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Simulated annealing approach for solving economic load dispatch problems with valve point loading effects

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Abstract

This paper presents Simulated Annealing (SA) algorithm for optimization inspired by the process of annealing in thermodynamics to solve economic load dispatch (ELD) problems. The proposed approach is found to provide optimal results while working with operating constraints in the ELD and valve point loadings effects. In order to prove the robustness of the algorithm it is investigated on four different standard test cases consisting of 3, 13, 40 generating unit system with valve point effect and a *Crete Island system* of 18 thermal generating units having convex fuel cost characteristics. The proposed method has been compared with other existing relevant approaches available in literatures. 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, Valve point loadings effects.

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1. Introduction

Economic operation is very important for a power system to get profits on the capital invested (Song *et al*., 1996). Operational economics involving power generation and delivery can be sub divided into two parts:1) minimization of power production cost, called economic load dispatch 2) minimization of transmission losses. Functionally Optimum Power Flow (OPF) combines the power flow with Economic Load Dispatch (ELD) problem (Sun *et al.* 1984; Yuryevich *et al*. 1999; AlRashidi *et al*.2007). The objective of OPF is to find the optimal settings of a given power system network that optimize a certain objective function (based on losses, reactive power, voltage or power flow violations etc.) while system security, and all operating constraints are satisfied. The most commonly used objective is the minimization of the overall fuel cost function along with minimization of active power loss, bus voltage variation, emission of power generating units, and power shedding. On the other hand, ELD is one of the most crucial issues of present energy management system. The objective of ELD in a power system is to discover the best possible combination of power output for all generating units which will minimize the total fuel cost as well as satisfying load and operational constraints. The ELD problem is extremely complex to work out because of its large dimension, a non-linear objective function, and various constraints. several analysis on the ELD have been carried out till now, suitable improvements in the unit outputs scheduling can contribute to significant cost savings (Choudhary *et al.* 1990; Happ *et al.* 1971) and also information in forming market clearing prices is provided by it.

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).

In order to get the qualitative solution for problem related to ELD, Artificial Neural Network (ANN) techniques such as Hopfield Neural Network (HNN) (Park *et al.*1993) have been used. The objective function of the ELD problem is transformed into a Hopfield energy function and arithmetical iterations are utilized to minimize the energy function. To solve the ELD problems for power generating units associated with continuous or piecewise quadratic fuel cost functions and for units with prohibited zone constraints Hopfield model has been employed. In the conventional HNN, the input-output correlation for its neurons can be depicted by sigmoid function. Hopfield model takes more iteration to present the solution and large computational time due to use of the sigmoid function to solve the ED problems.

Recently, various other nature inspired optimization techniques have proved their potential in handling various problems. The prominent among them are genetic algorithm (GA) (Walter *et al.,* 1993), evolutionary programming (EP) (Yang *et al.,* 1996), particle swarm optimization (PSO) (Park *et al.,* 2005), differential evolution (DE) (Coelho *et al.,* 2006) , Artificial Bee Colony Algorithm (ABC) (Hemamalini *et al.,* 2008), Biogeography-Based optimization(BBO) (Bhattacharya *et al.,* 2010), Bacterial foraging-based optimization (BFBO) (Padmanabhan *et al.,*2011) ,Firefly Algorithm (FA) (Yang *et al.*2012) etc. Improved fast evolutionary programming algorithm has been successfully applied for solving the ELD problem (Choudhary *et al.* 1990; Lee *et al.* 1984). Other algorithms like Hybrid genetic/simulated-annealing approach (GA/SA)(Wong *et al.* 1994), Hybrid particle swarm optimization sequential quadratic programming (PSO-SQP) (Aruldoss *et al.,* 2004), Chaotic particle swarm optimization (CPSO) (Jiejin *et al.,* 2007), new particle swarm with local random search (NPSO-LRS) (Selvakumar *et al.,* 2007), Improved particle swarm optimization (Ning *et al.* 2007), Self-Organizing Hierarchical particle swarm optimization (SOH-PSO) (Chaturvedi *et al.* 2008), Bacterial foraging optimization nelder mead hybrid algorithm (BFONM) (Panigrahi *et al.,* 2008), improved coordination aggregated based PSO (ICA_PSO)(John *et al.,* 2009), quantum-inspired PSO (QPSO)(Meng *et al.,* 2010), and modified group search optimizer algorithm (MGSO) (Zare *et al.,* 2012) have been applied to solve the ELD problem.

