

Economic load dispatch with the help of simulated annealing

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Abstract

This paper gives an effective simulated annealing (SA) algorithm with a single determination variable to solve the economic load dispatch (ELD) problems. The philosophy involves the introduction of a new decision variable through a discreet mathematical transformation of the relation between the decision variable and the optimal generations. The objectives of ELD problems in electric power generation is to programmed the devoted generating unit outputs so as to meet the compulsory 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 SA algorithm presented here is applied to two case studies, which analyze power systems having 6 and 10 generating units. The results determined by the proposed approach are compared to those found by MPSO.

Keywords

Economic load dispatch, Simulated annealing.

1. Introduction

Economic operation is very significant for a power system to get profits on the capital invested. Operational economics needing 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 load dispatch is to minimize the total cost of the generation while honoring the operational constraints of the available generation resources. 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 the 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 analyses on the ELD has been carried till now suitable improvements in the unit output scheduling can contribute to significant cost savings.

Classical methods like Newton-based and gradient methods cannot perform very well for problems having highly nonlinear characteristics with large number of constraints and many local optimum solutions. Dynamic programming is one of the approached to solve non-linear and discontinuous ELD problem, but it suffers from problem of curse of dimensionality or local optimality [1]. Methods based on artificial intelligence techniques, such as artificial neural networks, are presented [2-4]. However, neural network-based approaches may suffer from excessive numerical iterations, resulting in huge calculations. Heuristic search techniques, such as evolutionary programming [5], particle swarm optimization [6], genetic algorithms [7-9], differential evolution [10], tabu search [11] and ant colony optimization [12] have also been successfully applied to ELD problems.

Therefore the simulated annealing (SA) is the proposed manner so as to estimate the efficiency of the generators. So that the load that is to be shared to the generators in an economic way resulting in the reduction of economic load dispatch problems. The proposed approach is found to provide optimal results while working with the operating constraints in the ELD and valve point loading effects. In order to prove the robustness of the algorithm it is investigated on different standard test cases consisting of 6 and 10 generating unit systems.

2. Research method

2.1 Economic load dispatch formulation

“The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output from the generating units. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^N F(P_i) = \sum_{i=1}^N (a_i P_i^2 + b_i P_i + c_i) \quad (1)$$

Where F_T is total fuel cost of generation in the system (\$/hr), a_i , b_i , and c_i are the cost coefficient of the i^{th} generator, P_i is the power generated by the i^{th} unit and N is the number of generators.

The cost is minimized subjected to the following power balance and generator capacity constraints.

2.2 Equality constraints

$$\sum_{i=1}^N P_i - P_D - P_{Loss} = 0 \quad (2)$$

Where P_D is the total power demand and P_{Loss} is total transmission losses.

The transmission loss P_{Loss} can be calculated by using B matrix technique and is defined by (3) as,

$$P_{Loss} = \sum_{i=1}^N \sum_{j=1}^N P_i B_{ij} P_j \quad (3)$$

Where B_{ij} 's are the elements of loss coefficient matrix B.

2.3 Inequality constraint

$$H(x, P) \leq 0 \quad P_{i\min} \leq P_i \leq P_{i\max} \quad (4)$$

3. Optimization using simulated annealing

3.1 Analogy to simulated annealing

The simulated annealing algorithm was earlier inspired from the process of annealing in the metal works. Annealing involves heating and cooling a material to alter its physical properties due the changes in the internal structure. As the metal cools its new structure becomes fixed, consequently causing the metal to retain its newly obtained properties.

It is essentially 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 particularly 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.

3.2 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 $PT(s)$ that it has a configuration s depends on the energy of the corresponding configuration $E(s)$, and is subject to the Boltzmann distribution

$$P_t(s) = \frac{e^{-E(s)/kT}}{\sum_W e^{-E(w)/kT}} \quad (5)$$

Where, k is the Boltzmann constant and the sum $\sum W$ includes all possible states W . Metropolis [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 :

$$e^{-(E(\sigma)-E(g))/kT} \quad (6)$$

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

3.3 Critical parameters of simulated annealing

There are four control parameters in the simulated annealing process:

- Initial Temperature
- Final Temperature
- Temperature Decrement Rate
- Iteration parameter

a) Initial Temperature: The initial 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.

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 Rate:- 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 suggested the following way to decrement the temperature:

$$T(t) = d/\log(t) \quad (7)$$

Where d is a positive constant. An alternative is the geometric relation: $T(t) = a \cdot t$. Parameter a , is a constant near 1. In effect, its typical values range between 0.8 and 0.99.

d) Iterations Parameter:- 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. The temperature decrement should take place at a really slow pace that can be expressed as

$$T(t) = t / (1 + \beta t) \quad (8)$$

Where, β takes a very low value.

