Simulated Annealing Based Optimization for Solving Large Scale Economic Load Dispatch Problems

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Abstract

This paper presents a Simulated Annealing (SA) approach for solving Economic Load Dispatch (ELD) problems in electrical power system. The objectives of ELD problems in electric power generation is to programmed the devoted generating unit outputs so as to meet the mandatory load demand at lowest amount operating cost while satisfying all units and system equality and inequality constraints .Global optimization approaches is inspired by annealing process of thermodynamics. The proposed method works very fast, this aspect of algorithm is striking when applied for a large ELD system. Simulation has been performed over two different cases. Case study-I consist 38 generating units and Case study-II consist 110 generating units, both cases having convex fuel cost characteristics. The proposed method results have been compared with other relative existing approaches and finally SA proves luminous feasibility, robustness and fast convergence for optimization of ELD problems.

1. Introduction

The main aim of the economic dispatch is to include variables that affect operational cost, such as the generator distance from the load, type of fuel, load capacity and transmission line losses. By including these variables one will be able to perform economic dispatch and interconnected generators to minimize operating cost.

Economic dispatch is the process of allocating the required load demand between the available generating units such that the cost of operation is minimum as passable. The process of solving such a problem is referred to as optimization. ELD is a constrained nonlinear optimization problem.

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.

In recent times, different heuristic approaches have been proved to be effective with promising performance. These include evolutionary programming (EP) [1], genetic algorithm (GA) [2], differential evolution (DE) [3], particle swarm optimization (PSO) [4], etc. Improved fast Evolutionary programming algorithm has been successfully applied for solving the ELD problem [5, 6]. Other algorithms like improved coordination aggregated based PSO [7], SOH-PSO [8] and BFONM [9] are some of the, those which have been successfully applied to solve the ELD problem.

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.

2. 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

$$\text{Minimize} \quad F_t^{\cos t} = \sum_{i=1}^{N_G} f_i(P_i) \tag{1}$$

Where

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i, \quad i = 1,2,3,...,N_G \tag{2}$$

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. N_G 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

2.1 Power Balance Constraints or Demand Constraints: This constraint is based on the principle of equilibrium between total system generation $(\sum_{i=1}^{N_G} P_i)$ and total system loads (P_D) and losses (P_L). That is,

$$\sum_{i=1}^{N_G} P_i = P_D + P_L \tag{3}$$

Where the transmission loss P_L is expressed using B-coefficients [20] given by

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_i + B_{00} \tag{4}$$

2.2 The Generator Constraints: The power generated by each generator shall be within their lower limit P_i^{min} and upper limit P_i^{max} so that

$$P_i^{min} \le P_i \le P_i^{max} \tag{5}$$

3. Simulated Annealing Method

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 [10], simulated annealing is mainly applied to large-scale combinatorial optimization problems.

3.1 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 [11]. 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 *s* depends on the energy of the corresponding configuration *E(s)*, and is subject to the Boltzmann distribution

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

Where, k is the Boltzmann constant and the sum Σ_W includes all possible states W.

Metropolises [12] 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 $E(\sigma)$. 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 neighbor, 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 Control parameters of SA algorithm:

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 [11]. The parameters are the following:

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

a) Starting 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 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 [13]. 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 [14] suggested the following way to decrement the temperature:

$$T(t) = d/\log(t) \quad (8)$$

Where d is a positive constant.
An alternative is the geometric relation:

$$T(t) = a.t \quad (9)$$

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. [15] 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:

$$T(t) = t/(1+\beta.t) \qquad (10)$$

Where, β takes a very low value.

4. 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 $\Delta S=S_j-S_i$ and generate a random number uniformly distributed over $\Omega \in (0, 1)$.

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

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.

5. Results and Discussion

In this paper, to evaluate the effectiveness of the proposed SA approach, two case studies (38 and 110 generating units) of ELD problems were applied in which the objective functions were convex fuel cost characteristics in the power system operation.