Simulated Annealing (SA) is a stochastic optimization approach inspired by the natural process of annealing related to thermodynamics proposed by (Kirkpatrick *et al.,* 1983). SA approach has been previously applied to solve ELD problem (Wong *et al.*1993), dynamic economic dispatch problem (Panigrahi *et al.,* 2007) for small large dimensional ELD problems with convex cost characteristics (Vishwakarma *et al.,* 2012) .In this paper the potential of simulated annealing approach has been tested for large dimensional ELD problem with nonconvex cost characteristics. One of the test systems used is known be particularly difficult to optimize as it has multiple local minima (Sinha *et al.,* 2003).

In order to validate robustness and effectiveness of SA algorithm, this paper considers four standard ELD problems, namely, 3 13 and 40 generating unit system with valve-point loading effects and an 18 generating unit systems with quadratic cost function with varying percentage of the maximum power as demand.

The paper is organized as follows: brief description and mathematical formulation of ELD problems presented in Section 2. The concept behind the simulated annealing (SA) optimization is discussed in Section 3. Section 4 depicts realization process of the algorithm used for the test system. Section 5 related to discussion in contest of parameter settings for the used test cases to analyze performance of SA. Concluding remarks are presented in Section 6.

2. Economic Load Dispatch Formulation

The objective of ELD problem is to minimize the fuel cost of generating units for a specific period of operation so as to accomplish optimal generation dispatch among operating units while the system load demand, generator operational constraints, ramp rate limit and prohibited operating zones are satisfied. Two models for ELD are considered here, one with smooth cost function and other with non smooth cost function as below.

The objective function analogous to the generation cost can be approximated to be a quadratic function. Symbolically, it is represented as

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

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

is the expression for cost function of 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 generating units.

The sequential valve opening process for multi-valve steam is responsible for ripple in heat rate curve. These effects are included in cost function using sinusoidal component as

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin\left(f_i \left(P_i^{\min} - P_i \right) \right) \right| \tag{3}$$

Where e_i and f_i are the cost coefficients corresponding to valve point loading effect.
The ELD problem consists of minimizing F_t^{Cost} subjected to following constraints.

2. A) Power Balance Constraints: The total generation must fulfill the total demand plus losses. If total system load is P_D and losses are represented by P_L, then,

$$\sum_{i=1}^{N_G} P_i = P_D + P_L \tag{4}$$

Where transmission loss P_L is expressed using B- coefficients (wood et al, 1996), given by

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_i + B_{00} \tag{5}$$

2. B) Generator Capacity Constraints: For stable operation, real power generated by each generator restricted by their lower limit P_i^{min} and upper limit P_i^{max} as follows:

$$P_i^{min} \le P_i \le P_i^{max} \tag{6}$$

3. Optimization using Simulated Annealing

Simulated Annealing is basically a stochastic optimization technique inspired by the natural process of crystallization i.e. gradual cooling of metal. Annealing (in metallurgy & material science) is a process involving heating and controlled cooling of a material to get perfect crystal with minimum defects. There is a significant correlation between the terminology of thermodynamic annealing process (the behavior of systems with many degrees of freedom in thermal equilibrium at a finite temperature) and combinatorial optimization (finding global minimum of a given function based on many parameters).A detailed analogy of annealing in solids provides frame work for optimization. Table 1 depicts the key terms which are related with thermodynamic annealing and its association with optimization process.

Table 1: Association among thermodynamic simulation and Combinatorial Optimization

Thermodynamic annealing	Simulated annealing
System state	Feasible Solutions
Energy	Cost
Change of state	Neighboring Solutions
Temperature	Control Parameter
Frozen state	Heuristic Solution

The main advantage of SA approach is that it does not need large computer memory. Whenever a large number of local minima are available, then the search for global minima for a multidimensional function becomes quite a complex task. The main purpose of the optimization is to achieve fast convergence as well as better exploration capability. The SA method has ability to escape from local minima by incorporating a probability function in accepting and rejecting new solutions.

3. A) Annealing Process in Thermodynamics: Molecules of a metal become unstuck from their initial positions and wander randomly at high temperature. By gradual cooling thermal mobility is lost and atoms start to get arranged in the form of a crystal. If the reduction of temperature is done at a very fast rate, a meta-stable state (i.e. crystalline state transforms to an amorphous structure) is obtained which corresponds to a local minima of energy level (Kolahan *et al.* 2010).

For a thermal equilibrium state of a system for temperature *T,* afterward the probability $P_T(s)$ with its pattern *s* depends on energy level of corresponding pattern *E(s)*, and is depending on Boltzmann distribution

$$P_T(s) = \frac{e^{-E(s)/kT}}{\sum_W e^{-E(w)/kT}} \tag{7}$$

Where, k is known as Boltzmann constant and the sum Σ_W consists of all promising states of W.

