

# HYBRIDIZING EVOLUTIONARY PROGRAMMING, SIMULATED ANNEALING AND TABU SEARCH METHOD TO SOLVE THE UNIT COMMITMENT PROBLEM

C.CHRISTOBER ASIR RAJAN

Assistant Professor, Pondicherry Engineering College, Pondicherry - 605014  
+91-0413-2655281, +91-0413-2655101, [asir\\_70@hotmail.com](mailto:asir_70@hotmail.com)

**Abstract:** *This paper presents a new approach to solve the short-term unit commitment problem using hybrid algorithm based on Evolutionary Programming, Simulated Annealing and Tabu Search Method. The objective of this paper is to find the generation scheduling such that the total operating cost can be minimized, when subjected to a variety of constraints. This also means that it is desirable to find the optimal generating unit commitment in the power system for the next H hours. Evolutionary programming, which happens to be a Global Optimization technique for solving Unit Commitment Problem, operates on a system, which is designed to encode each unit's operating schedule with regard to its minimum up/down time. And Simulated Annealing and Tabu Search methods improve the status by avoiding entrapment in local minima. A thermal power station in India demonstrates the effectiveness of the proposed approach; extensive studies have also been performed for different IEEE test systems consist of 10, 26, 34 generating units. Numerical results are shown comparing the cost solutions and computation time obtained by the proposed hybrid method and other conventional methods like Dynamic Programming, Lagrangian Relaxation in reaching proper unit commitment.*

**Key words:** *Evolutionary Programming; Simulated Annealing; Tabu Search; Unit Commitment*

## 1. Introduction

The daily load pattern for a given power system exhibits large fluctuation between the minimum and the maximum demand. Adequate, reliable power must be synchronized prior to the actual occurrence of the load. As the load varies continuously with time, the optimum operating condition of units alters along with it. Hence, it is not economical to run all the units available in the power station, all the time. Therefore, the problem of determining the units of a plant that should operate for a given load for a particular time horizon is the UCP.

The Unit Commitment Problem (UCP) has been an active area of research for the past three decades. Deregulation has been introduced in many countries to meet the ever-increasing demand of electricity. Research endeavors, 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. The UCP [28] is a large-scale, non-linear, combinatorial optimization problem, which is used in power systems to properly schedule the ON/OFF status of all the generating units in the system.

The ultimate goal is to determine the minimum cost turn ON and turn OFF of power generating units to meet the load demand in addition to satisfying various operating constraints of the generating units. Generally the UCP has been difficult to solve in case of large power systems due to the complex nature of problem. The various operating constraints of the generating units make the problem highly non-linear. The exact solution of UCP can be obtained by a complete enumeration of all feasible combination of generating units, which would be a huge task.

Research endeavors, 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 [1-32] on the problem reveals that various numerical optimization 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 Simulated Annealing (SA), the Tabu Search method (TS), the Genetic Algorithm (GA), the Artificial Neural Network (ANN), the integration of Genetic Algorithm, Tabu search, Simulated Annealing (GTS), the TS and Decomposition method (TSD), the extended neighborhood search algorithm (ENSA), 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 would exhibit globally optimal solution with enhanced modeling capabilities. The LR approach [5-7] 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. And the total production costs and CPU time over the scheduled time horizon are less expansive than conventional methods and LR, GA, EP LRGA methods. The BB method [8] 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 [9], [14] 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 [10], [14] using fuzzy set solves the forecasted load schedules error but it will also suffer from complexity. The ANN [11], [28] has the advantages of giving good solution quality and rapid convergence. The level of accuracy of forecasting performance is improved. The improvement in forecasting calculation improves the quality of unit commitment scheduling and results in a large amount of cost savings. GA [12-13], [21-22] is more effective when the last data have similar characteristics. The cost effective schedule was produced by the intelligent mutation and grey zone modification methods. And the use of integer coding and new genetic operators differentiates the new GA from previous binary GA implementation. In addition, the new problem specific operators that drastically improve the performance of the algorithm are introduced. SA [15-18], [32] is a powerful, general-purpose stochastic optimization 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. TS [19-20] is a powerful, general-purpose stochastic optimization 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 EP [25-26], [30-31], 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.

