AN EVOLUTIONARY PROGRAMMING BASED TABU SEARCH METHOD FOR UNIT COMMITMENT PROBLEM WITH COOLING–BANKING CONSTRAINTS

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This paper presents a new approach to solve the short-term unit commitment problem using An Evolutionary Programming Based tabu search method with cooling and banking constraints. Numerical results are shown comparing the cost solutions and computation time obtained by using the evolutionary programming method and other conventional methods like dynamic programming, lagrangian relaxation.

K e y w o r d s: unit commitment problem, tabu search, evolutionary programming

1 INTRODUCTION

Unit commitment is the problem of selecting the generating units to be put into service during a scheduling period and for how long. The committed units must meet the system load and reserve requirements at minimum operating cost, subject to a variety of constraints. Unit commitment is an important optimization task in the daily operating planning of power system. The solution of unit commitment problem (UCP) is really a complex optimization problem. It can be considered as two linked optimization problems, the first is a combinatorial problem of generating units, which could be a very huge number. TS is a powerful optimization procedure that has been successfully applied to a number of combinatorial optimization problems. It has the ability to avoid entrapment in local minima. TS employ a flexible memory system (in contrast to 'memory less' systems, such as simulated annealing and genetic algorithm, and rigid memory system such as in branch-and-bound). Specific attention is given to the short-term memory component of TS, which has provided solutions superior to the best obtained with other methods for a variety of problems.

Research endeavours, therefore, have been focused on; efficient, near-optimal UC algorithms, which can be applied to large-scale, power systems and have reasonable storage and computation time requirements. A survey of existing literature [1–26] on the problem reveals that various numerical optimisation techniques have been employed to approach the complicated unit commitment problem. More specifically, these are the dynamic programming method (DP), the mixed integer programming method (MIP), the lagrangian relaxation method (LR), the branch and bound method (BB), the expert system (ES), the fuzzy theorem method (FT), the hop field method (H), the simulated annealing method (SA), the tabu search (TS), the genetic algorithm (GA), the artificial neural network (ANN), the evolutionary programming (EP) and so on. The major limitations of the numerical techniques are the problem dimensions, large computational time and complexity in programming.

The DP method [1–2], [13] is flexible but the disadvantage is the "curse of dimensionality", which results it may leads to more mathematical complexity and increase in computation time if the constraints are taken in to consideration. The MIP methods [3–4] for solving the unit commitment problems fail when the number of units increases because they require a large memory and suffer from great computational delay. The LR approach [5–8] to solve the short-term UC Problems was found that it provides faster solution but it will fail to obtain solution feasibility and solution quality problems and becomes complex if the number of units increased. The BB method [9] employs a linear function to represent fuel cost and start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a practical size. An ES algorithm [10], [13] rectifies the complexity in calculations and saving in computation time. But it will face the problem if the new schedule is differing from schedule in database. In the FT method [11], [13], [24] using fuzzy set solves the forecasted load schedules error but it will also suffer from complexity. The H neural network technique [12] considers more constraints but it may suffer from numerical convergence due to its training process. SA [14–17], [23–24] is a powerful, general-purpose stochastic optimisation technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it will take much time to reach the near-global minimum. The TS [18–20], [23] is an iterative improvement procedure that starts from some initial feasible solution and attempts to determine a better solution in the manner of a greatest-decent algorithm. However, TS is characterized by an ability to escape local optima by using a short-term memory of recent solutions.

GA [13], [21–24] is a general-purpose stochastic and parallel search method based on the mechanics of natural selection and natural genetics. It is a search method to have potential of obtaining near-global minimum. And it has the capability to obtain the accurate results within short time and the constraints are included easily. The

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ANN [12], [28] has the advantages of giving good solution quality and rapid convergence. And this method can accommodate more complicated unit-wise constraints and are claimed for numerical convergence and solution quality problems. The solution processing in each method is very unique. The EP [25–26] has the advantages of good convergent property and a significant speedup over traditional GA's and can obtain high quality solutions. The "curse of dimensionality" is surmounted, and the computational burden is almost linear with the problem scale.