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 was the following: Initial temperature = 300^{0}C, Final temperature =1e-10^{0}C, Cool Sched (α) = 0.8% and maximum number of generations = 1000. In each case study, 10 independent runs were made for each of the optimization methods

Each SA approach was implemented in MATLAB 7.1 and all the programs were run on a 2.4 GHz Pentium IV processor with 512 MB of RAM (Random Access Memory).

5.1 Case study I

This case study consists of 38 generating units. All units are within the convex fuel cost characteristics for the above system is taken from [16]. In this case, the load demand expected to be determined is PD = 6000 MW. The B matrix of the transmission loss coefficient is not considered in this system.

Table 2 shows the minimum, mean cost, standard deviations and CPU time per iteration, cost achieved by the SA approach. As indicated in Table 2, the SA was the approach that obtained the minimum cost for the ELD of 38 generating units. The best result obtained for solution vector P_i, i = 1 . . . 38 by SA with minimum cost of 9153496.59 $/h is given in Table 2 and Table 2 also compares the results obtained with the SPSO, PSO_Crazy, New PSO and PSO_TVAC [17] this paper with those of other studies reported in the literature and the convergence behavior of Case study I is shown in Figure 1.

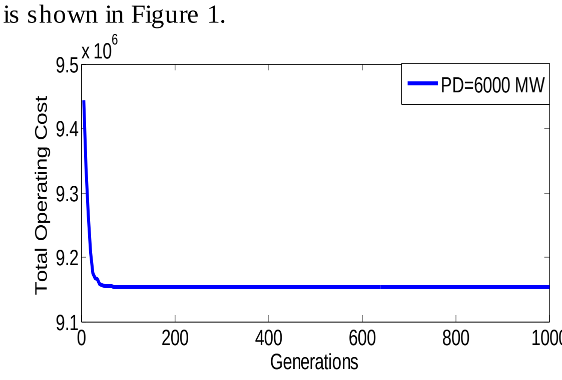

Figure 1. Convergence characteristics of 38 unit system (PD=6000MW)

Table2: Comparison of results for case study I

Generator Power O/P(MW)	SPSO	PSO_ Crazy	New PSO	PSO_ TVAC	SA
Pg1	519.097	366.631	550	443.659	405.6512

Pg2	437.92	550	512.263	342.956	405.6512
Pg3	374.789	467.129	485.733	433.117	408.6681
Pg4	394.877	370.471	391.083	500	408.6681
Pg5	356.603	425.712	433.846	410.539	408.6681
Pg6	380.358	415.226	358.398	482.864	408.6681
Pg7	300.234	339.872	415.729	409.483	408.6681
Pg8	335.871	289.777	320.816	446.079	408.6681
Pg9	238.171	195.965	115.347	119.566	114
Pg10	218.563	170.608	204.422	137.274	114
Pg11	196.63	138.984	114	138.933	114
Pg12	234.5	262.35	249.197	155.401	117.804
Pg13	111.529	114.008	118.886	121.719	110
Pg14	100.731	92.393	102.802	90.924	90
Pg15	122.464	89.044	89.039	97.941	82
Pg16	125.31	130.555	120	128.106	325
Pg17	155.981	167.85	156.562	189.108	157.0614
Pg18	65	65.754	84.265	65	65
Pg19	70.071	65	65.041	65	65
Pg20	263.95	199.594	151.104	267.422	272
Pg21	245.065	272	226.344	221.383	272
Pg22	191.702	130.379	209.298	130.804	260
Pg23	99.123	173.544	85.719	124.269	123.6755
Pg24	15.058	13.263	10	11.535	10
Pg25	60.06	112.161	60	77.103	107.5567
Pg26	91.14	105.898	90.489	55.018	84.8289
Pg27	41.006	35.995	39.67	75	35.3695
Pg28	20.399	22.335	20	21.682	20
Pg29	34.65	30.045	20.995	29.829	20
Pg30	20.957	24.112	22.81	20.326	20
Pg31	20.219	20.494	20	20	20
Pg32	25.424	20.011	20.416	21.84	20
Pg33	26.517	27.44	25	25.62	25
Pg34	18.822	18	21.319	24.261	18
Pg35	9.173	8.024	9.122	9.667	8
Pg36	26.507	25	25.184	25	25
Pg37	24.344	20	20	31.642	21.0081
Pg38	27.181	24.371	25.104	29.935	20.3849

