AN EVOLUTIONARY PROGRAMMING-BASED TABU SEARCH METHOD FOR SOLVING MULTI AREA UNIT COMMITMENT PROBLEM WITH IMPORT AND EXPORT CONSTRAINTS

K. VENKATESAN¹ V. MALATHI²
¹Professor, EEE Department, Sree Vydanikethan Engineering College, Tirupathi, A.P. India
²Assistant Professor-II, EEE Dept., SCVMV University, Enathur, Kanchipuram, T.N, India.
9751236990, venkatesanjntu7676@gmail.com
9751353281, maalu_1681@yahoo.com

Abstract: This paper presents a new approach to solve the multi area unit commitment problem (MAUCP) using an evolutionary programming-based tabu search (EPTS) method. The objective of this paper is to determine the optimal or a near optimal commitment schedule for generating units located in multiple areas that are interconnected via tie- lines. The evolutionary programming-based tabu search method is used to solve multi area unit commitment problem, allocated generation for each area and find the operating cost of generation for each hour. Joint operation of generation resources can result in significant operational cost savings. Power transfer between the areas through the tie- lines depends upon the operating cost of generation at each hour and tie-line transfer limits. The tie-line transfer limits were considered as a set of constraints during optimization process to ensure the system security and reliability. The overall algorithm can be implemented on an IBM PC which can process a fairly large system in a reasonable period of time. Case study of four areas with different load pattern each containing 26 units connected via tie- lines has been taken for analysis. Numerical results showed comparing the operating cost using evolutionary programming-based tabu search method with conventional dynamic programming (DP), evolutionary programming (EP), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Evolutionary Programming based Particle Swarm Optimization (EPPSO), Evolutionary Programming based Simulated Annealing (EPSSA) method. Experimental results shows that the application of this evolutionary programming-based tabu search method have the potential to solve multi area unit commitment problem with lesser computation time.

Key words: Dynamic Programming (DP), Evolutionary Programming (EP), Evolutionary Programming-based tabu search (EPTS), Multi Area Unit Commitment Problem (MAUCP), Tabu Search (TS).

1. Introduction

In multi area, several generation areas are interconnected by tie lines, the objective is to achieve the most economic generation to meet out the local demand without violating tie-line capacity limits constraints [1]. The main goal of this paper is to develop a multi area generation scheduling scheme that can provide proper unit commitment in each area and effectively preserve the tie line constraints. In an interconnected multi area system, joint operation of generation resources can result in significant operational cost savings [2]. It is possible by transmitting power from a utility, which had cheaper sources of generation to another utility having costlier generation sources. The total reduction in system cost shared by the participating utilities [3]. The exchange of energy between two utilities having significant difference in their marginal operating costs. The utility with the higher operating cost receives power from the utility with low operating cost. This arrangement usually on an hour to hour basis and is conducted by the two system operators.

In the competitive environment, customer request for high service reliability and lower electricity prices. Thus, it is an important to maximize own profit with high reliability and minimize overall operating cost [4].

Multi Area unit commitment was studied by dynamic programming and was optimized with local demands with a simple priority list scheme on a personal computer with a reasonable execution time [5]. Even though the simplicity and execution speed are well suited for the iterative process, the commitment schedule may be far from the optimal, especially when massive unit on/off transitions are encountered. The tie-line constraint checking also ignores the network topology, resulting in failure to provide a feasible generation schedule solution [5]. The transportation model could not be used effectively in tie line constraints, as the quadratic fuel cost function and exponential form of start up cost were used in this study.

An Evolutionary algorithm is used for obtaining the initial solution which is fast and reliable [6]. Evolutionary Programming (EP) is capable of determining the global or near global solution [7]. 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, from a considerably robust scheme for large scale real valued combinational optimization. In this work, the parents are obtained from a predefined set of solution (i.e., each and every solution is adjusted
to meet the requirements). In addition, the selection process is done using evolutionary strategy [8]-[10].

Tabu Search (TS) is a powerful optimization procedure that has been successfully applied to a number of combinational optimization problems [11]-[15]. It has the ability to avoid entrapment in local minima by employing a flexible memory system. Specific attention is given to the short term memory component of TS, which has provided solutions superior to the best obtained with other methods for a variety of problems.

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 MAUCP. Hence, in this paper, an attempt has been made to couple EP with TS for meeting these requirements of the MAUCP, which eliminates the above mentioned drawbacks. In case of TS, the demand is taken as control parameter. Hence, the quality of solution is improved. The algorithm is based on the annealing neural network. Classical optimization methods are a direct means for solving this problem. EP seems to be promising and is still evolving. EP has the great advantage of good convergent property, and, hence, the computation time is considerably reduced. The EP combines good solution quality for TS with rapid convergence for EP. The EP-based TS (EPTS) is used to find the multi area unit commitment. By doing so, it can help to find the optimum solution rapidly and efficiently [7].