The GTS [23] shows the reasonable combination of local and global search. It adopts the acceptance probability of SA to improve the convergence of the simple GA, and the tabu search is introduced to find more accurate solutions. The TSD [24] has considered the time varying start-up costs as well as the non-linearity in the hydrothermal systems. The proposed approach by this paper can be used in conjunction with the other optimization method to pursue a more comprehensive feasible solution if the initial solutions obtained by other optimization methods fail to satisfy some specific constraints. In ENSA [25], the constrained models for fuel limits, emission limits and generation capacity limits are discussed and used for typical models. Most suitably, and starts from an initial solution even though the solution may be feasible. The proposed method may be used for rescheduling purposes where the experience of human experts will be combined with the analytical method of optimal scheduling. The algorithm can also be used in other complicated mixed integer programming problems, such as integrated resource planning.

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 trial solutions and competition and selection based on the successive generations, form a considerably robust scheme for large – scale real - valued combinatorial optimization. In this proposed work, the parents are obtained from a pre-defined set of solution's i.e. each and every solution is adjusted to meet the requirements. And the selection process is done using Evolutionary Strategy (ES) [26-27], [30-31].

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, SA and TS for meeting these requirements of the UCP, which eliminates the above-mentioned drawbacks. In case of SA and 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 SA and TS with rapid convergence for EP. The hybridizing of EP, SA and TS (EPSATS) is used to find the short-term thermal unit commitment. By doing so, it can help to find the optimum solution rapidly and efficiently.

The application on the utility power system in India and IEEE test systems consists of 10, 26, 34 generating unit's shows that we can find the optimal solution effectively and these results are compared with the conventional methods.

## 2. Problem Formulation

The objective of unit commitment is to develop the most economical start up and shut down schedule for all the available generating units in the power station that satisfies the forecasted load demand and the units' operating requirements over the scheduling period. The major component of the operating cost, for thermal units is the fuel cost of the committed units and this is given in a quadratic form which is given in equation (1).

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

Where

$A_i, B_i, C_i$  ~ the cost function parameters of unit  $i$  (Rs./MW<sup>2</sup>hr, Rs./MWhr, Rs/hr)

$F_{it}(P_{it})$  ~ production cost of unit  $i$  at a time  $t$  (Rs/hr)

$P_{it}$  ~ 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  $i$  as given in (2).

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

Where

$So_i$  ~ unit  $i$  cold start – up cost (Rs)

$D_i, E_i$  ~ start – up cost coefficients for unit  $i$

The overall objective function of the UCP is given in (3).

$$F_T = \sum_{t=1}^T \sum_{i=1}^N (F_{it}(P_{it})U_{it} + S_{it}V_{it}) \text{ Rs/hr} \quad (3)$$

Where

$U_{it}$  ~ unit  $i$  status at hour  $t=1$ (if unit is ON)=0(if unit is OFF)

$V_{it}$  ~ unit  $i$  start up / shut down status at hour  $t=1$  if the unit is started at hour  $t$  and 0 otherwise.

$F_T$  ~ total operating cost over the schedule horizon (Rs/Hr)

$S_{it}$  ~ 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. [29]

### 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 given in (4).

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

Where

$PD_t$  ~ system peak demand at hour  $t$  (MW)

$N$  ~ number of available generating units

$U(0,1)$  ~ the uniform distribution with parameters 0 and 1

$UD(a,b)$  ~ 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. The reserves must be allocated appropriately among fast responding units and slow responding units. This allows the automatic generation control signal to restore frequency and interchange quickly, in the event of generating unit outage. This has to satisfy the equation given in (5).

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

Where

$P_{\max_i}$  ~ Maximum generation limit of unit  $i$

$R_t$  ~ spinning reserve at time  $t$  (MW)

$T$  ~ scheduled time horizon (24 hrs.)

### 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.

#### 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).

$$Ton_i \geq Tup_i \quad (6)$$

Where

$Ton_i$  ~ duration for which unit  $i$  is continuously ON (Hr)

$Tup_i$  ~ unit  $i$  minimum up time (Hr)

#### Minimum down time:

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

$$Toff_i \geq Tdown_i \quad (7)$$

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. Simulated Annealing

### 3.1 Simulated Annealing General Algorithm

Step (0): Find the Initial Feasible Solution By Optimum Allocation.