Table 3: Best results comparison for case study I

Methods	Total Power Gen. (MW)	Power Mismatch	Minimum Cost ($/hr)	Mean Cost ($/hr)
SPSO	5999.996	0.00399	9543984.777	----
PSO_ Crazy	5999.995	0.0050	9520024.601	----
New PSO	6000.003	0.0030	9516448.312	----
PSO_ TYAC	6000.005	0.0050	9500448.307	----
SA	**6000**	**0.0000**	**9153496.59**	**9153496.87**

5.2 Case study II

In this case study a large scale data consisting of 110 unit generating unit system is employed, having convex fuel cost characteristics without including line losses .The input data of the entire system is taken from S. O. Orero paper [18]. In this case study, there are three load demands, Low (PD = 10000 MW), Medium (PD = 15000 MW) and High (PD = 20000 MW) expected to be determined.

Tables 5 shows the Best Power Output of 110 unit system for PD=10000MW, PD=15000MW and PD=20000MW. As indicated in Table 4, the SA was the approach that obtained the minimum cost for the ELD of 110 generating units.

The best result obtained by SA with minimum cost for PD=10000MW, PD=15000MW and PD=20000MW of 131973.9018 $/h, 198352.6413 $/h and 313184.2522 $/h respectively is given in Table 4 and also compares the results obtained with the SAB, SAF [19] in this paper with those of other studies reported in the literature and the convergence behavior of Case study II is shown in Figure 2, and Table 6 shows Standard deviation and CPU time for different test cases.

Table 4: Best results comparison with different approaches for different loads for case study II

Algorithm	Power Demand					
	10000MW		15000MW		20000MW	
	Minimum Cost ($/hr)	Mean Cost ($/hr)	Minimum Cost ($/hr)	Mean Cost ($/hr)	Minimum Cost ($/hr)	Mean Cost ($/hr)
SAB	140385.7586	141213.42	206912.9057	207764.73	313279.8825	314271.74
SAF	141107.8541	141215.11	207380.5164	207813.37	314532.8747	314635.32
SA	**131973.9018**	**132102.35**	**198352.6413**	**201595.19**	**313184.2522**	**342654.68**

