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Simulated Annealing - Based Optimal Solution Methodology under Deregulation Power System Environment

Lokanatha Dhall Samanta*, Jitendra Kumar Das* and Bibhu Prasad Panigrahi**

In economic load dispatch solution procedure, the fuel cost characteristics of a thermal generator are usually approximated by (i) a quadratic function; (ii) piecewise quadratic function; and (iii) a polynomial function with order higher than two. When functions in (ii) and (iii) are adopted, the economic load dispatch problem may have several optimum solutions with one being the global optimum solution. To find the global or near global optimum solution, the new algorithm based on Genetic Algorithm (GA) or Simulated Annealing (SA), etc., for solving the economic dispatch problem is needed.

In this paper, the generation dispatch methodologies under deregulation power system environment have been developed. The classical economic dispatch algorithm relies on the convexity of the cost function. However, in deregulated power market, the market strategies make the seller's bidden cost function concave causing classical economic algorithm inapplicable. Here, a special type of algorithm is developed based on the deregulation strategy and also a heuristic algorithm is proposed which combines with the powerful searching mechanism of simulated annealing with mathematical foundation on global optimization.

Keywords: *Fuel cost, Genetic algorithm, Deregulation strategy, Simulated annealing.*

1.0 INTRODUCTION

The efficient and optimum economic operation and planning of electric generation system [1,2] have always occupied an important position in electrical power industry. In classical economic dispatch algorithm, the quadratic production cost function and the incremental costs are used to make the algorithm simple, efficient and accurate, and this algorithm depends heavily on production cost property, "the higher the output, the higher the incremental cost". But in a deregulated system, the production cost is replaced by the sellers' bidden cost function, including not only the production cost but also the market strategy; and the property of the bidden cost may become "the higher the output, the lower the incremental cost", making the classical economic dispatch inapplicable. To solve this problem [3,4], an efficient algorithm is provided which combines the powerful searching mechanisms of simulated annealing with the mathematical foundations on global solutions.

2.0 FORMULATION OF AUCTION-BASED DISPATCH PROBLEM FOR DEREGULATED POWER SYSTEMS

2.1 Notations

The following notations are used consistently.

*Synergy Institute of Engineering and Technology, Dhenkana, Odisha, India.
**Indira Gandhi Institute of Engineering and Technology, Sarang, Angul, Odisha, India.

N_g: the number of the sellers;

a_i, b_i, c_i: the parameters in the i-th seller's bidden cost function;

P_i: the contracted amount of i-th seller's bidden cost function;

P_{imax}, P_{imin}: the capacitnd lower limits of i-th seller's bidden amount;

PD: the total market demand;

λ, μ_{imax}, μ_{imin}: Lagrange multipliers;

$F_i(P_i)$: i-th sellers' bidden cost function;

$IC_i(P_i)$: i-th sellers' bidden incremental cost;

x: decision variable;

x*: optimal solution;

f (x): objective function;

D: constraint set;

N (x*, ε): neighborhood at x*;

R^n: n-dimensional real vector space.

2.2 Auction-Based Dispatch Problem

(1) Bidden Cost Function

In this paper, the seller's bidden cost [5–9] function is assumed to be a quadratic, which is in the form of

$$F_i(P_i)=a_i+b_i\times P_i+c_i\times P^2_i \tag{1}$$

Accordingly, the incremental cost is defined as the first-order derivative of the bidden cost function.

$$IC_i(P_i)=b_i+2\times c_i\times P_i \tag{2}$$

In a deregulated power market, the seller's objective is to make profits; the seller's bidden cost function consists of not only the production cost but also the market strategy.

(2) Formulation of Auction-Based Dispatch Problem

The auction-based dispatch problem is formulated as the least bidden cost optimization problem, in which the seller's total bidden cost is minimized while the balance of the supply and demand constraint and the capacity limit constraints are satisfied.

$$\sum_{i=1}^{N_g} F_i(P_i) \tag{3}$$

$$\text{s.t.} \sum_{t=1}^{N_g} P_i = P_D \tag{4}$$

$$P_{imin} \le P_i \le P_{imax},\ i\in[1,N_g] \tag{5}$$

The formulation seems to be the same as that of the classical economic dispatch problem, but the difference is that the objective function used here is the seller's bidden cost.

