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Full Length Research Paper

An evolutionary programming embedded Tabu search method for hydro-thermal scheduling with cooling – banking constraints

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This paper presents a new approach for solving the unit commitment problem (UCP) in hydro-thermal power system. The main objective of this paper is to find the generation scheduling by committing the generating units such that the total operating cost can be minimized by satisfying both the forecasted load demand and various operating constraints. It is a Global optimization technique for solving UCP, operates on a system, which is designed to encode each unit's operating schedule with regard to its minimum up/down time. In this method, the unit commitment schedule is coded as a string of symbols. An initial population of parent solutions is generated at random. Here the parents are obtained from a pre-defined set of solutions that is, each and every solution is adjusted to meet the requirements. Then, random recommitment is carried out with respect to the unit's minimum down times. Tabu search (TS) is a powerful optimization procedure that has been successfully applied to a number of combinatorial optimization problems. It avoids entrapment at local optimum by maintaining a short term memory of recently obtained solutions. The memory structure assists in forbidding certain moves that deteriorates the quality of the solution by assigning Tabu status to the forbidden solutions. The Tabu status of a solution can be overruled if certain conditions are satisfied expressed in the form of aspiration level (AL). AL adds flexibility in TS by directing the search towards attractive moves. The best population is selected by evolutionary strategy (ES). Numerical results are shown comparing the cost solutions and computation time obtained by using the proposed hybrid method with conventional methods like Dynamic Programming, and Lagrangian Relaxation etc.

Key words: Evolutionary programming, Tabu search, unit commitment, dynamic programming, lagrangian relaxation.

INTRODUCTION

The electrical power system has daily and weekly cycles. The optimization problem is how to schedule generation to minimize the fuel cost or to maximize the profit over a study period of typically a day, satisfying various constraints. The daily load pattern for a given system may exhibit large differences between minimum and maximum demand. It is not proper and economical to run all the units available all the time. Since the load varies continuously with time, the optimum condition of units may alter during any period.

Therefore, determining the units of a plant that should operate economically for a given load is the problem of unit commitment (UC). For total number of units of higher order, the problems associated with UC have generally been difficult to solve because of uncertainty of particular aspects of the problem. For instance the availability of fuel in precise, load forecast variable costs affected by the loading of generator units and the losses caused by reactive flows are some of the unpredictable issues. In order to reach a feasible solution for UCP, different considerations must be considered.

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A number of numerical optimization techniques have been employed to solve the complicated UCP. The major limitations of the numerical techniques are inability to handle problem dimensions, large computation time, more memory space and complexity in programming.

The two-stage method (Ferrero et al., 1998) has smaller computational requirements than that of the Simulated Annealing algorithm. The optimal generation from hydro and thermal resources is computed simultaneously in the two stage algorithm; there is no need for assuming constant operation of some reservoirs as in the Simulated Annealing method. No discretization of state and control variables is needed in the proposed method. The required storage as well as computing time in the proposed method are reduced as compared to those in the successive-approximations algorithm. The results (Martinez and Soares, 2002) revealed that the partial open-loop feedback control policy provided somewhat higher average and standard deviation for hydroelectric generation in all simulations performed. The higher standard deviation provided, however, not being compensated for by a slightly higher average generation, lead to higher final operating costs. The closed-loop feedback control policy was more efficient in the synthetically simulations. This advantage, however, reduced with the historical simulations, when the different control policies led to almost equivalent performances.

LR-DP method (Benhamida, 2009) is efficiently and effectively implemented to solve the UC problem. LR total production cost over the scheduled time horizon is less than conventional methods especially for the larger number of generating units. The augmented Lagrangian approach (Salem, 2001) presented in this paper accommodates further for pumped-storage units and line flow limitations and concurrently can produce accurate scheduling results. The approach produces feasible schedules and requires no iteration with economic dispatch algorithms. LR approach (Ngundam et al., 2002) to solve the 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 overall results obtained by the implemented Lagrangian relaxation approach (Alberto et al., 2003) are of very good quality and they are reached within little iteration. The proposed method could be of help for the solution of UC of hydrothermal power generation systems in the uncertain environment of the competitive electricity markets. The results revealed that the proposed method (Ruey-Hsun et al., 2009) is very effective in reaching an optimal generation schedule.

Test results and numerical experiences show that the solution technique (Gary et al., 2001) can give a near-optimal or optimal solution for the mixed integer linear programming (MILP) problem in an acceptable time. The solution of the hydrothermal problem not only provides MW schedules for hydro units and plants, but also indicates the hydro unit commitment status while minimizing the unit startup costs. MILP model allows to accurately represent most of the hydroelectric system characteristics, and turns out to be computationally solvable for a planning horizon of one week, proving the high efficiency of modern MILP software tools, both in terms of solution accuracy and computing time (Alberto et al., 2008). With the proposed (Costas et al., 2009) distributed implementation, even a small-sized generation company can perform overnight large Monte Carlo simulations on the company's personal computers exploiting their idle times under a simple hydrothermal problem communication protocol. The upper and lower bound estimates of the optimal value of the objective function are available with each iteration; a feasible solution to the original problem is available with each iteration; prior experience and feasible existing schedules can be directly incorporated into the computational procedure, introducing additional exclusion rules to improve the efficiency of the restricted integer algorithm (Baptistella and Gerome, 1980). Maximum intensity projection (MIP) methods (Mohan et al., 1992) 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 presented decomposition scheme (Wilfredo and Alberto, 2007) is simple, pure, and robust, even for dominant hydraulic power systems. It is also easy to implement, because it uses well-known, optimized, fast techniques, such as MIP and ac optimal power flow (OPF) algorithms. The chosen decomposition of the problem allows considering the network's entire modeling, with little impact on computing CPU time. Complex hydraulic chains or additional constrains can be easily modeled and/or added. In our studies (Tiago and Andre, 2009), reductions in the overall CPU time to solve the problem depended on the case, with a minimum reduction of two times as compared to the classical Multi Stage Benders Decomposition approach and four times as compared to the single linear program approach. This work (Srinivasa et al., 2009) builds a fuzzy rule base with the use of the area control error and rate of change of the error. The simulation results show that the proposed FLA based controller yields improved control performance than the dual mode controller.

