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Neural Based Tabu Search Method for Solving Unit Commitment Problem with Cooling-Banking Constraints

Charles Gnanakkan Christober Asir Rajan[1]

Abstract: This paper presents a new approach to solve short-term unit commitment problem (UCP) using Neural Based Tabu Search (NBTS) with cooling and banking constraints. 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 next H hours. A 7-unit utility power system in India demonstrates the effectiveness of the proposed approach; extensive studies have also been performed for different IEEE test systems consist of 10, 26 and 34 units. Numerical results are shown to compare the superiority of the cost solutions obtained using the Tabu Search (TS) method, Dynamic Programming (DP) and Lagrangian Relaxation (LR) methods in reaching proper unit commitment.

Keywords: Neural network, Tabu search, Unit commitment, Cooling-banking.

1 Introduction

Unit commitment in power systems refers to the optimization problem for determining the on/off states of generating units that minimize the operating cost for a given time horizon. The solution of the unit commitment problem is a complex optimization problem. The exact solution of the UCP can be obtained by a complete enumeration of all feasible combinations of generating units, which could be very huge number. The unit commitment has commonly been formulated as a non-linear, large scale, mixed-integer combinational optimization problem.

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

[1]Department of EEE, Pondicherry Engineering College, Pondicherry, India;
E-mail: asir_70@pec.edu; asir_70@hotmail.com

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 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 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 Hop Field method (H), the Simulated Annealing method (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 neighbourhood 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 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 [1,2,14]. 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. In [5-8] it was suggested that the LR approach 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 [10,14] 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. The FT method [11,14] using fuzzy set solves the forecasted load schedules error but it will also suffer from complexity. The H neural network technique [12,27] considers more constraints but it may suffer from numerical convergence due to its training process. SA [15-17] 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 [18,19] 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 GA [14,20,21] 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 ANN [13,27,29] 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 [25,26,31-33] 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 [22] 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 [23] has considered the time varying start-up costs as well as the non-linearity in the hydrothermal systems. It can be used as post processor for existing generation scheduling methods or in cases where rescheduling of units is required due to change in the system status. And the application of the modified Benders decomposition method is to solve with constraints that are difficult to formulate. In order to obtain the better results, the experience of the operators in applying some system specific conditions has been included in the Tabu Search method. 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 [24] the constrained models for fuel limits, emission limits and generation capacity limits are discussed and used for typical models. The method can make use of an algorithm that satisfies the objective of the sub problem. Most suitably, and starts from an initial solution even though the solution may be feasible. The higher integral economic effect is pursued, and the feasibility of the algorithm is maintained. 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.

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 NN with TS to develop the neural based tabu search method (NBTS) for meeting these requirements of the UCP, which eliminates the above-mentioned drawbacks. The algorithm is based on the annealing neural network. Classical optimization methods are a direct means for solving this problem. Artificial intelligence techniques seem to be promising and are still evolving. High quality solutions can be obtained from fast converging methods like tabu search. 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. Neural networks have the great advantage of parallel processing and, hence, the computation time is considerably reduced. The solution processing in each method is very unique. Several examples are solved to test the developed computer model. A 7-unit utility power system in India demonstrates the effectiveness of the proposed approach; extensive studies have also been performed for different IEEE test systems consist of 10, 26 and 34 units. Numerical results are shown to compare the superiority of the cost solutions obtained using the Tabu Search (TS) method, Dynamic Programming (DP) and Lagrangian Relaxation (LR) methods in reaching proper unit commitment.

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 [28]. 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 (1):

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

where:

A_i, B_i, C_i – the cost function parameters of unit i ($\text{Rs/MW}^2\text{hr}$, Rs/MWhr, Rs/hr),

$\text{F}_{it}(P_{it})$ – 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 in (2):

$$S_{it} = S_{oi}\left[1 - D_i\,\mathrm{e}^{(-T_{\mathrm{off}i}/T_{\mathrm{down}i})}\right] + E_i, \quad [\mathrm{Rs}] \tag{2}$$

where:

S_{oi} – 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 (3):

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

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].

A. 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. [28].

1) *Load Balance Constraints*

The real power generated must be sufficient enough to meet the load demand and must satisfy the following factors (4):

$$\sum_{i=1}^{N} P_{it}U_{it} = PD_t\ , \tag{4}$$

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) *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 (5):

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

where:

$P_{\max i}$ –Maximum generation limit of unit i,

R_t –spinning reserve at time t [MW],

T – scheduled time horizon [24 hr].