From the literature review, it has been observed that there exists a need for evolving simple and effective methods, for obtaining an optimal solution for the UCP. Hence, in this paper, an attempt has been made to couple EP with TS for meeting these requirements of the UCP, which eliminates the above-mentioned drawbacks. In case of TS, the demand is taken as control parameter. Hence the quality of solution is improved. The algorithm is based on the annealing neural network. Classical optimization methods are a direct means for solving this problem. EP seems to be promising and is still evolving. EP has the great advantage of good convergent property and, hence, the computation time is considerably reduced. The EP combines good solution quality for TS with rapid convergence for EP. The EP Based TS (EPTS) is used to find the short- term thermal unit commitment. By doing so, it can help to find the optimum solution rapidly and efficiently.

EP is capable of determining the global or near global solution. It is based on the basic genetic operation of human chromosomes. It operates with the stochastic mechanics, which combine offspring creation based on the performance of current trail solutions and competition and selection based on the successive generations, form a considerably robust scheme for large-scale real-valued combinational optimization. In this proposed work, the parents are obtained from a pre-defined set of solution's *ie* each and every solution is adjusted to meet the requirements. And the selection process is done using Evolutionary Strategy [8–9].

2 PROBLEM FORMULATION

The objective is to find the generation scheduling such that the total operating cost can be minimized, when subjected to a variety of constraints [27]. In the UCP under consideration, an interesting solution would be minimizing the total operating cost of the generating units with several constraints being satisfied. The major component of the operating cost, for thermal and nuclear units, is the power production cost of the committed units and this is given in a quadratic form

$$F_{it}(P_{it}) = A_i P_{it}^2 B_i P_{it} + C_i \text{ Rs/hr}, \qquad (1)$$

where, A_i, B_i, C_i – are the cost function parameters of unit i, (Rs/MW^{2}hr, Rs/MWhr, Rs/hr), $F_{it}(P_{it})$ – is the production cost of unit i at a time t (Rs/hr), P_{it} – is the output power from unit i at time t (MW).

The start up cost depends upon the down time of the unit, which can vary from a maximum value, when the unit i is started from cold state, to a much smaller value, if the unit i has been turned off recently. The start up cost calculation depends upon the treatment method for the thermal unit during down time periods. The start-up cost S_{it}, is a function of the down time of unit i given as

$$S_{it} = So_i[1 - D_i \exp(-Toff_i/\text{Tdown}_i)] + E_i \qquad (2)$$

where, So_i – is the unit i cold start-up cost (Rs), D_i, E_i – are the start-up cost coefficients for unit i.

The overall objective function of the UCP is then

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{N} \left(F_{it}(P_{it}) U_{it} + S_{it} V_{it} \right) \qquad (3)$$

where, U_{it} - is the unit i status at hour t =1 (if unit is ON) =0 (if unit is OFF), V_{it} – is the unit i start up/shut down status at hour t =1 if the unit is started at hour t and 0 otherwise, F_T – is the total operating cost over the schedule horizon (Rs/hr), S_{it} – is the start up cost of unit i at hour t (Rs).

2.1 Constraints

Depending on the nature of the power system under study, the UCP is subject to many constraints, the main being the load balance constraints and the spinning reserve constraints. The other constraints include the thermal constraints, fuel constraints, security constraints *etc* [27].

2.1.1 Load Balance Constraints

The real power generated must be sufficient enough to meet the load demand and must satisfy the following factors

$$\sum_{i=1}^{N} P_{it} U_{it} = PD_t. \qquad (4)$$

where, PD_t – is the system peak demand at hour t (MW), N – is the number of available generating units, $U(0, 1)$ – is the uniform distribution with parameters 0 and 1, $UD(a, b)$ – is the discrete uniform distribution with parameters a and b.