3.0 NECESSARY CONDITION FOR OPTIMAL SOLUTION

In problem (3), when

$$\sum_{t=1}^{N_g} P_{imin} > P_D \tag{6}$$

$$\text{or} \sum_{t=1}^{N_g} P_{imax} < P_D \tag{7}$$

there is no solution;

when $\sum_{t=1}^{N_g} P_{imin} = P_D$, each seller's contracted amount is at its capacity lower limit;

when $\sum_{t=1}^{N_g} P_{imax} = P_D$, each seller's contracted amount is at its capacity upper limit.

In the non-trivial case, when

$$\sum_{t=1}^{N_g} P_{imin} < P_D \text{ and } \sum_{t=1}^{N_g} P_{imax} > P_D$$

The following equations can be obtained from Kuhns–Tucker theorem,

$$\frac{\partial F_i}{\partial P_i} - \lambda - \mu_{imin} + \mu_{imax} = 0, \quad i = 1,.....,N_g$$

$$\sum_{i=1}^{N_g} P_i = P_D \tag{8}$$

$$\mu_{imin} \times (P_{imin} - P_i) = 0,\ i = 1,......,N_g \tag{9}$$

$$\mu_{i\max} \times (P_i - P_{i\max}) = 0,\ \ i = 1,\ldots\ldots, N_g \tag{10}$$

$$\mu_{i\min} \geq 0,\ i=1,\ldots,N_g \tag{11}$$

$$\mu_{i\max} \geq 0,\ i = 1,\ldots,N_g \tag{12}$$

- For the seller's contracted amounts that do not hit the capacity limits,

$$P_{i\min} < P_i < P_{i\max},\ i \in [1,N_g] \tag{13}$$

$$\frac{\partial F_i}{\partial P_i} = \lambda \tag{14}$$

- For the seller's contracted amounts that hit the capacity upper limits,

$$P_i = P_{i\max},\ i\in [1,N_g] \tag{15}$$

$$\frac{\partial F_i}{\partial P_i} = \lambda - \mu_{i\max} \leq \lambda \tag{16}$$

- For the seller's contracted amount that hit the capacity lower limits,

$$P_i = P_{i\min},\ i\in [1,N_g] \tag{17}$$

$$\frac{\partial F_i}{\partial P_i} = \lambda + \mu_{i\min} \leq \lambda \tag{18}$$

In the following parts throughout, the discussion focuses on the non-trivial case.

Theorem 1: A Necessary Condition for Optimal Solution

Suppose $P^* = (P^*_1 \ldots P^*_{Ng})$ is an optimal solution of problem (1.3), define

$\lambda = IC_i\ (P^*_i)$ for $P_{i\min} < P^*_i < P_{i\max}$, $i\in [1,N_g]$, then,

- $IC_i (P^*_i) \geq \lambda$ for $P^*_i = P_{i\min}$.
- $IC_i (P^*_i) \leq \lambda$ for $P^*_i = P_{i\max}$.

3.1 Global Optimization for Auction- Based Dispatch Problem

3.1.1 Some Definitions and Theorems for Global Minimization

To simplify the presentation, some definition and theorems for global minimization are studied based on the following optimization problem.

$$\min:\ f(x) \qquad \text{s.t. } x\in D \tag{19}$$

Definition 1: Global Minimizer and Global Minimum.

A point $x^*\in D$ satisfying $f(x^*) \leq f(x)\ \forall x\in D$ is called a global minimizer of f over D. The corresponding value of f is called the global minimum of f over D.

Definition 2: Local Minimizer.

A point $x^* \in D$ is called a local minimizer of f over D if there is an $\varepsilon>0$ such that
$f(x^*) \leq f(x),\ \forall x\in N(x^*, \varepsilon)D$

Theorem 2: Let $f:D\rightarrow R^1$ be convex and let $D \subset R^n$ be non-empty, compact and convex.

Then every local minimum of f over D is also global.

Theorem 3: Let $f:D\rightarrow R^1$ be concave and let $D \subset R^n$ be non-empty, compact and convex.

Then, the global minimum of f over D is attained at an extreme point. Some properties of the auction-based dispatch problem can be further exploited in order to design an efficient algorithm [10–13]. For example, in the auction-based dispatched problem, the objective function is quadratic and the constraint set contains only the liner constrains.