Metropolis *et al.* (1953) 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 have a configuration g, which corresponds to energy $E(g)$. If one of the molecules of the system is displaced from its initial position, then a new state σ corresponding to energy $E(\sigma)$ occurs. 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 :

$$e^{-(E(\sigma)-E(g))/KT} \tag{8}$$

3. B) Critical parameters of SA algorithm: For the successful application of the SA algorithm, the annealing schedule is vital. There are four control parameters that are directly associated with its convergence (to an optimized solution) and its efficiency (Kolahan *et al,* 2010). They are,

I) Initial Temperature

II) Final Temperature

III) Rate of Temperature Decrement and

IV) Iteration at each Temperature

I) 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. According to Dowsland *et al*. (1995), if the temperature of the system is raised quickly up to the initial value, where a certain percentage of the worst solutions is acceptable. After this, a gradual decrement of temperature is proposed.

II) 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 a appropriate low temperature or the value where the system get freeze at that temperature.

III) 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. According to Aarts *et al,*(1988) decrement of temperature at time "*t"* is:

$$T(t) = d/\log(t) \tag{9}$$

Where d is a positive constant.

The temperature decrement can also be implemented using $T(t+1) = aT(t)$ (10)

Where a, is a constant close to 1. Its effective range is $0.8 \leq a \leq 0.99$.

IV) Iterations at each Temperature

To enhance efficiency of the algorithm, selection of proper number of iterations is another important factor. Lundy *et al.* (1985) suggests the realization of only one iteration for each temperature and the fall in temperature should take place at a really slow rate which can be expressed as:

$$T(t) = t/(1+\beta.t) \tag{11}$$

Generally, β have very small value.

4. SA Algorithm Implementation of ELD Problems

Step1: For initialization, choose temperature T, parameter α and maximum number of iterations 'max tries', to generate an initial feasible solution by random process and store it as current solution Si. Then performs ELD in order to evaluate the total cost, F_{cost}, while satisfying power balance as well as generator constraints as in eq. (4) and eq. (6) respectively.

Step2: Set the iteration counter to μ=1

***Step3*:** Create an adjacent solution S_j through the rand operator and compute the new total cost, F_{cost}.

Step4: If the new solution is found to be better, accept it; otherwise find the deviation of cost $\Delta S=S_j-S_i$ and generate a random number $\Omega \in (0, 1)$ out of a uniform distribution using the following logic:

If $$e^{-\Delta S/t} \geq \Omega \in (0,1) \quad (12)$$

Accept the new solution S_j to replace S_i.

Step5: Reduce temperature by parameter α, until the stopping criterion is not satisfied

$T(t) = \alpha . T$, *and* go back to Step 2.

5. Results and Discussion

The proposed SA-based approach has been developed and implemented using the MATLAB software. In order to investigate the robustness of the proposed method we experimented with four standard test cases. They are 3 unit system, 13 unit system, 18 unit systems with a varying percentage of the maximum power as demand and a large system consisting of 40 generating unit. The programs were developed using MATLAB 7.1 and the system configuration is Pentium IV processor with 2.4 GHz speed and 512 MB RAM.

5.1 Selection of control Parameters

As in other evolutionary optimization approach, SA algorithm also needs appropriate selection control parameter before implementation. Because optimum parameter selection finally responsible for smooth fitness convergence. The following process has been applied to determine optimal values of parameters such as initial temperature, final temperature, consecutive rejection and maximum number of iterations, which is used here as a stopping criteria. A standard test system with 3 generating units [Walter *et al.* (1993)] having valve point loading effects is used to locate the best control parameters. Load demand of the system is set at 850MW. For conducting the test, the initial temperature is fixed at 300^0 C, alpha is increased from 0.5 to 0.99 in suitable steps and max tries is varied from 1000 to 10000 as shown in Table 2 and further initial temperature is increased from 100^0C to 400^0C as given in Table 3.

Table 2: Influence of parameters on SA performance
Initial Temperature=300^0 C

Max. Tries	**alpha**					
	0.5	0.6	0.7	0.8	0.9	0.99
1000	8424.69608	8369.93635	8343.93784	8241.18305	8234.07179	8234.07180
4000	8424.69608	8241.17563	8294.33710	8241.58756	8250.20597	8234.07173
7000	8424.69608	8241.17678	8241.18786	8234.07181	8241.58753	8234.07174
10000	8424.69608	8241.17981	8241.17469	8241.17537	8234.07175	**8234.07162**

Table 3: Effect of initial temperature on 3 unit non convex system (PD=850MW) with alpha=0.99, max. tries =1000

Initial Temperature (^{0}C)	**Pg1**	**Pg2**	**Pg3**	**Minimum Cost ($/hr)**	**Mean Cost ($/hr)**	**Max. Cost ($/hr)**	**Std. Deviation**
100	600.00	174.80	50.00	8369.93466	8446.23	8446.23	67.79
200	498.93	251.18	99.89	8241.20354	8288.51	8288.51	81.60
300	**300.27**	**400.00**	**149.73**	**8234.07162**	**8234.07**	**8234.07**	**00.00**
400	300.27	400.00	149.73	8234.07176	8234.07	8234.07	00.00

Over 20 repeated trials, the SA algorithm was successful in achieving a minimum cost $**8234.07162/hr** and standard deviation 0.00000 with the tuning parameters value: initial temperature=300^0C,alpha = 0.99; and max. tries = 10000, which is used for analysis of other problems.

