. If $E(\sigma)\leq E(g)$, then the new state is accepted. If $E(\sigma)>E(g)$, then the new state is accepted with probability :

$$e^{-(E(\sigma)-E(g))} / kT \quad (7)$$

Where, *k* is the Boltzmann constant.

Table 1: Connection between Thermodynamic and Combinatorial Optimization

Thermodynamics simulation	Combinatorial Optimization
System state	Feasible solutions
Energy	Cost
Change of state	Neighboring solutions
Temperature	Control parameter
Frozen state	Heuristic solution

The basic step of the simulated annealing algorithm is presented with the following Pseudo-code.

- Get the initial solution “S”.
- *Get the initial Temp T>0*
- While not yet frozen

(a)perform the following loop L times

**peak the random neighbour, S’ of S*

**let Δ=cost(S’)-cost(S)*

**If Δ≤0 ,set S’=S*

**If Δ>0, set S=S’ with probability* $e^{-\Delta/T}$

(b)set T=α T (reduce Temperature) Return S

3.2 Elements in Simulated Annealing:

For the successful application of the SA algorithm is the annealing schedule is vital, which refers to four control parameters that directly influence its convergence (to an optimized solution) and consequently its efficiency [9]. The parameters are the following:

a) Initial Temperature
b) Final Temperature
c) Temperature Decrement
d) Iterations at each Temperature

a) Initial Temperature:

The starting temperature must be set to a big enough value, in order to make possible a big probability of acceptance for non-optimized solutions during the first stages of the algorithm’s application. However, if the value of the starting temperature gets too big, SA algorithm becomes non-effective because of its slow convergence and in general, the optimization process degenerates to a random walk. On the contrary, if the

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starting temperature is low then there is a greater probability of achieving local minima. There is no particular method for finding the proper starting temperature that deals with the entire range of problems. Various methods for finding the appropriate starting temperature have been developed [12] suggests to quickly raise the temperature of the system initially up to the point where a certain percentage of the worst solutions is acceptable and after that point, a gradual decrement of temperature is proposed.

b) Final Temperature:

During the application of the SA algorithm it is common to let the temperature fall to zero degrees. However, if the decrement of the temperature becomes exponential, SA algorithm can be executed for much longer time. Finally, the stopping criteria can either be a suitable low temperature or the point when the system is "frozen" at current temperature.

c) Temperature Decrement :

Since the starting and final temperatures have been defined, it is necessary to find the way of transition from the starting to the final temperature. The way of the temperature decrement is very important for the success of the algorithm [13] suggested the following way to decrement the temperature:

$$T(t) = d \big/ \log(t) \tag{8}$$

Where d is a positive constant.

An alternative is the geometric relation:

$$T(t)=a.t \tag{9}$$

Where parameter a, is a constant near 1. In effect, its typical values range between 0.8 and 0.99.

d) Iterations at each Temperature:

For increased efficiency of the algorithm, the number of iterations is very important. Using a certain number of iterations for each temperature is the proper solution. [14] suggests the realization of only one, iteration for each temperature, while the temperature decrement should take place at a really slow pace that can be expressed as:

$$T(t) = t \big/ (1+\beta.t) \tag{10}$$

Where, β takes a very low value.

SA Algorithm Implementation of ELD Problems :

Step 1: Initialization of temperature, T , parameter α and maximum. Find randomly, an initial feasible solution, which is assigned as the current solution S_i and perform ELD in order to calculate the total cost, F_{cost}, with the preconditions (4) and (6) fulfilled.

Step 2: Set the iteration counter to μ=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 $\Delta S=Sj-Si$ and generate a random number uniformly distributed over $\Omega \in (0, 1)$.

If $$e^{-\Delta S/t} \geq \Omega \in (0,1) \tag{11}$$

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 return back to Step 2.

IV. CASE STUDIES

The efficiency of the proposed algorithm for solving Economic Load Dispatch (ELD) problem has been tested on two different power generating units – the 3 unit and IEEE 6 unit system including the transmission losses. The performances of these algorithms are evaluated and compared with classical Lambda Iteration Method (LIM) and other meta-heuristics available in literature. The algorithms are implemented in MATLAB R2009b platform on i5 processor, 2.53 GHz, 4 GB RAM personal computer.