2.1.2 Spinning Reserve Constraints

The spinning reserve is the total amount of real power generation available from all synchronized units minus the present load plus the losses. The reserve is considered to be a pre specified amount or a given percentage of the forecasted peak demand. It must be sufficient enough to meet the loss of the most heavily loaded unit in the system. This has to satisfy the equation given in (5).

$$\sum_{i=1}^{N} P \max_i U_{it} \geq (PD_t + R_t); \ 1 \leq t \leq T, \qquad (5)$$

where, $P \max_i$ – is the maximum generation limit of unit i, R_t – is the spinning reserve at time t (MW), T – is the scheduled time horizon (24 hr).
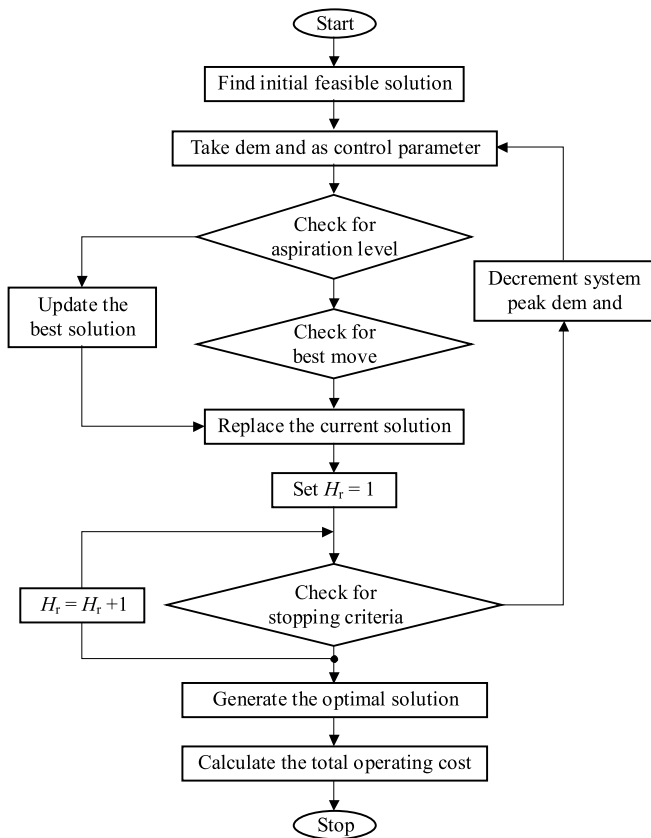
Fig. 1. Flowchart of Tabu Search Algorithm

2.1.3 Thermal Constraints

The temperature and pressure of the thermal units vary very gradually and the units must be synchronized before they are brought online. A time period of even 1 hour is considered as the minimum down time of the units. There are certain factors, which govern the thermal constraints, like minimum up time, minimum down time and crew constraints.

a) Minimum up time

If the units have already been shut down, there will be a minimum time before they can be restarted and the constraint is given in (6).

$$Ton_i = Tup_i\,, \qquad (6)$$

where Ton_i – is the duration for which unit i is continuously ON (hr), Tup_i – is the unit i minimum up time (hr).

b) Minimum down time

If all the units are running already, they cannot be shut down simultaneously and the constraint is given in (7).

$$Toff_i \geq Tdown_i\,, \qquad (7)$$

where, $Tdown_i$ – unit i minimum down time (hr), $Toff_i$ – duration for which unit i is continuously OFF (hr).

2.1.4 Must Run Units

Generally in a power system, some of the units are given a must run status in order to provide voltage support for the network.

3 TABU SEARCH

3.1 Overview

In solving the UCP, two types of variables need to be determined. The unit's status variables U and V, which are integer variables and the units, output power variables P that are continuous variables. The problem can then be decomposed into two sub problems, a combinatorial problem in U and V and a non-linear optimization problem in P. TS are used to solve the combinatorial optimization and the non-linear optimization is solved via a quadratic programming routine [18]. The flowchart for TS is shown in Fig. 1.

The proposed algorithm contains three major steps:
- First, generating randomly feasible trail solutions.
- Second, calculating the objective function of the given solution by solving the EDP.
- Third, applying the TS procedures to accept or reject the solution in hand.

3.2 Tabu Search General Algorithm

Step 0: Assume that the fuel costs to be fixed for each hour and all the generators share the loads equally.

Step 1: By optimum allocation find the initial feasible solution (U_i, V_i).

Step 2: Demand is taken as the control parameter.

Step 3: Generate the trial solution.