The heuristic search algorithms are efficiently used to commit fuel constrained units, pumped-storage units, and repairing violations due to ramp rate and transmission constraints. The proposed method (Vo and Weerakorn, 2008) obtains less production costs and faster computational time than Augmented Hopfield Neural Network and hybrid Lagrangian relaxation and quadratic programming. SAM (Kirkpatrick et al., 1983; Shokri et al., 1991; Zhuang and Galiana, 1990; Mantawy et al., 1998) is a powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability one.

But it takes too much time to reach the near-global minimum. It is an iterative improvement procedure that starts with some initial feasible solution and improves it to reach the better solution with computation time. It has the special characteristic of escaping the local optima by employing a flexible memory system. SAM utilizes a short term memory of recent solutions to lead the algorithm to a different direction away from the local optimum region to obtain better solutions that are near to global optimum. TSM (Mantawy et al., 1998; Whei-Min et al., 2002) 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.

TSD (Xaiomin and Shahidehpur, 1996) 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 Tabu Search method. The simulation results (Rudolf and Bayrleithner, 1999) reveal that the features of easy implementation, convergence in an acceptable time, and highly optimal solution in solving the unit commitment problem can be achieved. GA (Yong-Gang and Chun-Ying, 2000) 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 proposed GA (Esteban et al., 2003), using new specialized operators, have demonstrated excellent performance in dealing with this kind of problem, obtaining near-optimal solutions in reasonable times and without sacrificing the realism of the electric and economic models. Developed algorithms provide optimal unit commitment and also optimal MW values for energy, spinning reserve and non-spin. Presented algorithm and analysis could be beneficial to GENCO with big number of generators to maximize the profit and bid in competitive electricity market (Mariappane and Thyagarajah, 2009; Lal and Christober, 2011).

With this new approach (Werner and Verstege, 1999), decomposition into sub problems for the hydro and the thermal system is not necessary. Numerical experiments with a hydrothermal test system demonstrate the ability of the proposed method to solve the complex optimization problem with its wealth of constraints. Cau and Kaye (2002) performance compares favorably with constructive DP which is known to be faster than standard LP. It can be used for a rapid approximate optimal scheduling for large scale complex system with multiple cascaded and pumped storage. Results (Chakrabarti and Chattopadhyay, 2003) show that with quadratic thermal cost and without prohibited discharge zones, all EP-based algorithms converge faster during initial stages while Fast Evolutionary Programming and Classical Evolutionary Programming slow down in the latter stages compared to Improved Fast EP. Improved Fast EP performs the best amongst the three in solving this problem in terms of execution time, minimum cost, and mean cost.

From test results, Shyh-Jier (2001), and Venkatesan and Sanavullah (2012) have demonstrated the feasibility of ACM in the hydro-generation scheduling study. This method is also suitable to be implemented under a parallel computer system. The solution speed can be thus further improved. There is no obvious limitation on the size of the problem that must be addressed (Christober, 2010), 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 Genetic Algorithm methods which first generate all feasible solutions and then purge the infeasible ones (Nayak and Christober, 2011; Javadi et al., 2011, a).

The flexibility in the demand constraint both in terms of possibility of buying and selling in the market gives better indication of the likely future scenarios so that better bidding strategy can be made (Javadi et al., 2011, b; Chitra et al., 2009; Ganesan and Subramanian, 2012). More improvements could be made to the proposed algorithm in order to increase the speed convergence of the algorithm (Ahmed et al., 2006) and its execution time by improving the gradient method, and by adjusting adequately the penalty weight factor.

Hence, in this paper, an attempt has been made to couple EP with TSM [electromagnetic propagation tool (EPTSM)] with cooling-banking constraints for meeting these requirements of the UCP, which gives the better solution than the individual EP and TS methods with reasonable time. In case of TSM, the temperature and demand are taken as control parameter. Hence the quality of solution is improved. Classical optimisation 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. EP does not suffer from the drawback of handling non-continuous or non-differentiable objective functions as in some plants like Combined Cycle Co-generation plants. Encoding and decoding schemes essential in the GA approach are not needed, considerable computation time is thus saved. The EP combines good solution quality for TSM with rapid convergence for EP. And the selection process is done using ES. By doing so, it can help to find the optimum solution rapidly and efficiently. The validity and effectiveness of the proposed integrated algorithm has been tested with an IEEE test system consisting of 4 hydro generating units and 10 thermal generating units. The results are compared with the other methods.

PROBLEM FORMULATION

The main objective of UCP is to determine the on/off status of the generating units in a power system by meeting the load demand at a minimum operating cost in addition to satisfying the constraints (Allen and Wollenberg, 1984) of the generating units. The problem formulation includes the quadratic cost characteristics, startup cost of thermal power system and operating constraints of thermal and hydro generating units. The power generation cost for thermal power system is given in Equation 1a.

$$F_{s,it}(P_{s,it}) = A_i + B_i P_{s,it} + C_i P_{s,it}^{\ 2} \text{ (Rs/h)} \tag{1a}$$

where,

A_i, B_i, C_i - The Cost Function parameters of unit i (Rs/h, Rs/MWh, Rs/MW^{2}h).