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 (6).

$$T_{\text{on}i} \geq T_{\text{up}i}, \tag{6}$$

where:

$T_{\text{on}i}$ – duration for which unit i is continuously ON [hr],

$T_{\text{up}i}$ – 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 (7).

$$T_{\text{off}i} \geq T_{\text{down}i}, \tag{7}$$

where:

$T_{\text{down}i}$ –unit i minimum down time [hr],

$T_{\text{off}i}$ –duration for which unit i is continuously OFF [hr].

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

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.

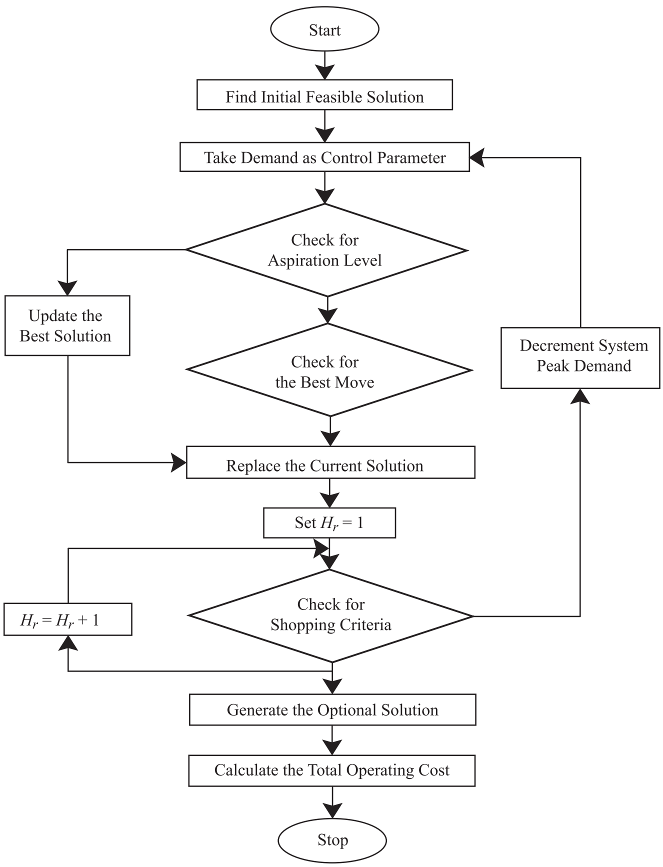

Fig. 1 – *Flowchart of Tabu Search Algorithm.*

A) ***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.

B) ***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].

C) ***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.

D) ***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.

E) ***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.

F) ***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 [18]. 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.

G) ***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” [18].

4 Neural Based Tabu Search Method

A. *Neural Networks*

1) *Training and Testing Phases*

The first phase of the execution namely the training phase lets the network to learn how to adopt its weights or parameters in small incremental steps. Presenting the network with examples called training patterns carries this out. Once the network has learnt the problem it may be presented with new unknown patterns. During the testing phase, the test patterns, which are independent data used only to asses the generalization of the network, are presented to the trained network and the actual output is produced.

2) *Training Algorithm*

1. Initialize random weights to the nodes from the input to the hidden layer (W_{1ij}) and hidden to the output layer (W_{2jk}).
2. Input the set of training pairs namely the actual input X_i and its target input TAR *i*.
3. Calculate the sum of the product of all the nodes namely $\Sigma X_i W_{1ij}$ and pass it through an activation function to get OUT X_j.
4. Similarly calculate the sum of the product of all the nodes to the output layer Σ OUT X_i W_{2jk} and pass it through an activation function to get the actual output OUT *k*.
5. Compare the actual output with the desired output; find the error difference between the two each time Find the sum of all such errors;
6. Check if this sum error is below the required. Level .If yes, takes these set of weights to be the fixed values of the trained set.
7. If no, back propagate the error, update both the set of weights and repeat the process until the condition is reached.

3) *Testing Algorithm*

1. Initialize random weights to the nodes from the input to the hidden layer (W_{1ij}) and hidden to the output layer (W_{2jk}).
2. Input the set of test data to the trained network.
3. Calculate the sum of the product of all the nodes to the hidden layer $\Sigma X_i W_{1ij}$ and pass it through an activation function to get OUT X_j.
4. Similarly calculate the sum of the product of all the nodes to the output layer Σ OUT X_i W_{2jk} and pass it through an activation function to get OUT *k*.
5. These sets of outputs that have been produced by the trained network correspond to the actual optimal outputs from the trained network.

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 is used to solve the combinatorial optimization and the nonlinear optimization is solved via a quadratic programming routine.