Step 4: Calculate the total operating cost, F_t, as the summation of running cost and Start up-shut down cost.

Step 5: Tabulate the fuel cost for each unit for every hour.

3.3 Generating Trial Solution

The neighbors should be randomly generated, feasible, and span as much as possible the problem solution space. Because of the constraints in the UCP this is not a simple matter. The most difficult constraints to satisfy are the minimum up/down times. The implementation of new rules to obtain randomly feasible solutions faster are done by the rules is described in [18].

3.3 Generating an Initial Solution

The TS algorithm requires a starting feasible schedule, which satisfies all the system and units constraints. This schedule is randomly generated. The algorithm given in [18] is used for finding this starting solution.

3.4 Operating Cost Calculation

Once a trail solution is obtained, the corresponding total operating cost is determined. Since the production cost is a quadratic function, the EDP is solved using a quadratic programming routine. The start-up cost is then calculated for the given schedule.

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3.7 Stopping Criteria

There may be several stopping criteria for the search. For this implementation, the search is stopped if the following conditions are satisfied:

- The load balance constraints are satisfied.
- The spinning reserve constraints are satisfied.

4 EVOLUTIONARY PROGRAMMING

4.1 Introduction

EP is a mutation-based evolutionary algorithm applied to discrete search spaces. David Fogel [29] extended the initial work of his father Larry Fogel [31] for applications involving real-parameter optimization problems. Real-parameter EP is similar in principle to evolution strategy (ES), in that normally distributed mutations are performed in both algorithms. Both algorithms encode mutation strength (or variance of the normal distribution) for each decision variable and a self-adapting rule is used to update the mutation strengths. Several variants of EP have been suggested [29].

4.2 Evolutionary Strategies

For the case of Evolutionary strategies D.B. Fogel remarks "evolution can be categorized by several levels of hierarchy: the gene, the chromosome, the individual, the species, and the ecosystem." Thus, while Genetic Algorithms stress models of genetic operators, Evolutionary Strategies emphasize mutational transformation that maintains behavioral linkage between each parent and its offspring at the level of the individual. Evolutionary Strategies are a joint development of Bienert, Rechenberg, and Schwefel. The first applications were experimental and addressed some optimization problems in hydrodynamics.

4.3 EP General Algorithm

Evolutionary programming [25–26], [29–31] is conducted as a sequence of operations and is given below.

1. The initial population is determined by setting $s_i = S_i \sim U(a_k, b_k)^k$ $i = 1, \ldots, m$, where S_i is a random vector, s_i is the outcome of the random vector, $U(a_k, b_k)^k$ denotes a uniform distribution ranging over $[a_k, b_k]$ in each of k dimensions, and m is the number of parents.

2. Each s_i, $i = 1, \ldots, m$, is assigned a fitness score $\vartheta(s_i) = G\big(F(s_i), v_i\big)$, where F maps $s_i \mapsto R$ and denotes the true fitness of s_i, v_i, represents random alteration in the instantiation of s_i, random variation imposed on the evaluation of $F(s_i)$, or satisfies another relation s_i, and $G\big(F(s_i), v_i\big)$ describes the fitness score to be assigned. In general, the functions F and G can be as complex as required. For example, F may be a function not only of a particular s_i, but also of other members of the population, conditioned on a particular s_i.

3. Each s_i, $i = 1, \ldots, m$, is altered and assigned to s_{i+m} such that $s_{i+m} = s_{i,j} + N(0, \beta_j \vartheta(s_i) + z_j)$, $j = 1, \ldots, k$. $N(0, \beta_j \vartheta(s_i) + z_j)$ represents a Gaussian random variable with mean μ and variance σ^2, β_j is a constant of proportionality to scale $\vartheta(s_i)$, and z_j represents an offset to guarantee a minimum amount of variance,

4. Each s_{i+m}, $i = 1, \ldots, m$, is assigned a fitness score $\vartheta(s_{i+m}) = G\big(F(s_{i+m}), v_{i+m}\big)$

5. For each s_i, $i = 1, \ldots, 2m$, a value w_i is assigned according to

$$w_i = \sum_{t=1}^{c} w_t^*, \qquad w_t^* = \begin{cases} 1 & \text{if } \vartheta(s_i) \leq \vartheta(s_t); \\ 0, & \text{otherwise,} \end{cases}$$

where $p = [2mu_1 + 1]$, $p \neq i$, $[x]$ denotes the greatest integer less than or equal to x, c is the number of competitions, and $u_1 \sim U(0, 1)$.