Definition 3: Quadratic Programming Problem

Global min $f(x) = x^TCx$, s.t : $x\in D$

Where, $D = \{ x \in R^n : Ax = b, x \geq 0 \}$ is a bounded polyhedron, C is an $n\times n$
Symmetric matrix, A is an $m\times n$ matrix and $b \in R^m$.

If C is positive definite, it is a Positive Definite Quadratic Programming (PQP) problem; if C is negative definite, it is a Negative Definite Quadratic Programming (NQP) problem; if C is indefinite, it is Indefinite Quadratic Programming (IQP) problem.

Theorem 4: The global optimal solution to the Indefinite Quadratic Programming problem occurs on a boundary point of D, not necessarily vertex.

3.2 Classical Economic Dispatch Algorithm

The classical economic dispatch algorithm relies heavily on the property of the production cost function: "the higher the output, the higher the incremental cost". In this case, the objective function is convex and quadratic [14–16]. To simplify the presentation, some test examples are given on the three-bus system as shown in Figure 1.

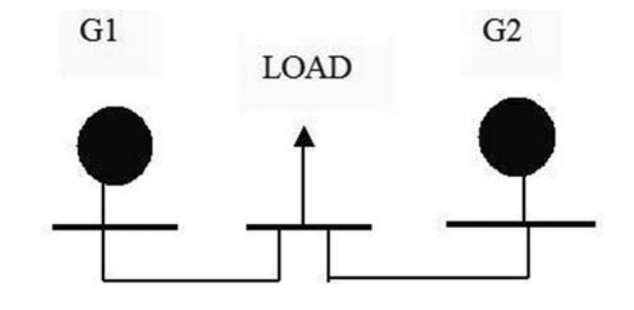

FIG. 1 A THREE-BUS TESTING SYSTEM

In this testing system, the generators have the capacity upper and lower limits as,

P_{1min} = 20 MW, P_{1max} = 100 MW, P_{2min} = 20 MW, P_{2max} = 100 MW.

[Example 1]

In the testing system, suppose the cost functions of the generators are,

$$F_1 = 2.5+0.25\times P_1+0.0014\times P_1^2 \quad (20)$$

$$F_2 = 5.0+0.18\times P_2+0.0018\times P_2^2 \quad (21)$$

which are convex functions.

Let P_D = 100 MW. According to Theorem 1,

$$IC_1 (P_1) = IC_2 (P_2) \quad (22)$$

$$P_1+P_2 = P_D \quad (23)$$

The solution is P_1=45.3 MW and P_2=54.7 MW with the total cost of ₹ 36.93/h, which is the global minimal solution.

3.3 Incapability of Classical Economic Dispatch Algorithm in Deregulated Power Systems

In a deregulated power system, the bidden cost function may no longer be convex. When the market strategy is considered, some of the seller's bidden cost functions may become "the higher the output, the lower will be the incremental cost" which may make the auction-based dispatch problem an IQP problem [14–16], and the classical economic dispatch algorithm will become inapplicable. Even worse, if all the bidden cost function is concave, the problem becomes the sufficient condition to maximize the total bidden cost, and the solution obtained from the classical economic dispatch algorithm will be the maximum global solution.

[Example 2]

In the testing system in Figure 1 are suppose the bidden cost functions of the sellers are

$$F_1=2.5+0.55\times P_1-0.0012\times P_1^2 \quad (24)$$

$$F_2=5.0+0.58\times P_2-0.0010\times P_2^2 \quad (25)$$

which are concave functions.

$$IC_1 (P_1) = IC_2 (P_2) \quad (26)$$

$$P_1 + P_2 = P_D \quad (27)$$

We have P_1=38.64 MW and P_2=61.36 MW with the total cost of ₹ 58.78/h, which is the global maximal solution. However, the global minimal solution is P_1=80 MW and P_2=20 MW with the total cost of ₹ 55.02/h.

3.4 Searching for Efficient Algorithms

The K-T theorem is revised to solve the economic load dispatch problem under deregulation environment**.**

The key question is to deal with the sellers with the concave bidden cost function. One idea is to set contracted amount of the sellers with the lowest IC (P_{max}) at its upper limit, but through perturbation analysis, it is impossible to proof that the solution obtained in this approach is the global optimum solution [14–16]. The following example illustrates the mistake of this idea.