Step (1): Demand and Temperature are taken as the Control Parameter.

Step (2): Generate the Trial Solution.

Step (3): Check for the stopping criterion.

(a) If satisfied, go to the Next Hour for Checking the Same.

(b) Else, Decrement the System Peak Demand for that instant and again generate the Trial Solution.

Step (4): Get the Optimal Schedule and

(a) Assuming the Fuel Cost to be Constant per hour. Equate the total power demand to the total no of units switched ON.

(b) From the Total Fuel Cost subtract the constant cost function  $C$ . Equate the Remaining Cost Value to the ON Units Equally.

(c) Assume the Initial Temperature of the turbine as 660 degrees and a generation of 210 MW.

(d) If the Demand Decreases/Increases, then the temperature should Decrease/Increase by an amount

$$C_{p_{k+1}} = C_{p_k} / ((1 + (C_{p_k} \cdot \ln(1 + \delta) / 3\sigma C_{p_k})) \quad (10)$$

Where,

$C_p$  ~ Control Temperature in Degrees.

$\delta$  ~ Distance Parameter.

$\sigma$  ~ Standard Deviation of the Cost Value Generated.

Step (5): Calculate the Total Operating Cost  $F_i$  as the Summation of Running Cost and Start up Shut down Cost by equation (3).

The flowchart of SA method is shown in Fig. 1.

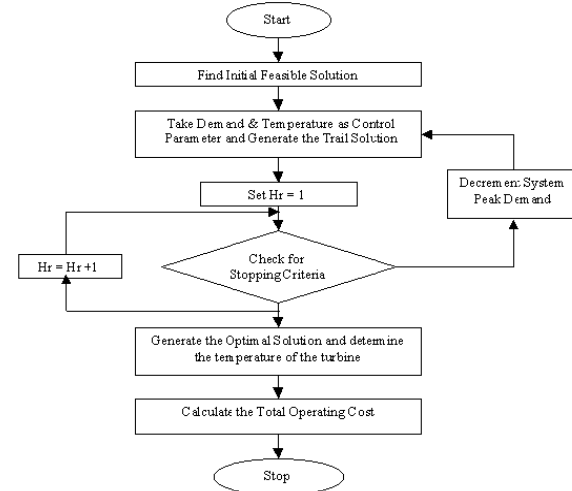


Fig.1 Flowchart of SA algorithm

### 3.2 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 [15].

### 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 [15] 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.

### 3.5 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. Tabu Search

### 4.1 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.

The procedural steps to generate trail solution, generate an initial solution, calculate the operating cost and stopping criteria for TS method is same as SA method. The flowchart for TS is shown in “Fig. 2”.

### 4.2 Tabu List

TL is controlled by the trial solutions in the order in which they are made. Each time a new element is added to the “bottom” of a list, the oldest element on the list is dropped from the “top”. Empirically, TL sizes, which provide good results, often grow with the size of the problem and stronger restrictions are generally coupled with smaller sizes [19]. Best sizes of TL lie in an intermediate range between these extremes. In some applications a simple choice of TL size in a range centered on seven seems to be quite effective.

### 4.3 Aspiration Criteria

This is another important criteria of TS arises when the move under consideration has been found to be tabu. Associated with each entry in the tabu list there is a certain value for the evaluation function called “Aspiration Level”. Normally, the Aspiration level

criteria are designed to override tabu status if a move is “good enough” [19].