6. The solutions s_i, $i = 1 \ldots, 2m$, are ranked in descending order of their corresponding value w_i [with preference to their actual scores $\vartheta(s_i)$ if there are more than m solutions attaining a value of c]. The first m solutions are transcribed along with their corresponding values $\vartheta(s_i)$ to be the basis of the next generation.

7. The process proceeds to step 3, unless the available execution time is exhausted or an acceptable solution has been discovered.

4.4 Evolutionary Programming for UCP

1. Initialize the parent vector $p = [p_1, p_2, \ldots, p_n]$, $i = 1, 2, \ldots, N_p$ such that each element in the vector is determined by $p_j \sim \text{random}(p_{j\min}, p_{j\max})$, $j = 1, 2, \ldots, N$, with one generator as dependent generator.

2. Initialize the parent vector $p = [p_1, p_2, \ldots, p_n]$, $i = 1, 2, \ldots, N_p$ such that each element in the vector is determined by $p_j \sim \text{random}(p_{j\min}, p_{j\max})$, $j = 1, 2, \ldots, N$, with one generator as dependent generator.

3. Calculate the overall objective function if the UCP is given in equation (3) using the trail vector p_i and find the minimum of F_{Ti}.

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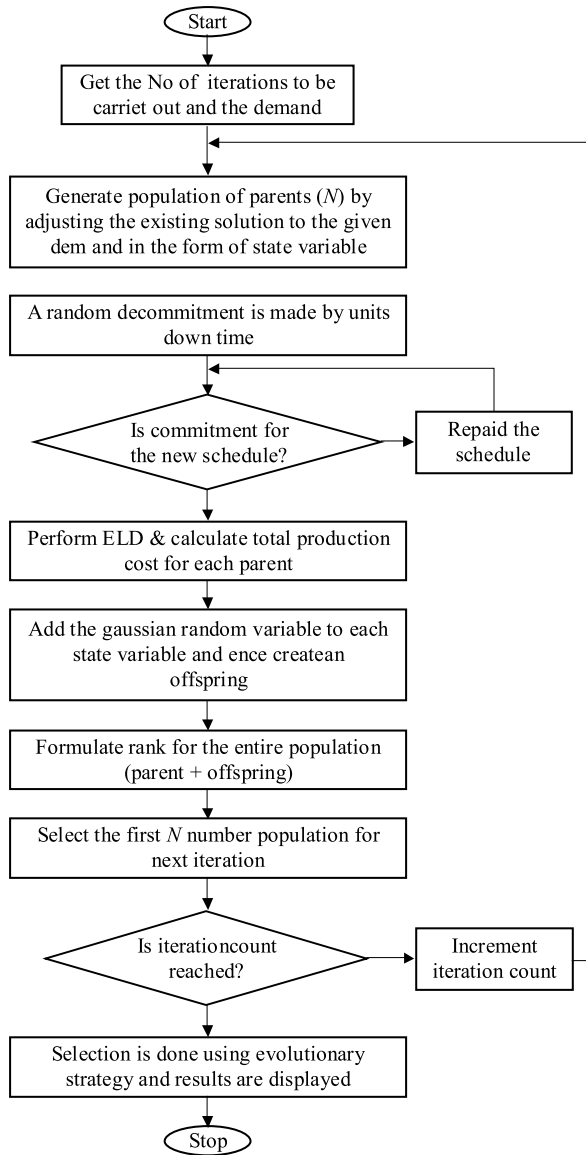
Fig. 2. Flowchart for EPTS for UCP

6. Create the offspring trail solution p'_i using the following steps.

  (a) Calculate the standard deviation

$$\sigma_j = \beta\big(F_{Tij}/\min(F_{Ti})\big)\big(P_{j\max} - P_{j\min}\big),$$

  (b) Add a Gaussian random variable $N(0, \sigma_j^2)$ to all the state variable of p_i, to get p'_i.