[Example 3]

In the testing system, suppose the hidden cost function of the sellers to be

$$F_1=2.5+0.58\times P_1-0.0012\times P_1^2 \quad (28)$$

$$F_2=5.0+0.55\times P_2-0.0010\times P_2^2 \quad (29)$$

which are concave.

If P_D=100 NW, IC_1 (P_{1max})=0.34 and IC_2 (P_{2max})=0.35.

According to the "set the contracted amount of the seller with the lowest IC (P_{max}) at its capacity upper limit", the solution is P_1=80 MW and P_2 = 20 MW with the total cost of ₹ 56.82/h.

In fact, the global minimal solution is P_2=20 MW and P_2=80 MW with the cost of Rs. 56.22/h.

For the bidden cost function of the seller could be either convex or concave, the auction-based dispatch problem may become an IQP problem. Because of the computational difficulty of the problem, so far only heuristics and some approximate alternatives have been developed. In the following test systems, the application of simulated annealing is proposed.

4.0 SIMULATED ANNEALING-BASED ECONOMIC DISPATCH ALGORITHM

One of the most important aspects of power system operation is to supply powers to the customers economically. Various optimizing techniques have been adopted for sharing the generated power in most economical manner. In the above methods, the fuel cost characteristics of a Thermal Generator [17–19] is usually approximated by (i) quadratic function; (ii) piecewise quadratic function; and (iii) polynominal functions of (ii) or (iii) are adopted. The economic dispatch problem may have several local optimum solutions with one being the global optimum solution. To find the global or near global optimum solution, a more general method for solving the economic dispatch problem is needed. One of the methods is the simulated annealing method which is a very powerful technique and has the ability to find the global or near global solutions for large combinatorial optimization problems.

4.1 Simulated Annealing Technique

The simulated annealing technique method takes the analogy between the physical annealing process of solids and the process of solving combinatorial optimization problems, such as the economic dispatch problem. In physical annealing, when a molten particle at a very high temperature is cooled slowly, the particle can reach the state of thermal equilibrium at each temperature. At any temperature T, the thermal equilibrium state is characterized by the Boltzmann probability factor (BPF), $\exp(-E_i/K_BT)$, where E_i is the energy of the configuration of the particle, K_B is the Boltzmann's constant and T is the temperature [17–19]. The probability of the particle having energy E_i, $P(E_i)$ is given by

$$P(E_i)=\frac{\exp(-E_i/K_BT)}{\sum_j \exp(-E_j/K_BT)} \quad (30)$$

where the summation term is the sum of BPFs of all the possible states that the particle can have at temperature T.

The denominator in Equation (30) suggests the examination of all possible states of the particle at temperature T. By checking the energy levels of the states of the particle against the previous state, the current state of the particle for the next temperature is found. The cooling process continues in the same manner until the temperature is sufficiently low for the particle to become a solid.

4.2 Acceptance Criteria

The acceptance criteria for accepting a state of the particle within a number of trials consist of a deterministic criterion and a probabilistic criterion [21,22]. They are summarized below.

(i) The state with a lower energy level will be accepted.

(ii) The state with a higher energy level will be accepted in a limited way with a probability of acceptance, $P(\Delta)$. The expression of the probability of acceptance adopted is

$$P(\Delta)=1/(1+\exp(\Delta/K_BT)) \quad (31)$$

where Δ is the increment in energy level between the current state of the particle and the state formed by a small random displacement of the current state.

Metropolis proposed that the acceptance of the new state with a higher energy level will be determined by comparing a random number generated from a uniform distribution on the interval between 0 and 1 with the value of acceptance probability P(Δ). If the random number is less than the value of P (Δ), the new state is accepted as the current state.

4.2.1 Cooling Schedule

The rate of cooling in the annealing process can be controlled by a number of different schedules. The cooling schedule adopted here is

$$T_k= r^{(k-1)}\times T_1 \quad (31a)$$

where k is the cooling step counter and r is a scaling factor less than 1. T_1 is the initial temperature.