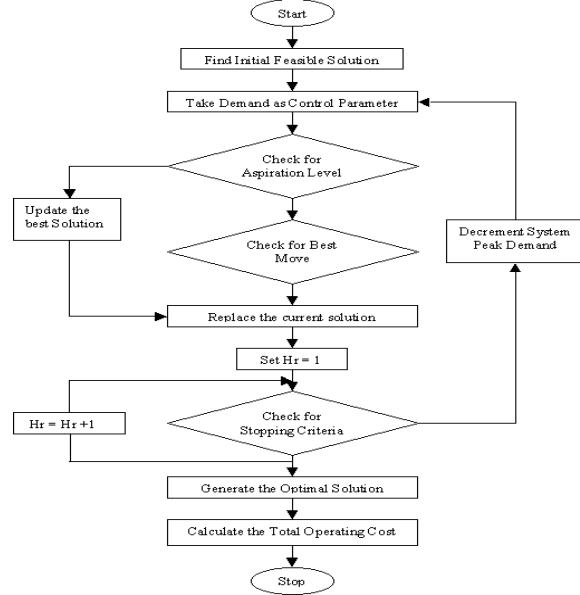


Fig. 2. Flowchart of Tabu Search Algorithm

## 5. Evolutionary Programming

### 5.1 Introduction

EP [30-31] is a mutation-based evolutionary algorithm applied to discrete search spaces. David Fogel (Fogel 1988) extended the initial work of his father Larry Fogel (Fogel, 1962) for applications involving real-parameter optimization problems. Real-parameter EP is similar in principle to 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 (Fogel, 1992).

### 5.2 Evolutionary Strategies

For the case of ES, 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 GA stresses 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. ES are a joint development of Bienenert, Rechenberg, and Schwefel. The first applications were experimental and addressed some optimization problems in hydrodynamics [30].

### 5.3 Evolutionary Programming for UCP

1. Initialize the parent vector  $p = [p_1, p_2, \dots, p_n]$ ,  $i = 1, 2, \dots, N_p$  such that each element in the vector is determined by  $p_j \sim \text{random}(p_{jmin}, p_{jmax})$ ,  $j =$

- 1,2,...N, with one generator as dependent generator.
2. Calculate the overall objective function if the UCP is given in equation (3) using the trail vector  $p_i$  and find the minimum of  $F_{Ti}$ .
3. Create the offspring trail solution  $p_i'$  using the following steps.
  - (a) Calculate the standard deviation  

$$\sigma_j = \beta(F_{Tij} / \min(F_{Ti}))(P_{j\max} - P_{j\min})$$
  - (b) Add a Gaussian random variable  $N(0, \sigma_j^2)$  to all the state variable of  $p_i$ , to get  $p_i'$ .
4. 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  $r = (2N_p \text{ random}(0,1) + 1)$
  - (b) Evaluate each trail vector by  $W_{pi} = \sum (W_x)$  Where  $x = 1, 2, \dots, N_p$ ,  $i = 1, 2, \dots, 2N_p$  such that  $W_x = 1$  if  $F_{Tij} / (F_{Tij} + F_{Tir}) < \text{random}(0,1)$ , otherwise,  $W_x = 0$ .
5. 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.
6. The above procedure is repeated from step (2) until a maximum number of generations  $N_m$  is reached.
7. Selection process is done using Evolutionary strategy.

## 6. EPSATS Hybrid Method for UCP

Evolutionary Strategies selects the initial status using Kuhn Tucker conditions and Economic Load Dispatch to determine the ON/OFF status for different generations.

1. Get the demand for 24 hours and number of iterations to be carried out.
2. Generate population of parents (N) by adjusting the existing solution to the given demand by ES to the form of state variables.
3. Use random recommitment to solve unit Up/Down time constraints. Here TS algorithm is used to find the nearest solution. The TL and aspiration criterion helps us not to trap on the wrong path of recommitment. If the constraints are not met then repair the schedule as given in section 6.1.
4. Perform ELD and calculate total production cost.
5. Add combined random variable (Cauchy and Gaussian) to each state variable and hence create an offspring. This will further undergo for some repair operations as given in section 6.2. Following these, the new schedules are checked in order to verify that all constraints are met.

6. Improve the status of the evolved offspring and verify the constraints by SA.
7. Formulate the rank for the entire population using Boltzman and SA weighting procedure of reference probability.
8. Select the best N number of population for next iteration.
9. Check for an iteration count reached. If Yes go to step 10 otherwise go to step 2.
10. Select the best population by ES [26-27].
11. Print the optimum schedule.

### 6.1 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 3.4 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.

### 6.2 Making offspring feasible

While solving the constrained optimization problem, there are various techniques to repair an infeasible solution [26-27]. 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.