EP is capable of determining the global or near global solution. It is based on the 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, from a considerably robust scheme for large-scale real-valued combinational optimization. In this proposed work, the parents are obtained from a predefined set of solution’s (i.e., each and every solution is adjusted to meet the requirements). In addition, the selection process is done using evolutionary strategy [8]-[10]. The application on this 26 unit shows that we can find the optimal solution effectively and these results are compared with the conventional methods.

### 2. Problem Formulation

The cost curve of each thermal unit is in quadratic form [3]

$$F(P^k_{gi}) = a^k_i (P^k_{gi})^2 + b^k_i (P^k_{gi}) + c^k_i \text{ Rs/hr}$$  \hspace{1cm} (1)

The incremental production cost is therefore

$$\lambda = 2a^k_i P^k_{gi} + b^k_i$$  \hspace{1cm} (2)

$$P^k_{gi} = \lambda - b^k_i / 2a^k_i$$  \hspace{1cm} (3)

The start up cost of each thermal unit is an exponential function of the time that the unit has been off

$$S(X_{i,j}^{off}) = A_i + B_i (1 - e^{-\frac{t}{\tau_i}})$$  \hspace{1cm} (4)

The objective function for the profit based multi-area unit commitment is to minimize the entire power pool generation cost as follows [1].

$$\min \sum_{j=1}^{N_t} \sum_{i=1}^{N_i} \sum_{k=1}^{N_h} \left[ I_{i,j}^k F^k_i (P^k_{gi}) + I_{i,j}^k (1-I_{i,j}^k) S(X_{i,j}^{off}) \right]$$  \hspace{1cm} (5)

To decompose the problem in above Eq. (5), it is rewritten as

$$\min \sum_{j=1}^{N_t} \left[ F(P^k_{gi,j}) \right]$$  \hspace{1cm} (6)

$$F(P^k_{gi,j}) = \sum_{i=1}^{N_i} F^k_i (P^k_{gi,j})$$  \hspace{1cm} (7)

Subject to the constraints of Eqs. (9), (11) and (14-18). Each $F^k_i (P^k_{gi,j})$ for $K=1 \ldots NA$ is represented in the form of schedule table, which is the solution of mixed variable optimization problem

$$\min \sum_{i,j} \left[ I_{i,j}^k F^k_i (P^k_{gi,j}) + I_{i,j}^k (1-I_{i,j}^k) S(X_{i,j}^{off}) \right]$$  \hspace{1cm} (8)

Subject to following constraints are met for optimization.

$$\sum_{i=1}^{N_i} P_{i,t} X_{i,t} \leq D_{i,t} \text{, } t = 1 \ldots \ldots T \hspace{1cm} (9)$$

$$\sum_{i=1}^{N_i} R_{i,t} X_{i,t} \leq SR_{i,t} \text{, } t = 1 \ldots \ldots T \hspace{1cm} (10)$$

Redefining the UC problem for the competitive environment involves changing the demand and reserve constrains from an equality to less than or equal to the forecasted level if it creates more profit. Here forecasted demand reserve and prices are important inputs to profit based UC Algorithm; they are used to determine the expected revenue, which affects the expected profit.

1) System power balance constraint

$$\sum_k P^k_{gi,j} = \sum_k D^k_j$$  \hspace{1cm} (9)

Sum of real power generated by each thermal unit must be sufficient enough to meet the sum of total demand of each area while neglecting transmission losses.

2) Spinning reserve constraint in each area

$$\sum_k P^k_{gi,j} \geq D^k_j + R^k_j + E^k_j - L^k_j$$  \hspace{1cm} (10)
3) Generation limits of each unit
\[ P_{i,j}^k \leq P_{i,j}^k \leq P_{i,j}^k \]
\[ i=1, \ldots, N_i, \quad j=1, \ldots, t, \quad k=1, \ldots, N_k \]  
\( \text{(11)} \)

4) Thermal units generally have minimum up time \( T_{on} \) and down time \( T_{off} \) constraints, therefore
\[ (X_{i,j-1}^{on} - T_{i}^{off}) (I_{i,j-1} - I_{i,j}) \geq 0 \]  
\[ (X_{i,j-1}^{on} - T_{i}^{off}) (I_{i,j-1} - I_{i,j}) \geq 0 \]  
\( \text{(12)} \)  
\( \text{(13)} \)