Table 5: Best power output of 110 unit system for various loads

Generator Power O/P	Power Demand (MW)			Generator Power O/P	Power Demand (MW)		
	10000	15000	20000		10000	15000	20000
Pg1	2.4018	2.4031	12	Pg56	25.2	25.2	96
Pg2	2.4	2.4	12	Pg57	25.2	50.0387	96
Pg3	2.4	2.4	12	Pg58	35	35	100
Pg4	2.4	2.4	12	Pg59	35	35.003	100
Pg5	2.4	2.4	12	Pg60	45	45	120
Pg6	4	4	20	Pg61	45	45	120
Pg7	4	4	20	Pg62	45	45	120
Pg8	4	4	20	Pg63	54.3	164.7334	185
Pg9	4	4	20	Pg64	54.3	184.4727	185
Pg10	15.2	15.778	76	Pg65	54.3	177.8478	185
Pg11	15.2	76	76	Pg66	54.3	185	185
Pg12	15.2	46.249	76	Pg67	70	70	197
Pg13	15.2	49.3024	76	Pg68	70	70	197
Pg14	25	25	100	Pg69	70	70	197
Pg15	25	25	100	Pg70	150	360	360
Pg16	25	25	100	Pg71	400	400	400
Pg17	109.546	155	155	Pg72	400	400	400
Pg18	95.5364	155	155	Pg73	60	104.8277	300
Pg19	110.3678	155	155	Pg74	50	146.4736	250
Pg20	105.0814	155	155	Pg75	35.2032	90	90
Pg21	68.9	68.9	197	Pg76	50	50	50
Pg22	68.9	68.9	197	Pg77	160	160	450
Pg23	68.9	68.9	197	Pg78	150	272.0709	600
Pg24	350	350	350	Pg79	50	147.4288	200
Pg25	400	400	400	Pg80	20	120	120
Pg26	400	400	400	Pg81	10	10	55
Pg27	140	500	500	Pg82	12	12	40
Pg28	140.3855	500	500	Pg83	20	20.0228	80
Pg29	50.0496	200	200	Pg84	50	200	200
Pg30	35.3865	100	100	Pg85	83.392	325	325
Pg31	10	10	50	Pg86	269.215	440	440
Pg32	12.2522	20	20	Pg87	10	35	35
Pg33	20	80	80	Pg88	20	20	55
Pg34	75	250	250	Pg89	20	75.0219	100
Pg35	196.4132	360	360	Pg90	40	220	220
Pg36	219.4718	400	400	Pg91	30.0073	45.2315	140
Pg37	14.7661	40	40	Pg92	40	77.5334	100
Pg38	20	70	70	Pg93	440	440	440
Pg39	25	100	100	Pg94	370.1674	500	500
Pg40	20	120	120	Pg95	600	600	600
Pg41	40	180	180	Pg96	305.6974	457.955	700
Pg42	50	220	220	Pg97	3.6	3.6	15
Pg43	440	440	440	Pg98	3.6	3.6	15
Pg44	560	560	560	Pg99	4.4	4.4	22
Pg45	660	660	660	Pg100	4.4	22	22
Pg46	421.9594	594.5063	700	Pg101	10	10	60
Pg47	5.4	5.4	32	Pg102	10	10	80
Pg48	5.4	5.4	32	Pg103	20	20	100
Pg49	8.4	8.4	52	Pg104	20	20	120
Pg50	8.4	8.4	52	Pg105	40	40	150
Pg51	8.4	8.4	52	Pg106	40	40	166.0789
Pg52	12	12	60	Pg107	50	50	131.9211
Pg53	12	12	60	Pg108	30	30	150
Pg54	12	12	60	Pg109	40	40	320
Pg55	12	12	60	Pg110	20	20	200

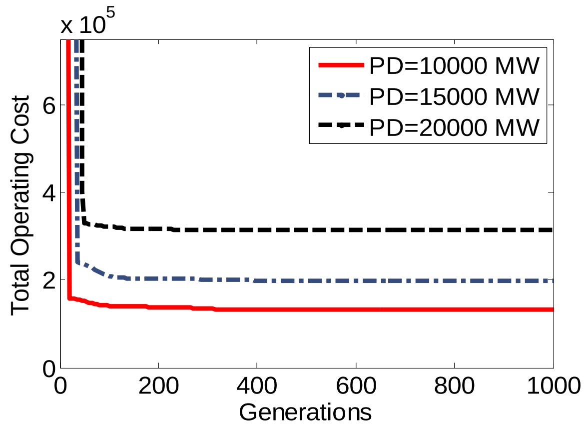

Figure 2. Convergence characteristics of 110 unit system with various loads

Table 6: Standard deviation and CPU time for different test cases

TEST CASES	Test case I	Test case II
Standard Deviation ($/hr)	0.1200	1.36
CPU time/iteration(sec)	0.237	0.245

6. Conclusions

This paper presents the Simulated Annealing (SA) approach for optimization of Economic Load Dispatch (ELD) problems. Practical generator operation is modeled using with piecewise quadratic cost functions. Algorithms have been developed for the determination of the global or near-global optimal solution for the ELD problems. The proposed SA approach has produced results comparable or better than those generated by other evolutionary algorithms and the solutions obtained have superior solution quality and good convergence characteristics and the strength of the method was demonstrated by the change in load demands of the problems. Because of in the deregulated environment where cost minimization not only the objective, but at the same time profit maximization is also concern. Fast and accurate economic load dispatch solution is as usual requirement in deregulated scenario as well. Therefore, results show that SA based optimization is a promising technique for solving complicated and large ELD problems in electrical power system.

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