## 7. Numerical Results

A thermal utility power system in India with seven generating units, each with a capacity of 210MW, 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 with IEEE test systems consists of 10, 26, and 34 generating units. 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 I and Table II for utility system. The status of unit  $i$  at time  $t$  and the start-up / shut - down status obtained are the necessary solution for SA, TS, EP, EPSATS, DP, LR methods for utility system. The comparison of the total costs and Central Processing unit (CPU) time is

shown in Table III for utility system, IEEE test systems of 10, 26, and 34 generating units. “Fig. 3” represents the total production cost obtained by each parent for four iterations in EP method. Similarly, for eight and ten iterations are obtained. “Fig. 4” gives the plot of EPSATS average performance from 100 runs. The “Fig. 5” gives the plot of No. of units switched ON during every hour. From these results, the EPSATS method had lesser total cost and took lesser CPU time in all the power systems considered including utility system.

In our proposed hybrid method, the EP, SA and TS method was used. As indicated in this paper, the EP algorithm has also proved to be an efficient tool for solving the important economic dispatch problem for units with “non-smooth” fuel cost functions as referred in [27]. Such functions may be included in the proposed EP search for practical problem solving. The proposed EPSATS 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. And with the use of Tabu Search method, the status is improved by avoiding the entrapment in local minima. By means of stochastically searching multiple points at one time and considering trail solutions of successive generations, the EPSATS approach avoids entrapping in local optimum solutions. Also, disadvantages of huge memory size required by the SA method are eliminated. Moreover, intellectual schemes of encoding and decoding entailed by the GA approach are not needed in the proposed EPSATS approach.

TABLE I  
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 II  
GENERATION SYSTEM OPERATION DATA

Unit	P <sub>min</sub> (MW)	P <sub>max</sub> (MW)	Running Cost			Start-up cost		
			C <sub>i</sub> (Rs)	B <sub>i</sub> (Rs/MWh)	A <sub>i</sub> (Rs/MWh <sup>2</sup> )	S <sub>0i</sub> (Rs)	D <sub>i</sub> (Rs)	E <sub>i</sub> (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	30	150	1450	75	0.106	5650	32	9
6	30	150	4950	65	0.0675	14100	37.5	4.5
7	75	200	4100	60	0.074	11350	32	5.5

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 EPSATS method obviously displays a satisfactory performance with respect to the quality of its evolved solutions and to its computational requirements.

TABLE III  
COMPARISONS OF COST AND CPU TIME FOR UTILITY AND IEEE 10, 26, 34 UNIT SYSTEMS

System	Methods	Total Cost (ru)	CPU Time (sec)
7 Unit (Utility)	SA	0.94780	84
	TS	0.95531	110
	EP	0.93461	66
	EPSATS	0.92009	60
	DP	1.00000	130
	LR	0.97483	115
10 unit (IEEE)	SA	0.94422	200
	TS	0.95322	230
	EP	0.94071	186
	EPSATS	0.91749	178
	DP	1.00000	260
	LR	0.97183	235
26 Unit (IEEE)	SA	0.93906	1810
	TS	0.94887	1820
	EP	0.92814	1785
	EPSATS	0.90536	1775
	DP	1.00000	1860
	LR	0.96642	1878
34 Unit (IEEE)	SA	0.93300	6800
	TS	0.94382	6842
	EP	0.92400	6792
	EPSATS	0.90318	6775
	DP	1.00000	6865
	LR	0.96197	6824