7. Select the first N_p individuals from the total $2N_p$ individuals of both p_i & p'_i using the following steps for next iteration.

  (a) Evaluate $r = (2N_p\mathrm{random}(0,1) + 1)$,

  (b) Evaluate each trail vector by $W_{pi} = \sum(W_x)$, where $x = 1, 2, \ldots, N_p$, $i = 1, 2, \ldots, 2N_p$ such that $W_x = 1$ if $F_{Tij}/(F_{Tij} + F_{Tir}) < \mathrm{random}(0,1)$, otherwise, $W_x = 0$.

8. Sort the W_{pi} in descending order and the first N_p individuals will survive and are transcribed along with their elements to form the basis of the next generation.

9. The above procedure is repeated from step 2 until a maximum number of generations N_m is reached.

10. Selection process is done using Evolutionary strategy.

5 EVOLUTIONARY PROGRAMMING BASED TABU SEARCH FOR UCP

5.1 Tabu Search

1. Take the parent as the initial feasible solution.

2. Take demand as control parameter and generate the trial solution.

3. Check for the stopping criterion.

4. If false, decrement system peak demand and go to step 2.

5. If true, generate the optimal solution and calculate the total operating cost.

5.2 EP based TS

In the TS technique for solving UCP, Initial Operating Schedule status in terms of maximum real power generation of each unit is given as input. As we know that TS is used to improve any given status by avoiding entrapment in local minima, the offspring obtained from the EP algorithm is given as input to TS and the refined status is obtained. And Evolutionary Strategy selects the final status.

1. Get the demand for 24 hours and the number of iterations to be carried out.

2. Generate population of parents (N) by adjusting the existing solution to the given demand to the form of state variables.

3. Unit down time makes a random recommitment.

4. Check for constraint in the new schedule by TS. If the constraints are not met then repair the schedule as given in Section 5-C.

5. Perform ELD and calculate total production cost for each parent.

6. Add the Gaussian random variable to each state variable and hence create an offspring. This will further undergo for some repair operations as given in Section 5-D. Following these, the new schedules are checked in order to verify that all constraints are met.

7. Improve the status of the evolved offspring and verify the constraints by TS.

8. Formulate the rank for the entire population.

9. Select the best N number of population for next iteration.

10. Has iteration count reached? If yes go to step 11 else go to step 2.

11. Select the best population (s) by Evolutionary strategy [29–31].

12. For the units, which are in the off states, calculate the cost for both cooling and banking.

13. Compare the cooling and banking costs, if banking cost is lesser than cooling, bank the unit.

14. Print the optimum schedule.

The flow chart for EPTS for UCP is shown in Fig. 2.

5.3 Repair Mechanism

A repair mechanism to restore the feasibility of the constraints is applied and described as follows:

- Pick at random one of the OFF units at one of the violated hours.

- Apply the rules in section 3-C to switch the selected unit from OFF to ON keeping the feasibility of the down time constraints.

- Check for the reserve constraints at this hour. Otherwise repeat the process at the same hour for another unit.

5.4 Making offspring feasible

While solving the constrained optimization problem, there are various techniques to repair an infeasible solution [29–31]. In this paper we have chosen the technique, which evolve only the feasible solutions. That is the schedule, which satisfies the set of constraints as mentioned earlier. Here, in this paper, the selection routine is involved as "culling force" to eliminate the feasible schedules. Before the best solution is selected by evolutionary strategy, the trail is made to correct the unwanted mutations.