B. *Neural Based Tabu Search Method to* UCP

1. The generation for a particular day and its corresponding status is input for training the network.
2. The unit ON–OFF status is obtained from the output of the testing phase of neural network.
3. This obtained output is given as the initial solution for the TS algorithm.
4. For the units, which are in the off states, calculate the cost for both cooling and banking.
5. Compare the cooling and banking costs, if banking cost is lesser than cooling, bank the unit.
6. Print the optimum schedule.
7. The running cost and the start up cost for each hour for the finally obtained status is calculated and their sum gives the operating cost for each hour.
8. The overall operating cost is calculated by summing the individual operating costs.

The flowchart for the neural network algorithm is shown in Fig. 2.

C. *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 the generating trail solution in TS algorithm 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;

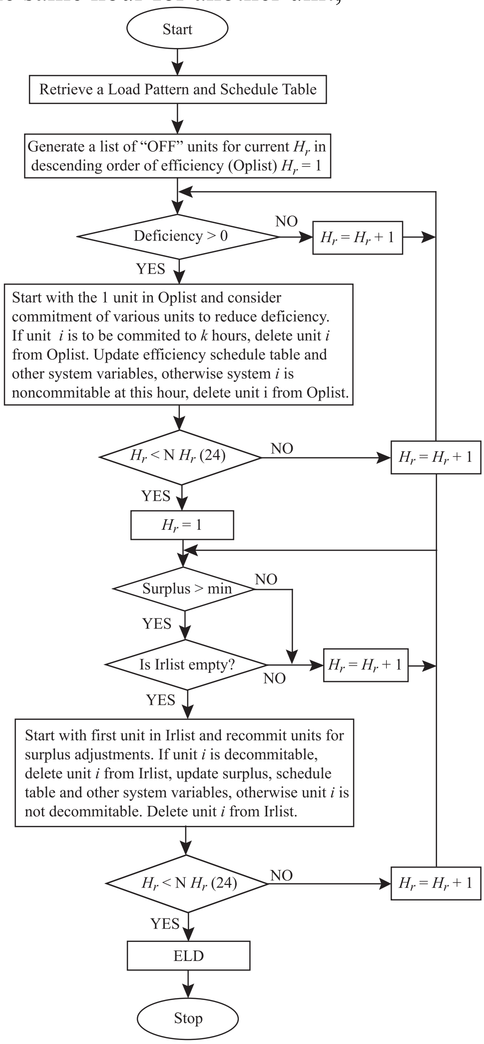

Fig. 2 – *Flow Chart of Neural Network Algorithm*.

D. *Making offspring feasible*

While solving the constrained optimization problem, there are various techniques to repair an infeasible solution [14,18]. 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.

E. *Implementation*

The training and identification phases' part using Neural Network is performed using the developed software in MATLAB package. The refined solution obtained from the process is then fed as the input to the TS process, which is software developed using Turbo C package. Fig. 2 shows the flow chart for the entire steps involved in Neural Networks. Figs. 3 and 4 show the training curve of Neural Network for 50000 and 500 Epochs.

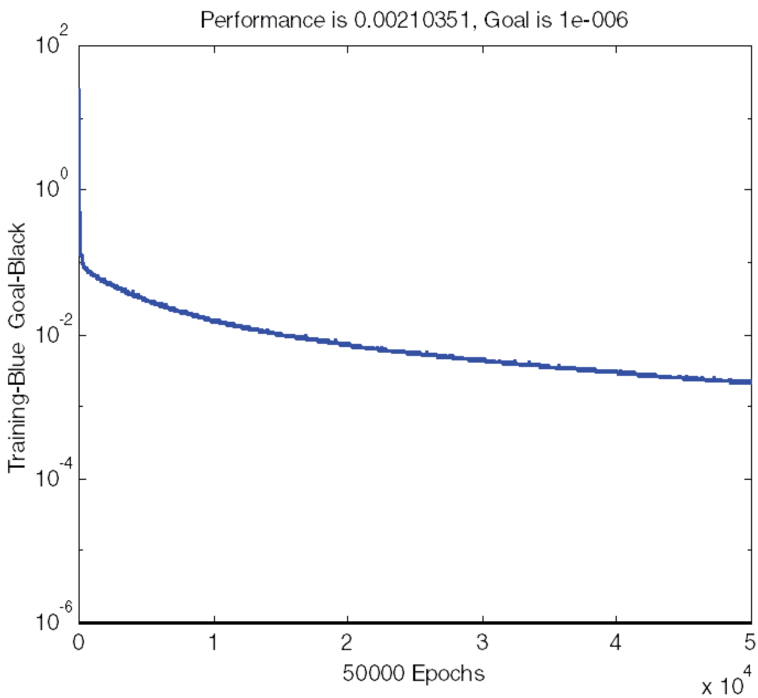

Fig. 3 – *Training Curve of Neural Network for* 50000 *Epochs*.