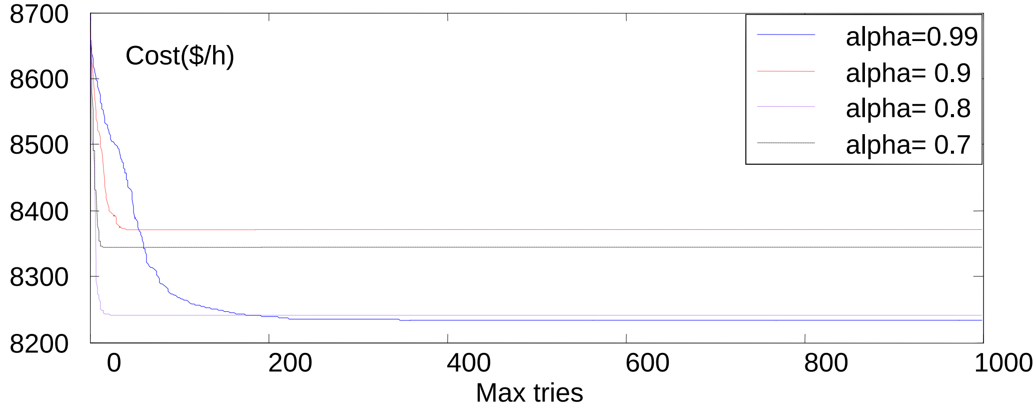

Figure 1: Convergence of 3 Generators system PD=850MW

Test Case 1: *Three Unit System*

The test system consists of 3 generating units with valve point loading effect with total load demand of 850 MW. Because of the small dimension of the problem, the global best cost of this example is known and the main target is to show that the global best output can also be obtained by the SA approach.Result obtained using SA method is and compared with genetic algorithm (GA), evolutionary programming (EP), Hybrid particle swarm optimization sequential quadratic programming (PSO-SQP), Artificial Bee Colony Algorithm (ABC) and modified group search optimizer algorithm (MGSO) in Table 4. The minimum cost attained by the SA method is 8234.07 $/hr which indicates that the SA approach is capable of producing the global best results.

Table 4: Comparison of Results for 3 unit system

Algorithm	**Pg1(MW)**	**Pg2(MW)**	**Pg3(MW)**	**PD (MW)**	**Min cost ($/hr)**	**Ave cost ($/hr)**
GA (Walter *et al*. 1993)	299.100	399.000	150.800	850	8239.20	----
EP (Yang H.T *et al*. 1996)	300.264	400.000	149.736	850	8234.07	8234.16
PSO-SQP (Aruldoss *et al.* 2004)	300.267	400.000	149.733	850	8234.07	8234.07
ABC (Hemamalini *et al* . 2008)	300.260	400.000	149.740	850	8234.07	----
MGSO (Zare *et al.* 2012)	300.2669	400.000	149.7331	850	8234.07	8234.07
SA	**300.2667**	**400.000**	**149.7333**	**850**	**8234.07**	**8234.07**

Test Case 2: *Thirteen Unit System (P_D=2520 MW)*

The system contains thirteen thermal generating units having non convex fuel cost characteristics. This system has more complexity and has multiple minima. For simulation purpose load demand on the system set at 2520 MW. The fuel cost coefficients are provided in (Sinha N. *et al.,* 2003). The best cost obtained using the SA method is $**24169.91769418** per hour. Table 5 compares the numerical results with those of other approach. Results shows that the SA algorithm is capable of finding better cost than genetic algorithm (GA), Hybrid genetic/simulated-annealing approach (GA-SA), Hybridization of EP with sequential quadratic programming(EP_SQP), Hybrid particle swarm optimization sequential quadratic programming (PSO_SQP) (Aruldoss *et al.* 2004), improved coordination aggregated based PSO (ICA-PSO) (Vlachogiannis *et. al*. 2009), and modified group search optimizer algorithm (MGSO) (Zare *et al.* 2012) and well comparable with differential evolution (DE) (Noman N *et al.* 2008). The convergence behavior is shown in Figure 2.