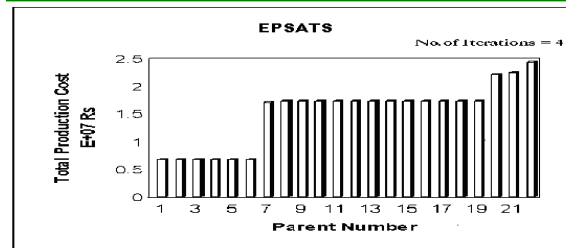


Fig. 3. Total production cost for 3 iterations

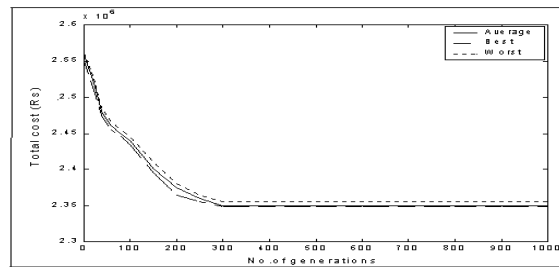


Fig. 4. EPSATS average performance from 100 runs

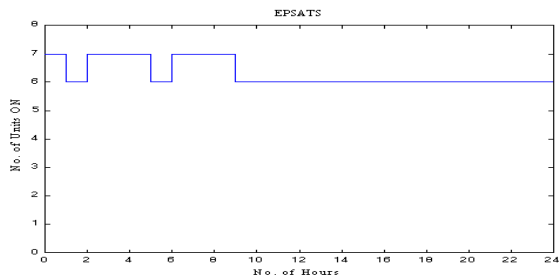


Fig. 5. No. of units switched ON during every hour

## 8. Conclusion

This paper presents a hybrid EPSATS method to the unit commitment problem. In this proposed work, the parents are obtained from a pre-defined set of solution's i.e. each and every solution is obtained from the SA and TS method. Then, a random recommitment is carried out with respect to the unit's 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 SA & TS), the EPSATS 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.