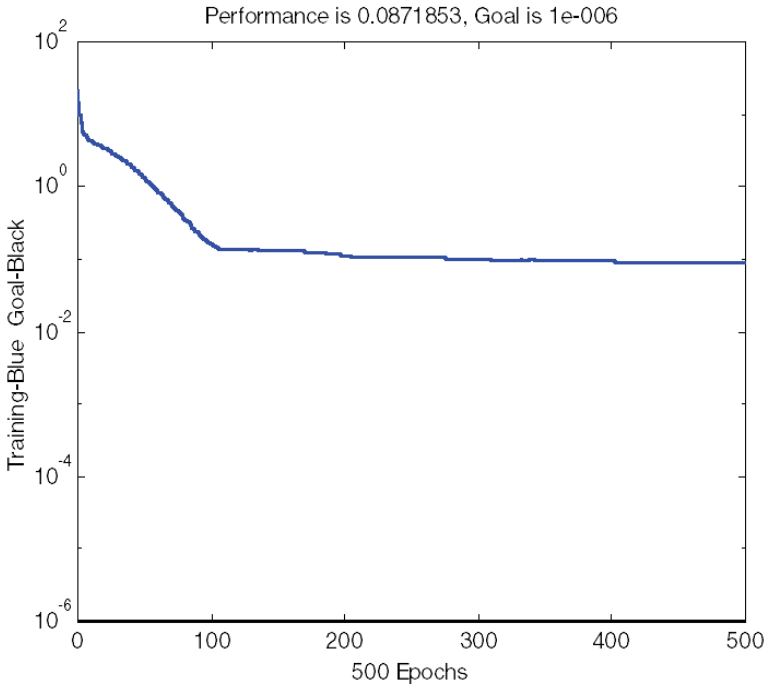

Fig. 4 – *Training Curve of Neural Network for* 500 *Epochs*.

5 Case Study

A TPS 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. 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, NN, NBTS, DP, LR methods for utility power systems. Figs. 3 and 4 represent the training curves of Neural Networks for 50000 and 500 epochs respectively. This infers us that performance is better for higher epochs. The comparison of the total costs and Central Processing unit (CPU) time is shown in **Table 3**. From the comparison, it was found that the NBTS method took lesser time and less cost when compared with the conventional and search methods.

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)	Running Cost			Start-up Cost		
			C_i (Rs)	B_i (Rs/MWh)	A_i (Rs/MWh^2)	So_i (Rs)	D_i (Rs)	E_i (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

Table 3
Comparisons of cost and CPU *time.*

System	Methods	Total Cost (p.u.)	CPU Time (s)
7 Unit (Practical)	DP	1.00000	130
	LR	0.97843	115
	TS	0.94580	80
	NN	0.94461	70
	NBTS (Without Cooling & Banking)	0.93392	60
	NBTS (With Cooling & Banking)	0.93056	58
10 Unit (IEEE)	DP	1.00000	260
	LR	0.97183	235
	TS	0.94222	200
	NN	0.93971	190
	NBTS (Without Cooling & Banking)	0.93090	180
	NBTS (With Cooling & Banking)	0.92710	176
26 Unit (IEEE)	DP	1.00000	1878
	LR	0.96642	1860
	TS	0.94706	1810
	NN	0.93814	1790
	NBTS (Without Cooling & Banking)	0.92900	1779
	NBTS (With Cooling & Banking)	0.92600	1770
34 Unit (IEEE)	DP	1.00000	6865
	LR	0.96197	6824
	TS	0.94300	6800
	NN	0.93400	6799
	NBTS (Without Cooling & Banking)	0.92718	6778
	NBTS (With Cooling & Banking)	0.92425	6770

6 Conclusion

This paper presents a new NBTS based algorithm with cooling-banking constraints for the UCP. The problem is highly combinatorial. Even moderate size problems are currently being solved with great difficulty. The proposed algorithm is based on the short-term memory procedure of the TS method. TS are characterized by its ability to escape local optima by using a short-term memory of recent moves. Moreover, TS permits backtracking to previous solutions, which may ultimately lead, via, a different direction, to better solutions. The successful implementation presented in this paper highlights the importance of NBTS approach as a powerful tool for solving difficult combinatorial optimization problems. Better solutions are also expected when employing sophisticated Tabu Search procedures. These include the use of intermediate and long-term memory, which could lead to new unexplored solutions to the problem. Probabilistic Tabu Search procedures could also be used. Further work in this area may include parallel processing of the TS, thus reducing the computation time, or exploring a wider solution space.

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