The key parameters of algorithm are Initial temperature, Final temperature, Cool Sched (α) and maximum number of generations which is used here as a stopping criteria to choose the best suitable values of key parameters. The setup of SA approach is listed below in Table III.

A. Test System I: 3 UNIT SYSTEM

In order to demonstrate the effectiveness of the SA algorithm, the ELD benchmark consisting of three generator units [10] is selected. The details of fuel cost coefficients and generating limits for each unit are given in Table I and hourly load distribution over 24 hour horizon is given in Table II respectively. The Transmission Loss Coefficient Matrix for calculating power loss of 3 Unit test system are obtained from [10].

Table I : Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	a_i ($)	b_i ($/MW)	c_i ($/MW^2)
1	100	220	176.9	13.5	0.1

2	10	100	129.9	32.6	0.1
3	10	20	137.4	17.6	0.1

Transmission Loss Coefficient Matrix

$$B_{ij} = \begin{bmatrix} 0.000014 & 0.000017 & 0.000015 \\ 0.000017 & 0.000060 & 0.000013 \\ 0.000015 & 0.00003 & 0.000065 \end{bmatrix}$$

$$B_{oo} = [0]$$

$$B_{oi} = [0 \quad 0 \quad 0]$$

Table II: Hourly Load

Hour	P_D(MW)	Hour	P_D(MW)
1	175.19	13	242.18
2	165.15	14	243.60
3	158.67	15	248.86
4	154.73	16	255.79
5	155.06	17	256
6	160.48	18	246.74
7	173.39	19	245.97
8	177.60	20	237.31
9	186.81	21	237.32
10	206.96	22	232.67
11	228.61	23	195.93
12	236.10	24	195.60

Table III: Parameters of SA used to implement ELD

Parameters of SA		*Notations Used*	*Values*
1.	Initial temperature	Tinit	100^0 C
2.	Final temperature	minT	1e-10^0C
3.	Cool Shed 0.8%	cool(α)	0.8%
4.	maximum number of tries	max_try	1000
5.	Maximum number of successes within one temperature.	max_success	50

Simulation results for test system I:

With the best values of Tinit = 100, α = 0.8 and minT = 1e-10 obtained from Table III, the SA algorithm was run for different values of demand ranging for 24 hours. For each demand, 50 independent trials with 1000 iterations per trial have been performed. The individual generator powers, minimum fuel cost, total power generated, power loss and the computational time required to obtain the simulation results are shown in Table V.

Comparative Analysis :

The results of the proposed SA for 6bus 3unit system are compared with other reported approaches such as PSO, GA and ABC. The economic dispatch obtained through the LI method was also used for comparison and all the results are shown in Table VI. The minimum cost for the demand for 24hour horizon compared to all others, while the proposed SA produced a cost of $161708.02, promisingly optimal and consistent. The power loss during the optimal dispatch was 81.4528MW relatively less than all other meta-heuristic algorithms

B. Test System II: IEEE 6UNIT SYSTEM:

The IEEE six unit test system has been adopted from [38], in which the fuel cost coefficients, and power limits are known. The specifications of the system for six generator test system are detailed in Table IV and hourly load distribution over 24 hour horizon is given in Table II respectively. The Transmission Loss Coefficient Matrix for calculating power loss of 6 Unit test system can be obtained from standard IEEE data. The various SA parameters used to implement ELD problem for 6unit generating system is similar to that of the three unit test system except for the dimension which is varied based on the size of the problem. Notations of the parameters and the range of values are given in Table III.

Transmission Loss Coefficient Matrix

$$\mathbf{B_{ij}} = 1{*}e^{-05}\begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 1.0 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0 & 2.4 & -0.6 & -0.8 \\ -0.5 & -0.6 & -1.0 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix}$$

$\mathbf{B_{oi}} = 1{*}e^{-04}$ [-3.908 -1.297 7.047 0.591 2.161 -6.635]

$\mathbf{B_{00}}$ = [0.056]

Table IV: Generating unit's capacity and Coefficients

Unit	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	a_i ($)	b_i ($/MW)	c_i ($/MW^2)
1	100	500	240	7.00	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.50	0.0080
6	50	120	190	12.0	0.0075

Simulation results for test system II:

With the best values of Tinit = 100, α = 0.8 and minT = 1e-10 from Table III the SA algorithm was run for different values of demand ranging for 24 hours. For each demand, 50 independent trials with 1000 iterations per trial have been performed. The individual generator powers, minimum fuel cost, total power generated, power loss and the simulation results are shown in Table VII.