$F_{s,it}(P_{s,it})$ - The generation cost of unit i at time t (Rs/h).

$P_{s,it}$ - The output power from unit i at time t (MW).

The overall objective function (Alberto et al, 2008) of UCP that is to be minimized is given in Equation 1b.

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{N} (F_{it}(P_{it})U_{it} + S_i V_{it}) \text{ (Rs/h)} \tag{1b}$$

where,

U_{it} – Unit i status at hour t

V_{it} – Unit i start up/ shut down status at time t

F_T – Total operating cost over the schedule horizon (Rs/h)

S_{it} – Startup cost of unit i at time t (Rs)

Constraints

Load power balance constraint

The real power generated by thermal and hydro generating units must be sufficient enough to meet the load demand and must satisfy the equation

$$\sum_{i=1}^{N} P_{s,it} + \sum_{j=1}^{M} P_{h,it} = P_{D,i} + P_{L,i} \quad 1 \le t \le T \tag{2}$$

Spinning reserve constraint

Spinning reserve is the total amount of generation available from all units synchronized on the system minus the present load plus the losses being supplied. The reserve is usually expressed as a percentage of forecasted load demand. Spinning reserve is necessary to prevent drop in system frequency and also to meet the loss of most heavily loaded unit in the power system.

$$\sum_{i=1}^{N} P_{\max,i} U_{it} \ge (P_{D,i} + R_t) \quad 1 \le t \le T \tag{3}$$

Thermal constraints

A thermal unit undergoes gradual temperature changes and this increases the time period required to bring the unit online. This time restriction imposes various constraints on generating unit. Some of the constraints are minimum up/down time constraint and crew constraints.

If the units are already running there will be a minimum time before which the units cannot be turned OFF and the constraint is given in Equation 4.

$$T_{on,i} \ge T_{up,i} \tag{4}$$

If the units are already OFF there will be a minimum time before which they cannot be turned ON and the constraint is given in Equation 5.

$$T_{off,i} \ge T_{down,i} \tag{5}$$

Must run units

Some units in the power system are given must run status in order to provide voltage support for the network.

Unit capacity limits

The power generated by the thermal unit must lie within the maximum and minimum power capacity of the unit.

$$P_{s,i}^{\ \min} \le P_{s,i} \le P_{s,i}^{\ \max} \tag{6}$$

Hydro constraints

Hydro plant generation limits

The power generated by the hydro units must be within the maximum and minimum power capacity of the unit (Ferrero, 1998)

$$P_{h,i}^{\min} \leq P_{h,i} \leq P_{h,i}^{\max} \tag{7}$$

Hydraulic network constraints

Physical limitations on reservoir storage volumes and discharge rates.

$$V_{h,i}^{\min} \leq V_{h,i} \leq V_{h,i}^{\max} \tag{8}$$

$$Q_{h,i}^{\min} \leq Q_{h,i} \leq Q_{h,i}^{\max} \tag{9}$$

The initial volume and the final volume that is to be retained at the end of scheduling period.

$$V_{h,it}^{t=0} = V_{h,i}^{begin} \tag{10}$$

$$V_{h,it}^{t=T} = V_{h,i}^{end} \tag{11}$$

The Continuity equation for hydro reservoir network is given in Equation 12.

$$V_h(i,t) = V_h(i,t-1) + I_h(i,t) - S_h(i,t) - Q_h(i,t) - \sum_{m=1}^{Ru}[Q_h(m,t-\Gamma(i,m)) + S_h(m,t-\Gamma(i,m))] \tag{12}$$

Hydro plant unit power generation characteristics

The hydro power generated is related to the reservoir characteristics as well as water discharge rates. Hydro power output is a function of the volume of the reservoir and discharge rate. The equation representing the hydro power generation characteristics is given in Equation 13.

$$P_h(i,t) = C_{1,i}V_h(i,t)^2 + C_{2,i}Q_h(i,t)^2 + C_{3,i}[V_h(i,t)Q_h(i,t)]C_{4,i}V_h(i,t) + C_{5,i}Q_h(i,t) + C_{6,i} \tag{13}$$

ELECTROMAGNETIC PROPAGATION *TOOL (EPTSM) FOR HYDRO THERMAL* UNIT COMMITMENT PROBLEM (*UCP)*

The TSM is integrated with evolutionary programming algorithm to escape local optima. Since Tabu search improves the solution without entrapment in local minima the population obtained in EP is refined using TSM.

Implementation of *electromagnetic propagation* tool (EPTSM)

In the proposed algorithm, an initial set of parent vectors are formed at random. The objective function values of all the parents are evaluated and their startup cost is added to get the operating cost of each parent vector. Mutation is performed to all the parents and off springs is formed. The objective function values of off springs are evaluated as in the case of parents. Then the parents and off springs are combined to get the total population. Each individual from the population is refined using Tabu search algorithm. Then a tournament competition and selection process is performed to refined population from Tabu Search to obtain better half population. They are given as parents to the next generation. The above described process is repeated until maximum number of iterations is reached.

Improvements performed in the algorithm

1. Each parent is mutated twice to get two off springs. Therefore the total population will be the sum of Np parents and 2Np off springs that is, totally 3Np population. This allows in exploring more areas of the possible solution space and increases the probability of obtaining global optimum solution.
2. In the mutation process, if a parent yields good offspring then the particular mutation value is given a score. If at each time the particular mutation value gives good offspring then its score is increased and other mutation values scores are reduced. Hence during the next iteration the mutation values with more scores are applied to get offspring with less objective function values and thereby increasing the probability of obtaining global optimum solution.