6 NUMERICAL RESULTS

A TPS in India with seven generating units, each with a capacity of 210 MW, has been considered as a case study. A time period of 24 hours is considered; the unit commitment problem is solved for these seven units and also compared. The required inputs for solving the UCP are briefed here. The total number of generating units, the maximum real power generation of each unit and the cost function parameters of each unit are tabulated for a day, respectively, as shown in Table 1 and Table 2 for TPS. The status of unit i at time t and the start-up/shut-down status obtained are the necessary solution for TS, EP, EPTS, DP, LR methods for TPS. The comparison of the total costs and Central Processing unit (CPU) time is shown in Table 3.
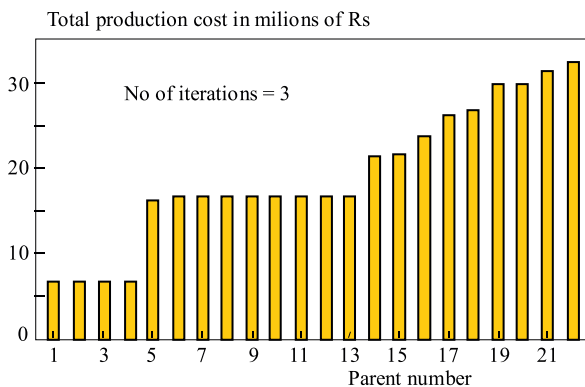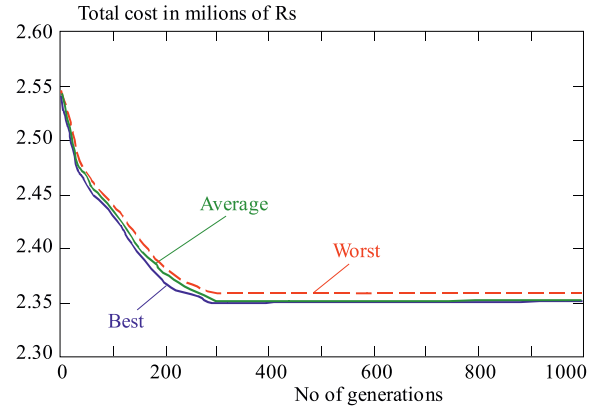
Fig. 3. Total production cost for 3 iterations

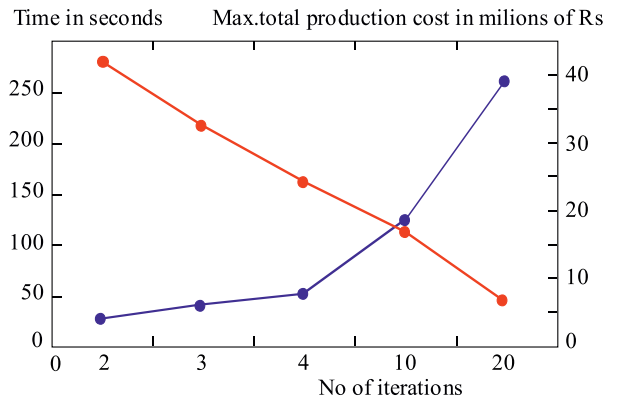**Fig. 4.** EP average performance from 100 runs

Fig. 5. No. of iterations vs time taken & max. production cost

Figure 3 represents the total production cost obtained by each parent for three iterations in EP method. Similarly, for four and ten iterations are obtained. Figure 4 gives the plot of EP average performance from 100 runs. Figure 5 gives the plot of No. of iteration versus the time taken to complete those iterations and the maximum production cost obtained under each iteration. From these results, the EPTS method with cooling-banking constraints had lesser total cost and took lesser CPU time.

The proposed EPTS approach was compared to the related methods in the references indented to serve this purpose, such as the DP with a zoom feature, the SA, and the GA approaches. Further SA can start with any initial solution and improves on it to find optimal solution with a high probability. By means of stochastically searching multiple points at one time and considering trail solutions of successive generations, the EPTS approach avoids entrapping in local optimum solutions. Also, disadvantages of huge memory size required by the TS method are eliminated. Moreover, intellectual schemes of encoding and decoding entailed by the GA approach are not needed in the proposed EPTS approach. The problem of power unbalance previously existing in the solution of GA is circumvented as well in this paper. In comparison with the results produced by the referenced techniques, the EPTS method obviously displays a satisfactory performance with respect to the quality of its evolved solutions and to its computational requirements.