4.2.2 Application to Optimization Problems

As the concept of the temperature in physical annealing has no equivalent in the problem being optimized, the temperature can be taken as the control parameter. Moreover, the cooling step counter k in Equation (31) can be regarded as the iteration counter. With the above considerations, the control parameter $\sigma_k=T_k$ and replacing K_BT by σ_k we have

$$P(\Delta)=1/(1+\exp(\Delta/\sigma_k)) \quad (32)$$

4.2.3 Economic Dispatch Algorithm Based on Simulated Annealing

For the economic dispatch problem, the increment in energy level Δ in Equation (32) is equivalent to the increment in fuel cost by ΔF_t, and hence the Equation (32) becomes

$$P(\Delta F_i)=1/(1+\exp(\Delta F_i/\sigma_k)) \quad (33)$$

Consider the case where there are N_g sellers. Assume that the power loading of 'N_g–1' generators are specified from the Equation (1). The power level of the remaining generator C, i.e. the dependent generator, is given by

$$P_r=P_D-\sum_{\substack{i=1\\ i\neq\gamma}}^{N_g} P_i \quad (34)$$

The loading levels of all the generators are then taken as the starting values in the iterative solution process, provided that they satisfy the constraints on the operation limits of the generators. The generation of a neighborhood solution of power loading is then computed in an iterative manner.

4.2.4 Generation of a Neighborhood Solution

At any iteration 'k', let the solution of the power loadings of any N_g–1 generators be held in vector P. To find a solution in the neighborhood of the loading in P, the amount of perturbation for each loading in P is first found according to probability distribution function (PDF). In the present work, the Gaussian PDF is assumed and its standard deviation is set to the product of the control parameter σ and a scaling factor γ. This means that the probability of generating a perturbation of the amount in the range between –σγ and +σγ is 68.26 %.

Let the perturbations be stored in vector N. A solution in the neighborhood of the loading in P is then given by (P+N). The power loading of the dependent generator is calculated according to Equation (34). The complete set of power loading of the N_g generators generated is then a new solution in the neighborhood of the current solution.

4.2.5 Initial Loading and Initial Control Parameter

While the values of generator loadings may be set arbitrarily at the beginning of the solution process in the simulated annealing-based algorithm, the initial settings of the loadings can be set on the basis that the generators share the total load demand in proportion to their ratings.

The initial value of the control parameter is usually set to a large value so that the neighborhood solutions with higher costs can be accepted. Consequently, as the control parameter [22–25] is reduced gradually from this very high initial value, it is possible for the solution process to 'jump' out of many local optimum points in seeking for the many local optimum solution. However, the control parameter value should not be too high, as many unfeasible solutions will be generated in a very large neighborhood space.

To determine the initial control parameter values, the probability of acceptance in Equation (19) can be approximated by a ratio X_0, such that

$$X_0=1/(1+\exp(\Delta C^+/\sigma_1)) \tag{35}$$

The ratio X_0 is defined as the ratio of the number of accepted higher cost solutions to the total number of higher cost solutions generated. In the above equation, ΔC^+ is the average increment in cost of higher cost solutions.

The value of X_0 can be obtained numerically by performing its iteration according to the simulated annealing-based algorithm prior to the actual first iteration. With the known value of $X_{0,}$ the value of the initial control parameter can then be estimated from

$$\sigma_1=|(\Delta C^+/\ln(1/X_0)-1) \tag{36}$$

The flowchart of the auction-based dispatch algorithm using simulated annealing is shown in Figure 2.

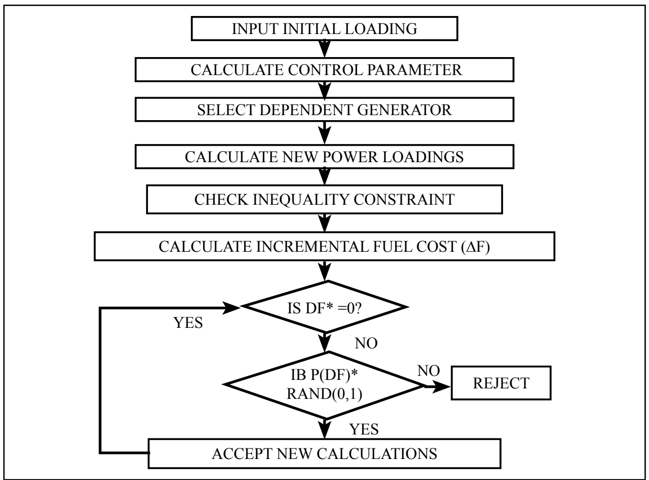

FIG. 2 FLOWCHART OF THE AUCTION-BASED DISPATCH ALGORITHM USING SIMULATED ANNEALING

The proposed algorithm is summarized as:

(i) Select a set of initial power loading for the Ng generators such that the operational limits and generator-load balance constraints are satisfied. Initialize k to 1 and calculate the total fuel cost.