Test Case 3: *40 unit system*

The test case consists of 40 generators with valve point loading and has a total load demand of 10,500 MW. The input data are given in [Sinha N *et. al*. (2003)]. This test case has larger and more complex than previous test cases. It has several local minima, and hence global minimum is very difficult to locate. The dispatched power generation results achieved using the proposed SA approach and other recently reported heuristic optimization approaches are given in Table 7. The optimum fuel cost achieved by the proposed SA algorithm is $121412.55369757, which is better than the value reported by all other heuristic methods. The comparison of minimum cost, average cost and maximum cost by the proposed approach with the other recently reported results obtained using firefly algorithm (FA), modified group search optimizer (MGSO)**,** hybrid swarm intelligence based harmony search algorithm (HHS), biogeography-based optimization (BBO), improved coordinated aggregation-based PSO (ICAPSO) ,bacterial foraging with nelder-mead (ABF_NM) local search, self-organizing hierarchical PSO (SOH_PSO) ,artificial bee colony(ABC) and other methods is depicted in Table 6. The minimum cost obtained by SA algorithm is better than all reported methods and the convergence characteristic is presented in Figure 3.

Table 5: Results for13 unit system for a demand of 2520 MW

Generator Power O/P(MW)	**GA**	**GA-SA**	**EP-SQP**	**PSO-SQP**	**DE**	**MGSO***	**ICA-PSO****	**Proposed SA**
Pg1	628.32	628.23	628.3136	628.3205	628.3185	628.3185	628.32	628.3185
Pg2	356.49	299.22	299.1715	299.0524	299.1993	299.1993	299.19	299.1993
Pg3	359.43	299.17	299.0474	298.9681	299.1993	294.4839	294.51	299.1993
Pg4	159.73	159.12	159.6399	159.4680	159.7331	159.7331	159.73	159.7331
Pg5	109.86	159.95	159.6560	159.1429	159.7331	159.7331	159.73	159.7331
Pg6	159.73	158.85	158.4831	159.2724	159.7331	159.7331	159.73	159.7331
Pg7	159.63	157.26	159.6749	159.5371	159.7331	159.7331	159.73	159.7331
Pg8	159.73	159.93	159.7265	158.8522	159.7331	159.7331	159.73	159.7331
Pg9	159.73	159.86	159.6653	159.7845	159.7331	159.7331	159.73	159.7331
Pg10	77.31	110.78	114.0334	110.9618	77.3999	77.3999	114.8	77.3999
Pg11	75.00	75.00	75.0000	75.0000	77.3999	77.3999	77.4	77.3999
Pg12	60.00	60.00	60.0000	60.0000	92.3999	92.3999	55	87.6845
Pg13	55.00	92.62	87.5884	91.6401	87.6845	92.3999	92.4	92.3999
Total Power Generation(MW)	2519.96	2519.99	2520	2520	2520	2520	2520	2520
Total Power Generation(MW)	2520	2520	2520	2520	2520	2520	2520	2520
Power Mismatch(MW)	0.0399	0.0100	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Minimum Cost ($/hr)	24398.23	24275.71	24266.44	24261.05	24169.9177	24173.88 855357	24178.69 823123	**24169.91 769418**

*Reported generation Cost: $/hr 24,164.0508;** Reported generation Cost: $/hr24168.91