Table 1. Daily Generation of Seven Units in MW

Hour	Pmax	I	II	III	IV	V	VI	VII
1	840	60	80	100	101	149	150	200
2	757	60	0	100	100	147	150	200
3	775	60	0	100	115	150	150	200
4	773	60	0	100	113	150	150	200
5	770	60	0	100	110	150	150	200
6	778	60	0	100	118	150	150	200
7	757	60	0	100	100	147	150	200
8	778	60	0	100	118	150	150	200
9	770	60	0	100	110	150	150	200
10	764	60	0	100	104	150	150	200
11	598	60	0	99	97	142	0	200
12	595	60	0	100	96	139	0	200
13	545	0	0	100	99	146	0	200
14	538	0	0	99	97	142	0	200
15	535	0	0	100	96	139	0	200
16	466	0	0	0	116	150	0	200
17	449	0	0	0	101	148	0	200
18	439	0	0	0	97	142	0	200
19	466	0	0	0	116	150	0	200
20	463	0	0	0	113	150	0	200
21	460	0	0	0	110	150	0	200
22	434	0	0	0	95	139	0	200
23	530	60	0	0	120	150	0	200
24	840	60	80	100	101	149	150	200

Table 2. Generation System Operation Data

Unit	P_{min} (MW)	P_{max} (MW)	C_i (Rs)	B_i (Rs/ MWh)	A_i (Rs/ MWh^2)	So_i (Rs)	D_i (Rs)	E_i(Rs) (Rs)
1	15	60	750	70	0.255	4250	29.5	10
2	20	80	1250	75	0.198	5050	29.5	10
3	30	100	2000	70	0.198	5700	28.5	10
4	25	120	1600	70	0.191	4700	32.5	9
5	50	150	1450	75	0.106	5650	32	9
6	50	150	4950	65	0.068	14100	37.5	4.5
7	75	200	4100	60	0.074	11350	32	5.5

7 CONCLUSION

This paper presents an EP based TS method with cooling-banking constraints the unit commitment problem. In this method, the essential processes simulated in the procedure are mutation, competition, and selection. The mutation rate is computed as a function of the ratio of the total cost by the schedule of interest to the cost of the best schedule in the current population. Competition and selection are applied to select from among the parents and the offspring, the best solutions to form the basis of the subsequent generation. In this proposed work, the parents are obtained from a pre-defined set of solution's *ie* each and every solution is obtained from the SA method. Then, a random recommitment is carried out

with respect to the unit minimum down times, and the selection process is done using Evolutionary Strategy.

In comparison with the results produced by the referenced techniques (EP, DP, LR and TS), the EPTS method obviously displays a satisfactory performance. There is no obvious limitation on the size of the problem that must be addressed, for its data structure is such that the search space is reduced to a minimum; No relaxation of constraints is required; instead, populations of feasible solutions are produced at each generation and throughout the evolution process; Multiple near optimal solutions to the problem involving multiple constraints and conflicting objectives can be obtained in a reasonable time with the use of heuristics; It works only with feasible solutions generated based on heuristics, thus avoiding the computational burden entailed by the GA methods which first generate all feasible solutions and then purge the infeasible ones.

Table 3. Comparisons of cost and CPU time

System	Methods	Total Cost (pu)	CPU Time (Sec)
7 Unit (Practical)	DP	1.00000	130
	LR	0.97843	115
	TS	0.94580	80
	EP	0.93461	66
	EPTS (Without Cooling & Banking)	0.92392	56
	EPTS (With Cooling & Banking)	0.92056	54
10 Unit (IEEE)	DP	1.00000	260
	LR	0.97183	235
	TS	0.94222	200
	EP	0.94071	186
	EPTS (Without Cooling & Banking)	0.92090	176
	EPTS (With Cooling & Banking)	0.91710	172
26 Unit (IEEE)	DP	1.00000	1878
	LR	0.96642	1860
	TS	0.93706	1810
	EP	0.92814	1785
	EPTS (Without Cooling & Banking)	0.90900	1774
	EPTS (With Cooling & Banking)	0.90600	1766
34 Unit (IEEE)	DP	1.00000	6865
	LR	0.96197	6824
	TS	0.93300	6800
	EP	0.92400	6792
	EPTS (Without Cooling & Banking)	0.90718	6772
	EPTS (With Cooling & Banking)	0.90425	6764

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