Electromagnetic propagation *tool (EPTSM) algorithm*

The proposed integrated algorithm combines EP and TS techniques to solve the UCP problem. The EP technique, hold the main responsibility of finding the optimal point and TS assists EP to converge towards the optimum point quickly. The search is basically done with EP, but additionally the TS is used to escape the search path from local optimum point. The algorithm for the proposed method is as follows:

1. Commit all the M hydro units and considering discharge rates (Q_h(i,t)) between the limits, calculate the volumes (V_h(i,t)) of the reservoirs from 1 to M.

$$V_h(i,t) = V_h(i,t-1) + I_h(i,t) - Q_h(i,t) - S_h(i,t) + \sum_{m=1}^{Ru}[Q_h(m,t-\tau(i,m)) + S_h(m,t-\varsigma(i,m))] \quad (14)$$

2. Calculate the power produced by each hydro unit ($P_h(i,t)$) from the values of discharge rates and volumes.

$$P_h(i,t) = C_{1,i}V_h(i,t)^2 + C_{2,i}Q_h(i,t)^2 + C_{3,i}(V_h(i,t) * Q_h(i,t)) + C_{4,i}V_h(i,t) + C_{5,i}Q_h(i,t) + C_{6,i} \quad (15)$$

3. Sum up all the hydro powers for each period and subtract the total hydro power from the power demand for each period.
4. Find the remaining load demand to be met with thermal power such that

$$\sum_{i \in Rs} P_s(i,t) + \sum_{i=Rh} P_h(i,t) = PD(t) + PL(t) \quad (16)$$

5. Obtain the power (P_{dt}) to be produced by thermal unit,

$$PD_t = PD - PD_h \quad (17)$$

and for the thermal system Unit Commitment is performed as below.
6. An initial population of "parent" solutions S_k, k=1,2,3…,M (where M is the number of parents), is generated at random.
7. The objective function value associated with each solution S_k is calculated by economically dispatching the hourly load to the operating units and by computing the total fuel and start-up/shut-down costs, that is,

$$TC(S_k) = TFC(S_k) + TSUC(S_k) + TSDC(S_k) \quad (18)$$

8. An offspring $S_k^{'}$ is created from each parent by adding a Gaussian random variable $N(0, \sigma^2_k)$ to the elements a_{ijk} of parent S_k:

$$a'_{ijk} = a_{ijk} + N(0, \sigma^2{}_k) \quad (19)$$

$$\sigma_k = \beta_i * \frac{TC(S_k) * p_i}{TC_{\min}} \quad (20)$$

Here, the value of β_i is chosen in such a manner that product β_i x p_i should guarantee a minimum variance. Normally constant scaling factor is used in conventional EP. In this non-linear scaling factor is used for better convergence. For the first 40% of the total number of generations (N1) the decrement in scaling factor 'g1' is calculated as

$$g1 = \frac{(\beta_{\max} - \beta_{mid})}{N1} \quad (21)$$

For the remaining 60% of the total number of generations (N2) the decrement in β is calculated as 'g2' as

$$g2 = \frac{(\beta_{mid} - \beta_{\min})}{N2} \quad (22)$$

9. Each feasible offspring $S_k^{'}$ is evaluated according to 7.
10. For each feasible candidate, parent or offspring, a value W_k is assigned.

$$W_k = \sum_{\zeta=1}^{c} W_\zeta \quad (23)$$

$$W_\zeta = \begin{cases} 1, if TC(S_k) \langle TC(S_r) \\ 0, otherwise; \end{cases} \quad (24)$$

where $r = [2Mu + 1]$, *r not equal to k*, *[x]* denotes the greatest integer less than or equal to *x*, *c* is the number of competitions, and *u* is a uniform random number ranging over *[0,1]*. Here, *c* is set at *1/10* of the population.

11. The feasible competitors are ranked in descending order of W_k. The first *M* solutions survive and are transcribed along with their elements to form the basis for TS Algorithm.
12. In TS Algorithm the temperature variable (C_p) is initially assigned to be relatively higher value.
13. The number of iteration 'n' to be performed for refining each individual solution is obtained and the process is done to every individual independently.
14. The initial solution is assigned as the current best solution 'Ui', the function to be checked is assumed to be minimum, in our case it is the cost 'Fi'.
15. Random perturbation is done to the current solution and the neighbouring solution 'Uj' is obtained whose feasibility is examined by checking to see if there is an uptime or downtime constraint.
16. Check if the cost Fj $\leq$ Fi, if less replace Uj and Fj as current solutions for Ui and Fi, if greater check if exp [(Fi-Fj)/Ck] $\geq$ U (0, 1), if satisfied, set Ui =Uj.
17. The iteration count 'n' is decremented and another neighbouring solution is generated. When the iteration count **'n'** reaches zero, the temperature variable C_p is lowered to a new value.
18. The entire process terminates when sufficient iterations have occurred at the specified lowest temperature and this process is repeated to all the individual solution till all the Np solutions are refined.
19. The refined Np number of population is passed on to