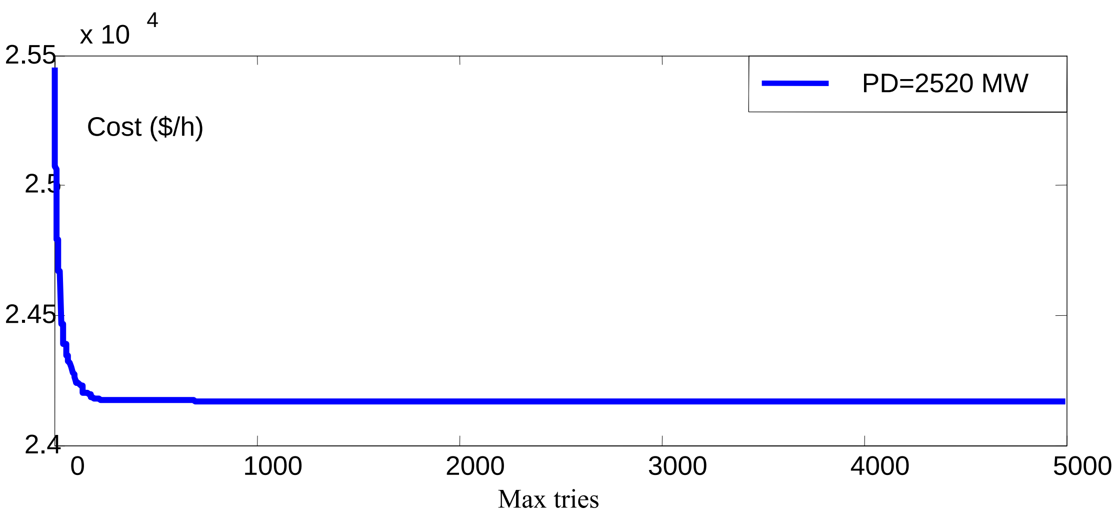

Figure 2: Convergence of 13 Generators system with PD=2520MW

Table 6: Comparison of Results for 40 unit system

Solution technique	Production cost ($/hr)		
	Min cost	Avg cost	Max cost
IFEP (Sinha *et al.* 2003)	122624.3500	123382.0000	125740.6300
NPSO_LRS (Selvakumar *et al* . 2007)	121664.4308	122209.3185	122981.5913
ABC (Hemamalini *et al* .2008)	121432.3900	121995.82	122123.77
SOH_PSO (Chaturvedi *et al.* 2008)	121501.1400	121853.57	122426.3000
ABF_NM (Panigrahi *et al.* 2008)	121423.6379	121814.9465	-------
DE (Noman N *et al.* 2008)	121416.29	121422.72	121431.47
ICA_PSO (Vlachogiannis *et. al.* 2009)	121413.20	121428.14	121453.56
BBO (Bhattacharya *et al.* 2010)	121426.9530	121508.0325	121688.6634
HHS (Pandi *et al* . 2011)	121415.5922	121615.8544	-------
FA (Yang *et al.* 2012)	121415.0522	121416.57	121424.56
MGSO (Zare *et al.* 2012)	121,412.5693	-------	-------
SA	**121412.55369757**	121418.05	121425.27579

Table 7: Comparison of Results for 40 unit system (MD=10500 MW)

Power O/P (MW)	**SA**	**MGSO**	**FA**	**HHS**	**BBO**	**SOH_PSO**	**NPSO_LRS**
P_1	110.8003	110.7999	110.8099	110.9030	110.8158	110.80	113.9761
P_2	110.7998	110.8003	110.8059	110.8642	111.0896	110.80	113.9986
P_3	97.3999	97.4003	97.40230	97.4039	97.40261	97.40	97.4241
P_4	179.7331	179.7336	179.7332	179.7339	179.7549	179.73	179.7327
P_5	87.7999	87.7999	92.7070	91.4353	88.20832	87.80	89.6511
P_6	140	140	140.0000	139.9999	139.9886	140.00	105.4044
P_7	259.5994	259.5996	259.6004	259.6181	259.5935	259.60	259.7502
P_8	284.5997	284.5997	284.6004	284.6035	284.6174	284.60	288.4534
P_9	284.5997	284.6	284.6004	284.6164	284.6479	284.60	284.6460
P_{10}	130	130	130.0028	130.0000	130.0298	130.00	204.8120
P_{11}	94	94	168.8008	168.8046	94.01459	94.00	168.8311
P_{12}	94	94	168.8008	168.7989	94.26367	94.00	94.0000
P_{13}	214.76	214.7595	214.7606	214.7624	304.5153	304.52	214.7663
P_{14}	394.2794	394.2794	304.5204	394.2790	394.264	304.52	394.2852
P_{15}	394.2794	394.2794	394.2801	304.5197	304.5057	394.28	304.5187
P_{16}	394.2794	394.2794	394.2801	394.2787	394.2472	394.28	394.2811
P_{17}	489.2794	489.2794	489.2801	489.2876	489.3273	489.28	489.2807
P_{18}	489.2794	489.2794	489.2801	489.2806	489.3047	489.28	489.2832
P_{19}	511.2794	511.2794	511.2817	511.2844	511.3087	511.28	511.2845
P_{20}	511.2794	511.2794	511.2817	511.2829	511.2495	511.27	511.3049
P_{21}	523.2794	523.2794	523.2793	523.2794	523.3217	523.28	523.2916
P_{22}	523.2794	523.2794	523.2793	523.2783	523.3144	523.28	523.2853
P_{23}	523.2794	523.2794	523.2832	523.2812	523.3629	523.28	523.2797
P_{24}	523.2794	523.2794	523.2832	523.2810	523.2883	523.28	523.2994
P_{25}	523.2794	523.2794	523.2793	523.2815	523.2989	523.28	523.2865
P_{26}	523.2794	523.2794	523.2793	523.2828	523.2802	523.28	523.2936
P_{27}	10	10	10	10.0003	10.02817	10.00	10.0000
P_{28}	10	10	10	10.0000	10.00321	10.00	10.0001
P_{29}	10	10	10	10.0000	10.0288	10.00	10.0000
P_{30}	87.7999	87.7999	87.8008	88.7063	88.14595	97.00	89.0139
P_{31}	190	190	189.9989	189.9999	189.9913	190.00	190.0000
P_{32}	190	190	189.9989	190.0000	189.9888	190.00	190.0000
P_{33}	190	190	189.9989	190.0000	189.9998	190.00	190.0000
P_{34}	164.7998	164.8025	164.8036	164.8519	164.8452	185.20	199.9998
P_{35}	200	194.3935	164.8036	164.8967	192.9876	164.80	165.1397
P_{36}	194.3973	200	164.8036	164.8205	199.9876	200.00	172.0275
P_{37}	110	110	110	110.0000	109.9941	110.00	110.0000
P_{38}	110	110	110	109.9997	109.9992	110.00	110.0000
P_{39}	110	110	110	110.0000	109.9833	110.00	93.0962
P_{40}	511.2794	511.2794	511.2794	511.2836	511.2794	511.28	511.2996
Total Cost ($/h)	121412.5536975	121,412.5693	121415.0522	121415.5922	121426.593	121501.14	121664.4308