Table V: Simulation results for 3 Unit Test System

P_D	P_L	P_{G1}	P_{G2}	P_{G3}	F_T
175.19	2.476	123.84	33.83	20	5258.82
165.15	2.254	118.85	28.54	20	4865.21
158.67	2.1176	115.64	25.14	20	4617.65
154.73	2.037	113.69	23.08	20	4469.12
155.06	2.0436	113.85	23.25	20	4481.49
160.48	2.1552	116.54	26.09	20	4686.45
173.39	2.4354	122.95	32.88	20	5187.52
177.60	2.5311	125.04	35.1	20	5354.85
186.81	2.748	129.61	39.95	20	5727.71
206.96	3.2587	139.61	50.61	20	6576.0
228.61	3.8629	150.37	62.11	20	7537.54
236.10	4.0854	154.09	66.09	20	7882.36
242.18	4.2711	157.11	69.34	20	8166.87
243.60	4.3151	157.82	70.09	20	8233.92
248.86	4.4803	160.44	72.9	20	8484.24
255.79	4.7033	163.88	76.61	20	8818.79
256	4.7101	163.99	76.72	20	8829.01
246.74	4.4133	159.38	71.77	20	8382.98
245.97	4.3891	159.0	71.36	20	8346.32
237.35	4.1232	154.71	66.76	20	7940.51
237.31	4.122	154.69	66.74	20	7938.65
232.67	3.9826	152.39	64.27	20	7723.67
195.93	2.973	134.13	44.77	20	6106.1
195.60	2.9647	133.97	44.60	20	6092.25

Total cost of Production=$161708.02
Total Power Loss = 81.4528MW

Comparative Analysis:

The results of the proposed SA for 6unit test system are compared with other reported approaches such as PSO, GA and ABC. The economic dispatch obtained through the LI method was also used for comparison and all the results are shown in Table VIII. The minimum cost for the demand for 24hour horizon compared to all others, while the proposed SA produced a cost of 319473.4224$/hr, promisingly optimal and consistent. The power loss during the optimal dispatch was 233.3689MW relatively less than all other meta-heuristic algorithms.

Table VI: Comparison of results for 3 UNIT System

METHOD	TOTAL LOSS	TOTAL COST
LI	121.6972	163472.92
GA	82.4528	161718.62
PSO	83.2822	161920.37
SA	81.4528	161708.02
ABC	82.1764	161715.5

Table VII: Simulation results for 6 Unit Test System

Hour	P_D	P_L	F_T
1	1293	13.1278	15859.506
2	1253	12.2331	15307.41
3	1240	11.9945	15132.0543
4	1223	11.6872	14903.5351
5	1202	11.3148	14622.4852
6	1190	11.1057	14462.4993
7	1175	10.848	14263.1443
8	1160	10.5946	14064.4858
9	1145	10.3453	13866.5234
10	1130	10.1002	13669.2565
11	1119	9.9231	13525.0357
12	1102	9.6537	13302.8836
13	1095	9.5444	13211.6682
14	1080	9.3132	13016.7153

15	1065	9.0861	12822.4553
16	1050	8.8633	12628.8878
17	1035	8.6361	12436.0259
18	1020	8.4026	12243.9743
19	1009	8.2339	12103.6647
20	999	8.0823	11976.4983
21	985	7.8731	11799.0852
22	970	7.6527	11609.8018
23	955	7.4363	11421.3474
24	940	7.2239	11233.7216

Total cost of Production=319473.4224 $
Total Power Loss = 233.3629 MW

Table VIII: Comparison of results for 6 UNIT System

METHOD	TOTAL LOSS	TOTAL COST
LI	237.4495	319565.79
GA	234.1986	319553.21
PSO	235.5858	320135.86
SA	233.3629	319473.4224
ABC	234.0993	319496.21

V. CONCLUSION

The problem of generating optimal maintenance schedules of generating units for the purpose of maximizing economic benefits and improving reliable operation of a power system, satisfying system constraints is solved in this paper using SA algorithm. An appropriate planning and scheduling of available generating units may save millions of dollars per year in production cost. The feasibility of the proposed method for solving ELD problems is verified by using 3 and 6 generator test systems. Also different algorithms like ABC, GA, PSO and classical lambda iteration method are tested on each of the test system and their results are compared with proposed algorithm (SA). From the result, it is clear that the proposed algorithm has the ability to find the better quality solution and has better convergence characteristics, computational efficiency and less CPU time per iteration when compared to other methods such as ABC, GA, PSO. It is evident from the comparison that the SA based optimization with different demands and constraints provide a competitive performance in terms of optimal solution. Therefore, SA algorithm with optimum combination of parameters like cool shed, maximum try and initial temperature i.e., SA based optimization is a promising alternative approach for solving complicated problems in power system.