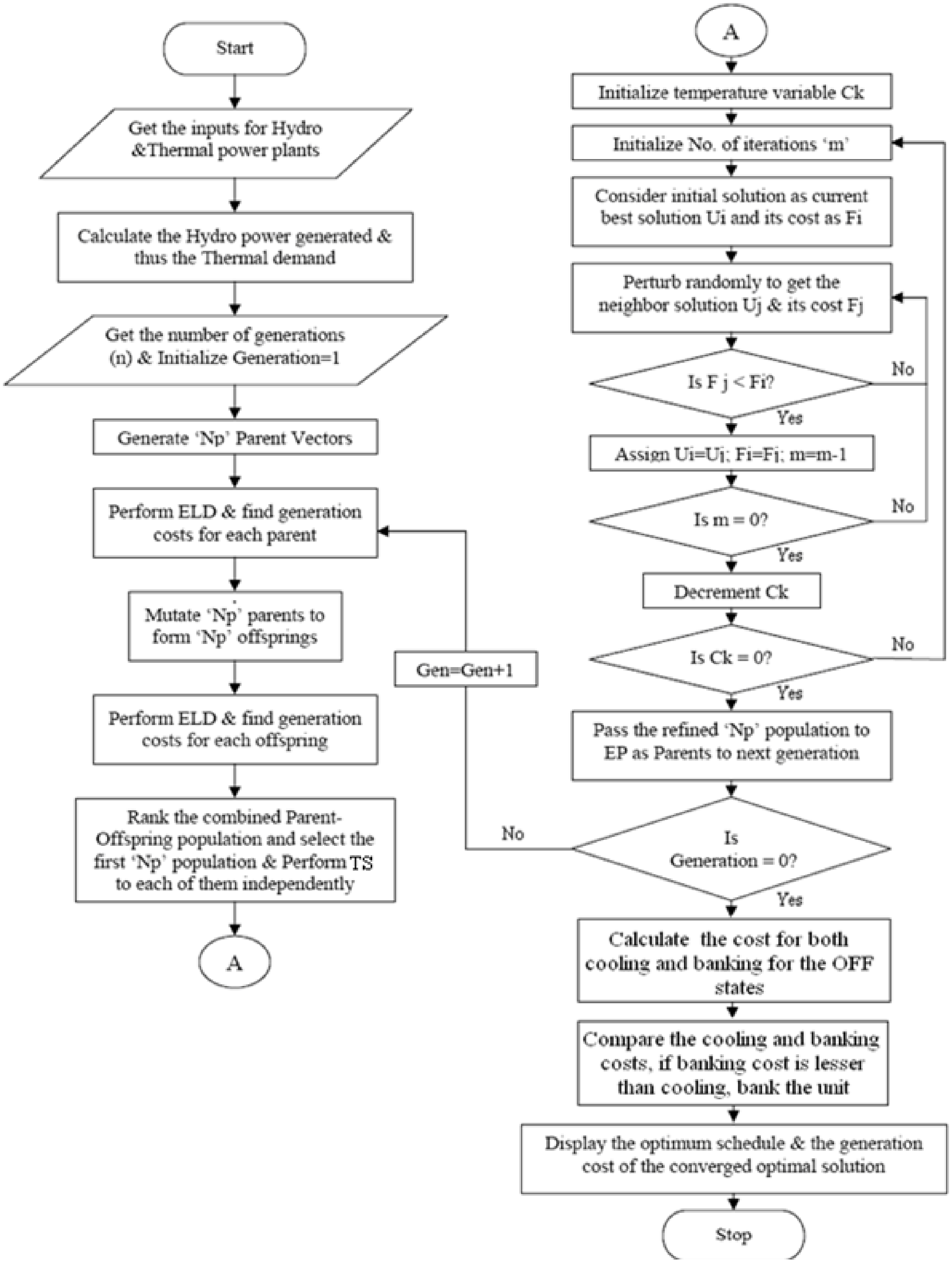


Figure 1. EPTSM flowchart for Hydro-Thermal UCP.

the EP part as the parents for next generation. And this process is repeated till the convergence in production cost is reached along with the optimum schedule having satisfied the constraints

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

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

22. Print the optimum schedule.

The diagrammatic description of the proposed hybrid EPTSM algorithm is shown in Figure 1.

Table 1. IEEE thermal test system.

Unit	Pmax (MW)	Pmin (MW)	A ($ / H)	B ($/ MWH)	C ($/ W^2H)	Min Up (H)	Min Down (H)	Hot Start Cost ($)	Cold Start Cost ($)	Cold Start Hours (H)	Initial Status (H)
1	455	150	1000	16.19	0.00048	8	8	4500	9000	5	8
2	455	150	970	17.26	0.00031	8	8	5000	1000	5	8
3	130	20	700	16.60	0.002	5	5	550	1100	4	-5
4	130	20	680	16.50	0.00211	5	5	560	1120	4	-5
5	162	25	450	19.70	0.00398	6	6	900	1800	4	-6
6	80	20	370	22.26	0.00712	3	3	170	340	2	-3
7	85	25	480	27.74	0.00079	3	3	260	520	2	-3
8	55	10	660	25.92	0.00413	1	1	30	60	0	-1
9	55	10	665	27.27	0.00222	1	1	30	60	0	-1
10	55	10	670	27.79	0.00173	1	1	30	60	0	-1

Table 2. Hydrodischarge coefficient.

Plant No.	C1	C2	C3	C4	C5	C6
1	-0.0042	-0.42	0.03	0.9	10	-50
2	-0.004	-0.3	0.015	1.14	9.5	-70
3	-0.0016	-0.3	0.014	0.55	5.5	-40
4	-0.003	-0.31	0.027	1.44	14	-90

Termination criterion of the algorithm

The algorithm can be terminated at any time if it satisfies certain conditions. There may be several possible conditions for termination of the algorithm. But the best conditions are selected by the quality of the solution obtained after termination. In this algorithm two possible conditions for termination have been applied. The algorithm will be terminated if the following conditions are satisfied:

1. Given maximum number of iterations have been performed (or)
2. The best operating cost obtained repeats successively for certain number of iterations.

CASE STUDY

An IEEE test system consisting of 4 hydro generating units and 10 thermal generating units has been considered as a case study (Mohan et al., 1992). A time period of 24 h is considered and the unit commitment problem is solved for these 10 units power system. The required inputs for solving the UCP are tabulated below. The IEEE thermal test system is shown in Table 1, hydro discharge coefficients, reservoir volumes and discharge limits and inflows to the reservoir are shown in Tables 2, 3 and 4. The daily load pattern considered is shown in Table 5.