(ii) Calculate the control parameter using equation (31a).

(iii) For any iteration k and for a pre-specified number of trials in the chain of neighborhood solution within the iteration, determine the best loading of all the generators in the neighborhood of the current loading setting by the following steps.

4.3 At Iteration 'k' and Trail 'm'

(a) Select randomly a generator as a dependent generator. From the known current loadings of the generators, set dependent generator loading to P_r, and set the loading of the remaining $(N_g–1)$ generators in P(k, m).

(b) Generate vector $N^{(k, m)}$.

(c) From new power loading vector P, using $(P^{(k, m)}+N^{(k, m)})$.

(d) Using Equation (4.20), find the new power loading, P_r of the dependent generator.

(e) If the power limits satisfy the operating limits in the inequality constraints, calculate the new total cost. Otherwise, discard the new power loading and return to step [iii(a)].

(f) Calculate the increment in total fuel cost ΔF_t, by subtracting the cost associated with the new loading label.

(g) Check with the new power loading that can be accepted:

1. If $(\Delta F_t \leq 0)$, the new power loadings are accepted as the current solution in the next trial as described by

$$P^{(k, m+1)}=P^{(k, m)}+N^{(k, m)} \tag{37}$$

and

$$P_{r(k, m+1)}=P_r \tag{38}$$

2. If $(\Delta F_t>0)$, and $[P(\Delta F_t)>\text{random }(0,1)]$ then

$$P^{(k, m+1)} = P^{(k, m)} + N^{(k, m)} \quad (39)$$

and

$$P_r^{(k, m+1)} = P_r \quad (40)$$

otherwise

$$P^{(k, m+1)} = P^{(k, m)} \quad (41)$$

and

$$P_r^{(k, m+1)} = P_r \quad (42)$$

3. If k is greater than the maximum number of iteration, stop. Otherwise, increment iteration counter k by 1 and go to step (2).

4. If ($\Delta F_t \leq 0$), the new power loadings are accepted as the current solution in the next trial as described by

$$P^{(k, m+1)} = P^{(k, m)} + N^{(k, m)} \quad (43)$$

and

$$P_r^{(k, m+1)} = P_r \quad (44)$$

5. If ($\Delta F_t > 0$), and [$P(\Delta F_t)$> random (0,1)] then $P^{(k,m+1)} = P^{(k,m)} + N^{(k,m)}$ and $P_r^{(k,m+1)} = P_r$, otherwise $P^{(k,m+1)} = P^{(k,m)}$ and $P_r^{(k,m+1)} = P_r$

6. If k is greater than the maximum number of iteration, stop. Otherwise, increment iteration counter k by 1 and go to step (2).

5.0 SIMULATION RESULTS

The proposed algorithm is applied to two different test cases and the results are compared with genetic algorithm methods also.

Case 1

Considering a system containing a set of three generators in a simple six-bus power system, taking the values of unit generation P_i, a quadratic input–output curve data is obtained using the following equation for each generator.

$$F_i(P_i) = c_i \times P_i^2 + b_i \times P_i + a_i \quad (45)$$

The cost/unit fuel is assumed to be the same for all units. The system load is 850 MW. The constraints for these equations and the unit operating ranges are given in Table 1.

TABLE 1

THREE SELLERS TESTING EXAMPLE

Unit	Lower limit (MW)	Upper limit (MW)	c_i	b_i	a_i
1	100	600	0.001562	7.92	561
2	100	400	0.00194	7.85	310
3	50	200	0.00482	7.97	78

The optimal dispatch result obtained from the proposed algorithm (Simulated Annealing) is given in Table 2 and compared with Genetic Algorithm (Table 3). In both the tables, results for five different runs are presented as both are randomization algorithms.