REFERENCE

[1] H.T. Yang, P.C. Yang and C.L. Huang, “Evolutionary Programming based economic dispatch for units with non-smooth fuel cost functions”, *IEEE Trans. Power Syst.*, 1996, Vol. 11, no. 1, pp. 112-118.

[2] D.C. Walter and G.B. Sheble, “Genetic algorithm solution of economic dispatch with valve-point loading*”* *IEEE Trans. Power Syst.*, 1993, Vol. 8, No. 3, pp. 1125-1132.

[3] J.H. Park, Y.S. Kim, I.K. Eom, and K. Y Lee., “Economic Load Dispatch for price wise Quadratic Cost Function Using Hop field Neural Network”, *IEEE Trans. on Power Systems*, 1993, Vol. 8, No. 3, pp. 1030-1038.

[4] B.H. Choudhary and S. Rahman, “A review of recent advances in economic disp atch”, *IEEE Trans Power Syst.*, 1990, Vol. 5, No. 4, pp. 1248–59.

[5] K.Y. Lee, “Fuel cost minimization for both real and reactive power dispatches”, *IEE Proc C, Gen Transm Distrib* 1984., Vol. 131, No. 3, pp. 85–93.

[6] G.V. John lachogiannis and K.Y. Lee, “Economic load dispatch – a comparative study on heuristic optimization techniques with an improved coordinated aggregation-based PSO”, IEEE *Trans. Power Syst.*, 2009. Vol. 24, No. 2, pp. 991-1001.

[7] K. T. Chaturvedi, M. Pandit and L. Srivastava, “Self-Organizing Hierarchical Particle Swarm Optimization for Non-Convex Economic Disp atch”, *IEEE Trans. Power Syst.* 2008, Vol. 23, No. 3, pp. 1079-1087.

[8] S. Kirkpatrick, C. Gellat and M. Vecchi, “Optimization by Simulated Annealin g”, *Science,* 1983, Vol. 220, pp. 45-54.

[9] Farhad Kolahan and Mahdi Abachizadeh, “Optimizing Turning Parameters for cylindrical Parts using simulated Annealing Method”, *International journal of Engineering and Applied Science*, 2010, Vol. 6, No. 3, pp.149-152.

[10] Y. Fu, M. Shahidehpour, and Z. Li, “Security-constrained unit Commitment with AC constraints*,” *IEEE Trans. Power Syst.*,vol. 20, no.3, pp. 1538–1550, Aug. 2005.

[11] J.B. Park, K.S. Lee, J. R. Shin and K.Y. Lee, “A particle swarm optimization for economic dispatch with non-smooth cost functions”, *IEEE Trans. Power Syst.*, 2005, Vol. 20, No. 1, pp. 34-42.

[12] Dowsland K.A., 1995. Simulated Annealing in Modern Heuristic Techniques for Combinatorial Problem. *McGraw- Hill.*

[13] E. Aarts, Jan H.M. Korst, Peter Laarhoven and J. M. Van, "A Quantitative Analysis of the Simulated Annealing Algorithm", *A Case Study for the Travelling Salesman Problem. Journal of Statistical Physics* 1988, Vol. 50, pp.1-2.

[14] M. Lundy, "Applications of the annealing algorithm to combinatorial problems in statics*", Biometrika*, 1985, Vol. 75, pp. 191-198.

[15] M.A. Sydulu, "Very fast and effective non-iterative Lamda Logic Based" algorithm for economic dispatch of thermal units," *In: Proceedings of IEEE region 10 conference TENCON,* 1999, Vol. 2, pp. 1434–7.

[16] Aarts E., Korst Jan H.M., Laarhoven Peter and Van J. M., 1988. A Quantitative Analysis of the Simulated Annealing Algorithm. *A Case Study for the Travelling Salesman Problem. Journal of Statistical Physics.* Vol. 50, pp. 1-2.