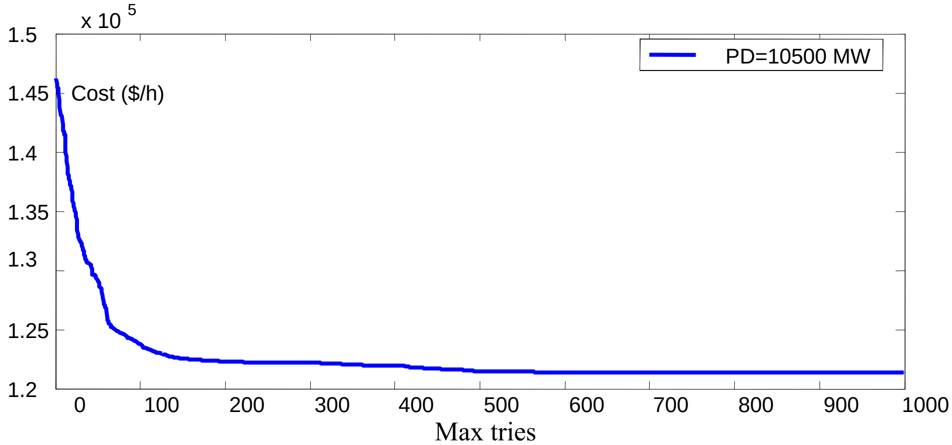

Figure 3: Convergence of 40 generators system with PD=10500MW

Test Case4: *Eighteen Unit System (P_D=433.22 MW)*

The fourth test case considers the Greek island of Crete consisting of 18 thermal units system. The technical limits and the quadratic cost coefficients for the above system is adopted from (Ioannis *et al*. 2003).The maximum power output of the generators set is 433.22MW. Various tests were made with a varying percentage of the maximum power as demand. Table 8 summarizes the test results in terms of optimum power generation dispatch, and it is evidently seen from Table 9 that the proposed technique provided better results compared to other reported evolutionary algorithm techniques**.** Hence it is clear that the SA performs very well for finding the optimum solution of the ELD problems, while it takes relatively low computational time per iteration. Figure 4 shows the convergence behavior of test case 4 with a varying percentage of the maximum power as demand.

Table 8: Comparison of Results for 18 unit system (MD=433.22 MW)

Unit power output(MW)	0.70*MD	0.80*MD	0.90*MD	0.95*MD
Pg1	15.0000	15.0000	15.0000	15.0000
Pg2	45.0000	45.0000	45.0000	45.0000
Pg3	25.0000	25.0000	25.0000	25.0000
Pg4	25.0000	25.0000	25.0000	25.0000
Pg5	25.0000	25.0000	25.0000	25.0000
Pg6	3.0000	3.0485	8.2379	13.7063
Pg7	3.0000	3.1334	8.2379	13.7063
Pg8	12.2800	12.2800	12.2800	12.2800
Pg9	12.2800	12.2800	12.2800	12.2800
Pg10	12.2800	12.2800	12.2800	12.2800
Pg11	12.2800	12.2800	12.2800	12.2800
Pg12	14.8322	20.9144	24.0000	24.0000
Pg13	3.0000	3.0000	3.1636	6.4132
Pg14	21.0494	30.2892	36.2000	36.2000
Pg15	23.1610	32.5145	42.5270	45.0000
Pg16	24.0457	32.7503	37.0000	37.0000
Pg17	24.0457	33.8056	43.4116	45.0000
Pg18	3.0000	3.0001	3.0000	6.4132
Total power output (MW)	**303.254**	**346.576**	**389.898**	**411.559**
Minimum Cost ($/hr)	**20386.30950**	**23855.85595**	**27653.78063**	**29731.06662**
Average cost($/h)	**20389.0000**	**23856.4600**	**27655.5700**	**29731.6500**
Standard deviation($/hr)	**2.39**	**0.88**	**2.94**	**0.85**
CPU time/iteration(sec)	**0.037**	**0.030**	**0.042**	**0.043**