## References

- [1] W.L.Snyder, H.D.Powell, and C.Rayburn, "Dynamic Programming approach to Unit Commitment", *IEEE Trans. Power Systems*, Vol.3, No.2, pp. 339-350, 1987.
- [2] Y.Y.Hsu., Su, C.C.Liang, C.C.Lin.C.J. and C.T.Huang., "Dynamic Security Constrained Multi-Area Unit Commitment", *IEEE Trans. Power Systems*, Vol.6, pp.1049-1055, 1991.
- [3] Tao Li, Mohammad Shahidehpour, "Price-Based Unit Commitment: A Lagrangian Relaxation Versus Mixed Integer Programming", *IEEE Trans. Power Systems*, Vol. 20, No. 4, pp. 2015-2025, 2005.
- [4] Samer Takriti and John R.Birge, "Using Integer Programming To Refine Lagrangian – Based Unit Commitment Solutions", *IEEE Trans. Power Systems*, Vol.15, No.1, pp.151-156, 2000.
- [5] A.G.Bakirtzis, C.E.Zoumas, "Lambda of Lagrangian relaxation solution to unit commitment problem", *IEE Proc. Generation, Transmission and Distribution*, Vol.147, No.2, pp.131-136, 2000.
- [6] Chuan-ping Chang, Chih-wen Liu, Chun-chang Liu, "Unit Commitment by Lagrangian Relaxation and Genetic Algorithms", *IEEE Trans. Power Systems*, Vol.15, No.2, pp.707-714, 2000.
- [7] Weerakorn Ongsakul, Nit Petcharakas, "Unit Commitment by Enhanced Adaptive Lagrangian Relaxation", *IEEE Trans. Power Systems*, Vol. 19, No. 1, pp. 620-628, 2004.
- [8] A.I.Cohen and M.Yoshimura, "A Branch and Bound Algorithm for Unit Commitment", *IEEE Trans. Power and Apparatus*, Vol. 102, No.2, pp.444-451, 1983.
- [9] Z.Ouyang, S.M.Shahidehpour, "Short term Unit Commitment Expert System", *International Journal of Electrical Power System Research*, Vol. 20, pp.1-13, 1990.
- [10] C.C.Su, Y.Y.Hsu, Fuzzy Dynamic Programming: an application to Unit Commitment, *IEEE Trans. Power Systems*, Vol.6, No.3, pp.1231-1237, 1991.
- [11] Titti Saksornchai, Kittipong Methaprayoon, "Improve the Unit Commitment Scheduling by Using the Neural Network Based Short-term Load Forecasting", *IEEE Trans. Power Systems*, Vol. 41, No.1, pp. 169-179, 2005.
- [12] T. Senjyu, A.Y. Saber, T. Miyagi, K. Shimabukuro, N. Urasaki and T. Funabashi, "Fast Technique for Unit Commitment by Genetic Algorithm Based on Unit Clustering", *IEE Proc. Generation, Transmission and Distribution*, Vol. 152, No.5, pp. 705-713, 2005.
- [13] Ioannis G. Damousis, Anastasios G. Bakirtzis, Petros S. Dokopoulos, "A Solution to the Unit Commitment Problem Using Integer-Coded Genetic Algorithm", *IEEE Trans. Power Systems*, Vol. 19, No. 2, pp. 1165-1172, 2004.
- [14] N.P.Padhy, "Unit Commitment using Hybrid Models: A Comparative Study for Dynamic Programming, Expert Systems, Fuzzy System and Genetic Algorithms", *International Journal of Electrical Power & Energy Systems*, Vol.23, No.1, pp.827-836, 2000.
- [15] Zhuang.F., F.D.Galiana, "Unit Commitment by Simulated Annealing", *IEEE Trans. Power Systems*, Vol. 5, No. 1, pp. 311-318, 1990.
- [16] S.Kirkpatrick, C.D.Gelatt, Jr., M.P.Vecchi, "Optimisation by SA", *Science*, Vol. 220, pp. 4598, 1983.
- [17] Shokri Z. Selim, K.Alsultan, "A Simulated Annealing Algorithm for the Clustering Problem", *Pattern Recognition*, Vol. 24, No. 10, pp. 1003-1008, 1991.
- [18] A.H.Mantawy, Youssef L. Abdel-Magid, Shokri Z. Selim, "A Simulated Annealing Algorithm for Unit Commitment", *IEEE Trans. Power Systems*, Vol. 13, No. 1, pp. 197-204, 1998.
- [19] A.H.Mantawy, Youssef L. Abdel-Magid, Shokri Z.Selim, "A Unit Commitment By Tabu Search", *IEE Proc. Generation, Transmission and Distribution*, Vol. 145, No. 1, pp.56-64, 1998.
- [20] Whei-Min Lin, Fu-Sheng Cheng, Ming-Tong Tsay, "An Improved Tabu Search for Economic Dispatch With Multiple Minima", *IEEE Trans. Power Systems*, Vol.17, No.1, pp.108-112, 2002.
- [21] Yong-Gang Wu, Chun-Ying Ho, Ding-Yi Wang, "A Diploid Genetic Approach to Short-Term Scheduling of Hydro-Thermal System", *IEEE Trans. Power Systems*, Vol.15, No.4, pp.1268-1274, 2000.
- [22] Ying-Yi Hong, Chih-Yuan Li, "Genetic Algorithm Based Economic Dispatch for Cogeneration Units Considering Multiplant Multibuyer Wheeling", *IEEE Trans. Power Systems*, Vol.17, No.1, pp.134-140, 2002.
- [23] A.H.Mantawy, Youssef L. Abdel-Magid, Shokri Z.Selim, "Integrating Genetic Algorithm, Tabu Search And Simulated Annealing For The Unit Commitment Problem", *IEEE Tans. Power Systems*, Vol.14, No.3, pp.829-836, 1999.
- [24] X.Bai, M.Shahidehpour, "Hydro-Thermal Scheduling by Tabu Search and Decomposition Method", *IEEE Trans. Power Systems*, Vol.11, No.2, pp.968-975, 1996.
- [25] X.Bai, M.Shahidehpour, "Extended Neighbourhood Search Algorithm For Constrained Unit Commitment", *Electrical Power and Energy Systems*, Vol.19, No.5, pp.349-356, 1997.
- [26] K.A.Juste, H.Kita, E.Tanaka, J.Hasegawa, "An Evolutionary Programming Solution to the Unit Commitment Problem", *IEEE Trans. Power Systems*, Vol.14, No.4, pp.1452-1459, 1999.
- [27] H.T.Yang, P.C.Yang and C.L.Huang, "Evolutionary Programming Based Economic Dispatch for Units with Non-smooth Fuel Cost Functions", *IEEE Trans. Power Systems*, Vol.11, No.1, pp.112-117, 1996.
- [28] Teuvo Kohonen, "An Introduction to Neural Computing", *Neural Networks Journal*, Vol. 1, No.1, pp. 3-16, 1998.
- [29] A.J.Wood And B.F.Woolenberg, *Power Generation and control 2<sup>nd</sup> Edn.*, New York: John Wiley and Sons., 1996.
- [30] D.B.Fogel, *Evolutionary Computation, Toward a New Philosophy of Machine Intelligence*, New York: IEEE Press, 1995.
- [31] T.Back, *Evolutionary Algorithms in Theory and Practice*, New York: Oxford University Press, 1996.
- [32] L.J.Fogel, A.J.Owens, M.J.Walsh, *Artificial Intelligence through Simulated Evolution*, New York: John Wiley & Sons, inc., 1996.