4. Advantage of simulated annealing

When there is a large number of local optimal values which are available in the system, then it increases the complexity of finding the optimal point. So the main task in the optimization is to achieve fast convergence as well as good exploration capacity.

Apart from the above there are a few advantages of simulated annealing. They are as follows:

- i. Simulated Annealing doesn't need large memory for computations
- ii. It is quite robust with respect to non-quadratic surfaces. Simulated algorithm has very limited assumptions when solving optimization problem.

5. 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 (5) and (7) 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

$$e^{-\Delta S/t} \geq \Omega \in (0,1) \quad (8)$$

Accept the new solution S_j to replace S_i .

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

6. Simulated annealing algorithm

1. Choose an initial temperature T , final temperature T' , a decrement parameter b and the iteration values C_i .
2. Set the iteration counter C to zero (0).
3. Generate an initial solution S_i randomly and compute its cost function $F_{cost}(S_i)$.
4. Generate an adjacent solution S_j randomly and compute its cost function $F_{cost}(S_j)$.
5. If $F_{cost}(S_j) \leq F_{cost}(S_i)$ then accept the new solution, if $F_{cost}(S_j) > F_{cost}(S_i)$ then let $\Delta S = F_{cost}(S_j) - F_{cost}(S_i)$ generate a random number $\omega \in (0,1)$ and accept it if $e^{-\Delta S/t} \geq \omega$. If there is an accepted new solution, replace the initial one with the new.
6. Decrease the temperature $T(t) = b \cdot T(t-1)$.
7. If $T \leq T'$ then Algorithm ends. If $T > T'$ then turn back to step 4 and repeat.

7. Result and discussion

In this paper, to evaluate the effectiveness of the proposed SA approach, two case studies 06 and 10 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, Cooling Schedule (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 = 3000^oC, Final temperature = 1e-100^oC, Cooling Schedule (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 2017 and all the programs were run on a intel core i3 processor with 4 GB of RAM (Random Access Memory).

7.1Case study I

This case study consists of 6 generating units. All units are within the convex fuel cost characteristics for the above system is taken from [13]. In this case, the load demand expected to be determined is PD = 700 MW. The B matrix of the transmission loss coefficient is not considered in this system.

Table 1 shows the minimum, mean cost, standard deviations and CPU time per iteration, cost achieved by the SA approach. As indicated in Table 1, the SA was the approach that obtained the minimum cost for the ELD of 6 generating units. The best result obtained for solution vector $P_i, i = 1 \dots 6$ by SA with minimum cost of **36912.14 Rs/h** is given in Table 1 and Table 2 also compares the results obtained with the MPSO, this paper with those of other studies reported in the literature and the convergence behavior of Case study

Table2 Comparison of results for case study I (P_D=700 MW)

Generator Power O/P(MW)	MPSO	SA
P _L	19.42	19.41
P _{g1}	28.103	28.2
P _{g2}	10.00	10.0
P _{g3}	118.28	118.96
P _{g4}	118.58	118.67
P _{g5}	232.05	230.76
P _{g6}	232.05	212.73
Fuel Cost (Rs/hr)	36912.22	36912.14

7.2Case study II

In this case study a large scale data consisting of 10 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 [14]. In this case study PD = 2000 MW expected to be determined. Tables 2 shows the Best Power Output of 10 unit system for PD=2000 MW. As indicated in Table 3, the SA was the approach that obtained the minimum cost for the ELD of 10 generating units.

The best result obtained by SA with minimum cost for PD=2000MW is **111259.5 Rs/hr** is given in Table 3 and also compares the results obtained with the MPSO

Table3 Comparison of results for case study II (PD=2000 MW)

Generator Power O/P(MW)	MPSO	SA
P _L	87.017	87.006
P _{g1}	55	54.9
P _{g2}	80	80
P _{g3}	106.86	108.5
P _{g4}	99.315	100
P _{g5}	82.932	80.459
P _{g6}	83.853	82.81
P _{g7}	300	300
P _{g8}	339	340
P _{g9}	470	470
P _{g10}	470	470
Fuel Cost (Rs/hr)	111266.1	111259.5

8. Conclusion

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 arisen for the determination of the global or near-global optimal solution for the ELD problems. The proposed SA approach has produced results corresponding or better than those generated by other evolutionary algorithms and the solutions obtained have super ordinate solution quality and good intersection characteristics and the strength of the method was demonstrated by the change in load demands of the problems. Because of in the exempted environment where cost minimization not only the objective, but at the same time profit maximization is also concern. Fast and precise economic load dispatch solution is as usual demand in deregulated scenario as well.

Therefore, results show that SA based optimization is an assuring technique for solving complicated and large ELD problems in electrical power system.

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