The cost convergence graph of EPTSM and hydro and thermal generations are shown in Figures 2 and 3. The operating cost comparison of EPTSM with EP, TSM, LR and DP is shown in Table 6. By analyzing the graphs between the cost and iterations, as iterations increased the cost will be reduced with the slight increase of computation time. From the results obtained, we observed that EPTSM with cooling-banking constraints approaches to near optimal solution.

Conclusion

This paper gives an efficient, fast and robust

Table 3. Reservoir volume and discharge limits (× 10^{-4} M^3).

Plant No.	Vmin	Vmax	Vini	Vend	Qmin	Qmax	Ph min (MW)	Ph max (MW)
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	13	25	0	500

Table 4. Inflows to the reservoir (× 10^{-4} M^3).

Unit	1	2	3	4	5	6	7	8
1	12	12	11.8	11.7	11.7	11.6	11.5	11.4
2	6	6	6.5	6.7	6.8	6.9	7	7.2
3	3	4	5	6	7	8	8.8	8.9
4	3	2	2	0	0	0	0	0

Table 5. Load pattern for 24 h.

Hour	Demand (MW)	Hour	Demand (MW)
1	1358	13	1567
2	1357	14	1539
3	1187	15	1374
4	1321	16	1356
5	1500	17	1555
6	1501	18	1372
7	1468	19	1380
8	1298	20	1390
9	1292	21	1469
10	1176	22	1391
11	1521	23	1276
12	1399	24	1553

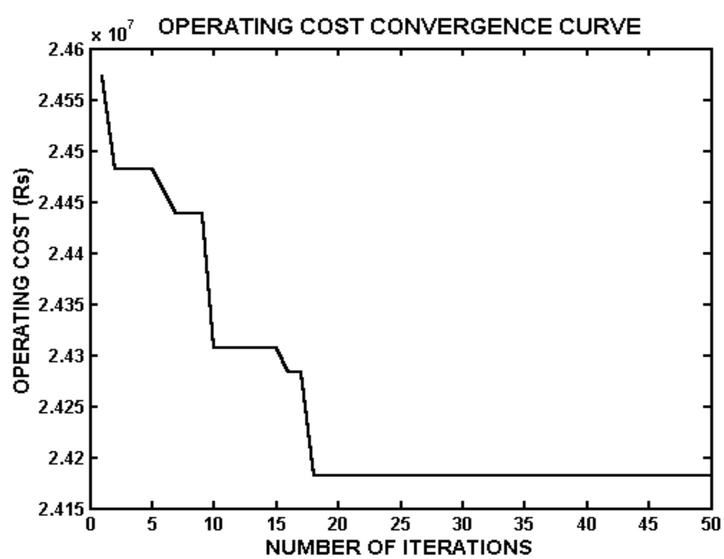
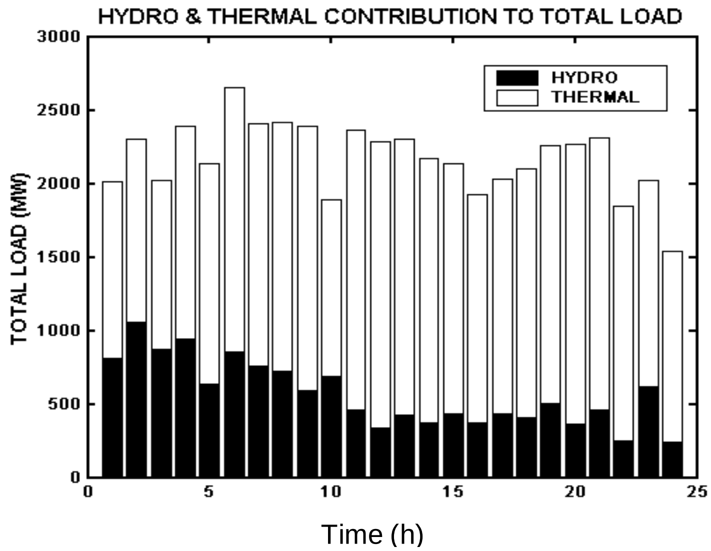


Figure 2. Cost convergence characteristics for 50 Iterations.



Figuer 3. Hydro and thermal generations.

Table 6. Production for different technique.

Techniques used	Iterations	Production cost (Rs.)	Computation time (s)
DP	-	32774013	83.90
LR	-	30656586	73.65
TSM	25	24363089	39.07
EP	25	24240650	26.91
EPTSM	25	24181789	24.45
EPTSM (C & B)	25	24164478	24.10

UCP through EPTSM with cooling-banking constraints. EP is characterized by its good convergent property and significant speedup over traditional GA's. An initial parent vector is formed at random. Then mutation is applied to obtain offspring. Best solutions are selected from the combined population of both parents and off springs for next generation. TSM is characterized by its ability to escape from the local optima by employing short term memory structure. Also it has a strategy called AL which directs the search towards attractive moves leading to a better solution. The effectiveness of the algorithm is proved by considering IEEE thermal and IEEE hydro test systems. The good convergent property of EP and TSM ability to avoid entrapment in local optima are integrated to form new hybrid algorithm for solving UCP which showed better results. Further improvements in the application of mutation operator to find better off springs will help in searching more areas in solution space resulting in global optimum solution. On comparing the results obtained from the different techniques, EPTSM with cooling-banking constraints obviously displays a satisfactory performance. Thus, the solution obtained from EPTSM has better quality in terms of economy and computation time.