TABLE 2

RESULT OF PROPOSED ALGORITHM (SIMULATED ANNEALING)

Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Cost/h
393.112	334.636	122.252	8194.4
393.112	334.636	122.252	8194.4
393.112	334.636	122.252	8194.4
393.112	334.636	122.252	8194.4
393.112	334.636	122.252	8194.4

TABLE 3

RESULT FROM GENETIC ALGORITHM [20]

Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Cost/h
393.17	334.604	122.226	8194.4
343.779	400	106.221	8207.7
433.181	366.819	50	8224.0
400	400	50	8227.9
350.086	299.914	200	8228.7

Case 2

To test an example with concave functions, eight sellers with the same cost functions and capacity, upper and lower limits are used as shown in Table 4.

TABLE 4

EIGHT SELLERS TESTING EXAMPLE.

Unit	Lower limit (MW)	Upper limit (MW)	c_i	b_i	a_i
i	20	100	–0.001562	7.92	100

where i = 1,2,…,8
the load = 450 MW

TABLE 5								
RESULT OF PROPOSED ALGORITHM (8-SELLERS CASE)								
Unit-1 (MW)	**Unit-2 (MW)**	**Unit-3 (MW)**	**Unit-4 (MW)**	**Unit-5 (MW)**	**Unit-6 (MW)**	**Unit-7 (MW)**	**Unit-8 (MW)**	**Cost (Rs/hr)**
20	100	100	20	20	100	70	20	4307
20	100	100	20	20	100	20	70	4307
20	100	20	100	100	20	70	20	4307
20	100	20	20	100	100	70	20	4307
100	100	20	20	20	100	20	70	4307

Table 5 shows the results for five different runs. It is observed from this table that with different runs also the optimal cost is found to be the same. In the above example, the solution set has a good diversity in the searching space. Here the algorithms are implemented in MATLAB and tested in Pentium-4 machine. The computing time for case 1 is found to be less than 2 seconds and for case 2 is found to be 32 seconds.

6.0 DESIGN CRITERIA

Design criteria of simulated annealing-based algorithm are discussed below.

A lot of fine-tuning was required in the algorithm. There was no available literature regarding the selection of the constants used in the algorithm namely ‘r’, ‘k’, ‘m’, ‘T’ and ‘γ’. Hence, the program was subjected to hundreds of test runs and selected the final configuration.

The basic steps are outlined below.

(i) Selection of temperature ‘T’ and selection of ‘r’.

The temperature T and scaling factor were chosen as were given in ref. [21]. The initial temperature was taken to be 50000 and was reduced in steps. The constants ‘r’ was to vary between 0.85 and 0.97. The best results were obtained for r = 0.95.

(ii) Selection of scaling factor ‘γ’.

The scaling factors were tested for values 0.1 (case 1) and 0.01 (case 2) and found suitable.

(iii) Selection of ‘k’ and ‘m’.

Selection of the number of iterations (k) and moves (m) was purely through trial and error method. Here, it is inferred that greater the randomness in the procedure, better will be the solution obtained. Hence, the number of moves were increased compared to the number of iterations. The decrease in temperature value depends upon the measure of ‘k’. The value of ‘k’ and ‘m’ for case 1 are 100 and 20, respectively, whereas they are 400 and 50, respectively, for case 2.

6.1 Advantages

The advantages of the proposed simulated annealing-based algorithm are summarized below.

(i) The solution process is independent of fuel cost characteristics function of generators.

(ii) Its convergence property is not affected by the inclusion of inequality constraints due to the operation limits of generators.

(iii) Exact dispatch solution to meet the load demand and transmission losses is guaranteed.

(iv) The necessity to evaluate Lagrange’s multiplier and penalty factors are avoided.

(v) Computer memory requirement is low.

6.2 Disadvantages

The main disadvantage of the proposed algorithm is that it has a higher computation time. However, the speed of the algorithm can be greatly reduced by means of parallel processing. This can be achieved further by developing the present algorithm into a form suitable for execution in a multiprocessor system.

7.0 CONCLUSION

Deregulation leads the electricity industry to focus attention on the cost of generation and provides an incentive for generators to reduce their costs and minimize risks. The proposed algorithm combines the powerful searching mechanism of Simulated Annealing with the mathematical foundations for global optimization. It gives the auction-based dispatch problem efficiently and accurately. The proposed algorithm can be easily extended to consider more constraints, such as the system loss and the spinning reserve constraints as well. This can be further explored for its suitability to be applied to solve the generation dispatch problem for a short-term hydrothermal generation scheduling, short-term multiple-fuel-constrained generation scheduling, etc.

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