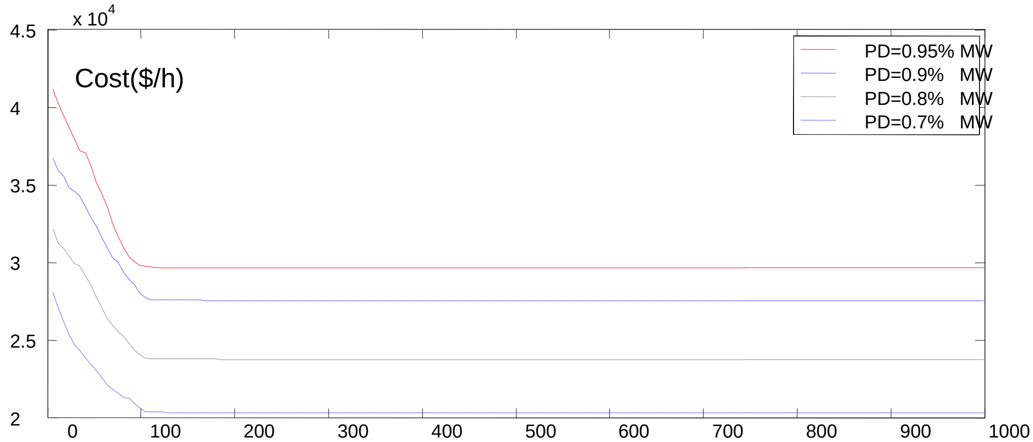

Figure 4: Convergence Characteristics of Eighteen Unit System with various loads

Table 9: Comparison of Results for 18 unit system

Solution technique	**0.95*MD**	**0.90*MD**	**0.80*MD**	**0.70*MD**
λ-iteration (Ioannis G. *et al.,*2003)	29731.05	27652.47	23861.58	20393.43
Binary GA (Ioannis G. *et al.,*2003)	29733.42	27681.05	23980.24	20444.68
Real-coded GA (Ioannis G. *et al.,*2003)	29731.05	27655.53	23861.58	20396.39
ABC (Dixit G. *et al.,*2011)	29730.80	27653.30	23859.40	20391.60
SA	**29731.066620**	**27653.780630**	**23855.855950**	**20386.309503**

Table 9 shows that the minimum fuel cost obtained by the SA algorithm in case of varying percentage of the maximum power demand is better than all other reported results.So it can be concluded that the SA method is computationally more efficient as compared to previously reported methods.

6. Conclusion

This paper has proposed the SA algorithm for ELD problems, a stochastic optimization technique based on the process of annealing in thermodynamics is presented. In this work we have investigated the potential of the SA algorithm in solving particularly non-smooth cost functions. The ELD problem has become a very important issue with the depleting reserves of coal and the increase in fuel prices. An appropriate planning and scheduling of available generating units may save millions of dollars per year in production cost. First a study was carried out to determine the optimal values of tuning parameters of the SA and then the best set of parameters were fixed for the rest of the studies. Selection of optimum combination of parameters for SA algorithm is an essential task, since the success of the algorithm depends on it. The feasibility of the proposed method for solving ELD problems is verified by using 3, 13, 40 and 18 generator test systems, out of which the first three test cases are with valve-point loading effects. The outcome of the analysis supports the claim that the proposed method was found to provide better solutions than solutions of other methods reported so far. Test case four considers the Greek island of Crete consisting of 18 thermal units system, in which the robustness of the SA method was verified by the change in load demands of the problem. The obtained SA results for this problem were not the best, but very close to previously mentioned methods. Considering all the results of ELD problems with different characteristics, dimensions, demands and constraints, it can be concluded that SA is powerful optimization technique for constrained optimization. The results obtained are either better or are matching in accuracy with previously proposed methods. Therefore, SA based optimization is a promising alternative approach for solving complicated problems in power system. The findings of this paper confirm that the proposed SA algorithm can be applied for solving other power system problems with different levels of complexity.

Nomenclature

F_t^{cost}	: Total power production cost
$f_i(P_i)$	: Fuel cost corresponding to ith generator for output power P_i
a_i, b_i , c_i	: Cost coefficients of ith generator
P_i	: Real power output (MW) of ith generator corresponding to time period t
e_i , f_i	: Cost coefficients to effectively model the valve point loading effect
B_{ij}, B_{i0}, B_{00}	: Loss coefficients
P_D	: Power demand
P_L	: Power loss
P_i^{max}	: Upper bound for power outputs of the ith generating unit
P_i^{min}	: Lower bound for power outputs of the ith generating unit

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