Nomenclature

E_c : Energy of the current configuration
E_{Config}: Energy of a given configuration
E_t : Energy of the trail configuration
F_{it} (P_{it}): Production cost of unit i at a time t (Rs/h.)
F_T: Total operating cost over the scheduled horizon (Rs/H)
K : Constant
N: Number of available generating units
P_{Config} : Probability of a given configuration
PD_t : System peak demand at hour t (MW)
P_{it} : Output power from unit i at time t (MW)
P_{maxi} : Maximum generation limit of unit i (MW)
P_{mini} : Unit i minimum generation limit (MW)
R_t : Spinning reserve at time t (MW).
S_{it} : Start up cost of unit i at hour t (Rs).
S_{oi} : Unit i cold start – up cost (Rs).
T : Scheduled time horizon (24 h)
$Tdown_i$: Unit i minimum down time (H)
$Toff_i$: Duration for which unit i is continuously OFF (H)
Ton_i : Duration for which unit i is continuously ON (H)
$Tshut_i$: Instant of shut down of a unit i (H)
$Tstart_i$: Instant of start up of a unit i (H)

Tup_i : Unit i minimum up time (H)
U (0,1) : Uniform distribution with parameters 0 and 1
U_{it} : Unit i status at hour t = 1 (if unit is ON) = 0 (if unit is OFF)
UD(a,b) : Discrete uniform distribution with parameters a and b.
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: Composite cost function
F_i : Fuel cost of i^{th} thermal unit in Rs/h
$P_s(i,t)$: Generation of i^{th} thermal unit at time t in MW
$P_h(i,t)$: Generation of i^{th} hydro unit a time t in MW
$V_h(i,t)$: Storage volume of i^{th} reservoir at time t in m^3
$Q_h(i,t)$: Water discharge rate of i^{th} reservoir at time t in m^3
$P_D(t)$: Power demand at time t in MW
$P_L(t)$: Total Transmission line losses at time t in MW
$S_h(i,t)$: Spillage of i^{th} reservoir at time t in m^3
$I_h(i,t)$: Inflow rate of i^{th} reservoir at time t in m^3
$H_i(t)$: Net head of i^{th} reservoir at time t in m^3
α,β,γ : Thermal generation cost coefficients
$C_{i,1}$ to $C_{i,6}$: Hydro power generation coefficients
$\tau_{i,m}$: Water transport delay from reservoir σ to i
R_u : Set of upstream units directly above i^{th} hydro unit
R_h / R_s : Set of Hydro/Thermal plants in the system
i,m : Reservoir index, index of reservoir upstream of the i^{th} reservoir
t,T : Time index, scheduling period
V,i^{begin} : Initial storage volume of i^{th} reservoir in m^3
V,i^{end} : Final storage volume of i^{th} reservoir in m^3
P_i : Output generation for unit i in MW
P_L : Total current system load in MW
PT_L : Total system transmission losses in MW
OBJ : Objective cost function
***F_i* :** *Cost function for unit i.*

REFERENCES

Ahmed B, Abdelmalik B, Salah EZ (2006). Optimal Hydropower Generation Management. J. Electr. Eng. 6(2):21-26.

Alberto B, Antonio F, Fabrizio L, Carlo AN (2003). Lagrangian Heuristics Based on Disaggregated Bundle Methods for Hydrothermal Unit Commitment. IEEE Trans. Power Syst. 18(1):313-323.

Alberto B, Claudia D, Andrea L, Silvano M (2008). An MILP Approach for Short-Term Hydro Scheduling and Unit Commitment with Head-Dependent Reservoir. IEEE Trans. Power Syst. 23(3):1115-1124.

Allen JW, Wollenberg BF (1984). Power Generation, Operation and Control. John Wiley & Sons p. 444.

Baptistella LFB, Gerome JC (1980). Decomposition approach to problem of unit commitment schedule for hydrothermal systems. IEE Proc. Gener. Transm. Distrib. 127(6):250-258.

Benhamida F (2009). A Hybrid Lagrangian Relaxation – Dynamic Programming Solution to the Unit Commitment Problem. J. Electr. Eng. 9(4):31-40.

Cau TDH, Kaye RJ (2002). Evolutionary Optimization Method for multistorage hydrothermal scheduling. IEE Proc. – Gener. Transm. Distrib. 149(2):152-156.

Chitra SS, Kumudini DRP, Christober ARC (2009). A Hybrid Approaches for the Profit Based Unit Commitment Problem in the Deregulated Markets. J. Electr. Eng. 9(3):35-41.

Christober ARC (2010). Hybridizing Evolutionary Programming, Simulated Annealing, Tabu Search Method to Solve the Unit Commitment Problem. J. Electr. Eng. 10(1):34-41.

Costas GB, Stylianos EP, Anastasios GB (2009). Simulation of Optimal Medium-Term Hydro-Thermal System Operation by Grid Computing. IEEE Trans. Power Syst. 24(3):1208-1217.

Esteban G, Julian B, Hugh R (2003). Short-Term Hydrothermal Generation Scheduling Model Using a Genetic Algorithm. IEEE Trans. Power Syst. 18(4):1256-1264.

Ferrero RW, Rivera JF, Shahidehpour SM (1998). A Dynamic Programming Two-Stage Algorithm For Long-Term Hydrothermal Scheduling Of Multi reservoir Systems. IEEE Trans. Power Syst. 13(4):1534-1540.

Gary WC, Mohamed A, James GW, José M, Tony B, Steve R, Christoforidis M (2001). Experiences With Mixed Integer Linear Programming Based Approaches on Short-Term Hydro Scheduling. IEEE Trans. Power Syst. 16(4):743-749.

Kirkpatrick S, Gelatt CD, Vecehi MP (1983). Optimisation by Simulated Annealing. Science 220(1):4598.

Javadi MS, Meskarbashi A, Azami R, Hematipour G, Javadinasab A (2011). Security Constrained Unit Commitment in Iran's Electricity Market. Int. Rev. Model. Simul. 4(6):3104-3112.

Javadi MS, Meskarbashi A, Azami R, Hematipour G, Javadinasab A (2011). Emission Controlled Security Constrained Unit Commitment Considering Hydro-Thermal Generation Units. Int. Rev. Model. Simul. 4(6):3243-3250.

Mantawy AH, Youssef L, Abdel-Magid, Shokri ZS (1998). A Simulated Annealing Algorithm for Unit Commitment. IEEE Trans. Power Syst. 13(1):197-204.

Mantawy AH, Youssef LA, Shokri ZS (1998). A Unit Commitment By Tabu Search. IEE Proc. Gener. Transm. Distrib. 145(1):56-64.

Mariappane E, Thyagarajah K (2009). A Genetic Algorithm Approach to Price-Based Unit Commitment. J. Electr. Eng. 9(4):41-46.

Martinez L, Soares S (2002). Comparison between Closed-Loop and Partial Open-Loop Feedback Control Policies in Long Term Hydrothermal Scheduling. IEEE Trans. Power Syst. 17(2):330-336.

Mohan MR, Kuppusamy K, Abdullah KM (1992). Optimal Short-term Hydro-Thermal Scheduling using Decomposition Approach and Linear Programming Method, Int. J. Electr. Power Energy Syst. 14(1):39-44.

Ngundam JM, Kenfack F, Tatietse TT (2002). Optimal Scheduling of Large–Scale Hydrothermal Power Systems Using the Lagrangian Relaxation Technique. Int. J. Electr. Power Energy Syst. 22(1):237-245.

Nidul S, Chakrabarti R, Chattopadhyay PK (2003). Fast Evolutionary Programming Techniques for Short-Term Hydrothermal Scheduling. IEEE Trans. Power Syst. 18(1):214-220.

Nimain CN, Christober CAR (2011). Thermal Unit Commitment Scheduling Problem in Utility System by Simulated Annealing Embedded Evolutionary Programming Method. Int. Rev. Model. Simul. 4(6):3188-3194.

Lal RRS, Christober CAR (2011). A Hybrid Particle Swarm Optimization Employing Genetic Algorithm for Unit Commitment Problem. Int. Rev. Electr. Eng. 6(7):3211-3217.

Rudolf A, Bayrleithner R (1999). A Genetic Algorithm for Solving the Unit Commitment Problem of a Hydro Thermal Power System. IEEE Trans. Power Syst. 14(4):1460-1468.

Ruey-Hsun L, Ming-Huei K, Yie-Tone C (2009). Co evolutionary Algorithm Based on Lagrangian Method for Hydrothermal Generation Scheduling. IEEE Trans. Power Syst. 24(2):499-507.

Ganesan S, Subramanian S (2012). Reliability Constrained Thermal Unit Commitment Solution Using a Hybrid Approach. Int. Rev. Model. Simul. 5(1):434-441.

Salem A (2001). Hydrothermal Scheduling by Augmented Lagrangian: Consideration of Transmission Constraints and Pumped-Storage Units. IEEE Trans. Power Syst. 16(4):750-756.

Shokri ZS, Alsultan K (1991). A Simulated Annealing Algorithm for the Clustering Problem. Patt. Recognit. 24(10):1003-1008.

Shyh-Jier H (2001). Enhancement of Hydroelectric Generation Scheduling Using Ant Colony System Based Optimization Approaches. IEEE Trans. Energy Convers. 16(3):296-301.

Srinivasa RC, Siva NS, Sangameswara RP (2009). Automatic generation control of TCPS based hydrothermal system under open market scenario: A fuzzy logic approach. Int. J. Electr. Power Energy Syst. 31(1):315–322.

Venkatesan T, Sanavullah MY (2012). Implementation of Modified SFLA for the Thermal Unit Commitment Problem. Int. Rev. Model Simul. 5(1):450-457.
Tiago Norbiato dos Santos, Andre LD (2009). A New Multi period Stage Definition for the Multistage Benders Decomposition Approach Applied to Hydrothermal Scheduling. IEEE Trans. Power Syst. 24(3):1383-1392.
Vo ND, Weerakorn O (2008). Enhanced merit order and augmented Lagrange Hopfield network for hydrothermal scheduling. Int. J. Electr. Power Energy Syst. 30(1):93–101.
Werner TG, Verstege F (1999), An Evolution Strategy for Short-Term Operation Planning of Hydrothermal Power Systems. IEEE Trans. Power Syst. 14(4):1362-1368.
Whei-Min L, Fu-Sheng C, Ming-Tong T (2002). An Improved Tabu Search for Economic Dispatch With Multiple Minima, IEEE Trans. Power Syst. 17(1):108-112.
Wilfredo SS, Alberto V (2007). Hydrothermal Scheduling Using Benders Decomposition: Accelerating Techniques. IEEE Trans. Power Syst. 22(3):1351-1359.
Xaiomin B, Shahidehpur SM (1996). Hydro-Thermal Scheduling by Tabu Search and Decomposition. IEEE Trans. Power Syst. 11(2):968-974.
Yong-Gang W, Chun-Ying H (2000). A Diploid Genetic Approach to Short-Term Scheduling of Hydro-Thermal System. IEEE Trans. Power Syst. 15(4):1268-1274.
Zhuang F, Galiana FD (1990). Unit Commitment by Simulated Annealing. IEEE Trans. Power Syst. 5(1):311-318.