5) In each area, power generation limits caused by tie-line constraints are as follows
\[ \sum_i P_{i,j}^k \leq D_j^k + E_{i,j}^k \]  
\( \text{Upper limits} \)  
\( \text{(14)} \)
\[ \sum_i P_{i,j}^k \geq D_j^k - L_j^k \]  
\( \text{Lower limits} \)  
\( \text{(15)} \)
\[ \sum_i E_{i,j}^k \geq D_j^k + W_j = 0 \]  
\( \text{Import/Export balance} \)  
\( \text{(16)} \)

6) Area generation limits
\[ \sum_{k=1}^{N_k} P_{i,j}^k \leq \sum_{k=1}^{N_k} P_{i,j}^k - R_j^k \]  
\( \text{Upper limits} \)  
\( \text{(17)} \)
\[ \sum_{k=1}^{N_k} P_{i,j}^k \geq \sum_{k=1}^{N_k} P_{i,j}^k - R_j^k \]  
\( \text{Lower limits} \)  
\( \text{(18)} \)

The objective is to select \( \lambda_{sys} \) at every hour to minimize the operation cost.
\[ P_{i,j}^k = D_j^k + E_{i,j}^k - L_j^k \]  
\( \text{(19)} \)

where
\[ P_{i,j}^k = \sum_{i=1}^{N_i} P_{i,j}^k \]  
\( \text{(20)} \)

3. Tie Line Constraints
To illustrate the tie-line flow in a multi-area system, the four area system given in Fig.1 is studied. An economically efficient area may generate more power than the local demand, and the excessive power will be exported to other areas through the tie lines [1]. For example assume area 1 has the excessive power the tie line flows would have directions from area1 to other areas, and the maximum power generation for area1 would be the local demand in area1 plus the sum of all the tie line capacities connected to area1. If we fix the area 1 generation to its maximum level than the maximum power generation in area 2 could be calculated in a similar way to area 1. Since tie line C12 imports power at its maximum capacity, this amount should be subtracted from the generation limit of area 2. According to power balance equation (9) some areas must have a power generation deficiency and requires generation imports. The minimum generation limits in these areas is the local demand minus all the connected tie-line capacities. If any of these tie-lines is connected to an area with higher deficiencies, then the power flow

\[ \lambda_{max,i} \leq \lambda_{sys} \leq \lambda_{min,i} \]  
\( \text{(21)} \)
\[ \lambda_{min,i} > \lambda_{sys} \]  
\( \text{(22)} \)

\[ \lambda_{sys} \]  
\( \text{(23)} \)

\[ D_j^k - L_j^k \leq \sum_i P_{i,j}^k \leq D_j^k + E_{i,j}^k \]  
\( \text{Upper limit} \)  
\( \text{(24)} \)
\[ - L_j^k \leq \sum_i P_{i,j}^k - D_j^k \leq E_{i,j}^k \]  
\( \text{Lower limit} \)  
\( \text{(25)} \)
\[ \lambda_{sys} \]  
\( \text{(26)} \)

\[ \lambda_{max,i} \geq \lambda_{sys} \]  
\( \text{(27)} \)
directions should be reserved.

![Diagram](https://example.com/diagram)

**Fig. 1. Multi-area connection and tie-line limitations**

**4. Tabu Search**

4.1. Overview

In solving the MAUCP, two types of variables 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 combinational problem in U and V and a nonlinear optimization problem in P. TS is used to solve the combinational optimization, and the nonlinear optimization is solved via a quadratic programming routine [17]. The proposed algorithm contains three major steps:

First, generating randomly feasible trial solutions; Second, calculating the objective function of the given solution by solving the Economic Load Dispatch (ELD); Third, applying the TS procedures to accept or reject the solution in hand.

4.2. TS General Algorithm

The flowchart for TS general algorithm is shown in Fig. 2.

- **Step 1:** Assume that the fuel costs to be fixed for each hour and all of the generators share the loads equally.
- **Step 2:** By optimum allocation, find the initial feasible solution \((U_i, V_i)\).
- **Step 3:** Demand is taken as the control parameter.
- **Step 4:** Generate the trial solution.
- **Step 5:** Calculate the total operating cost \(F_t\) as the summation of running cost, start up and shut down cost. Step 6: Tabulate the fuel cost for each unit for every hour.

4.3. Generating Trial Solution

The neighbours should be randomly generated, feasible, and span as much as possible the problem solution space. Because of the constraints in MAUCP, 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 is done by the rules described in [17].

4.4. Generating an Initial Solution

The TS algorithm requires a starting feasible schedule, which satisfies all of the system and units constraints. This schedule is randomly generated. The algorithm given in [17] is used to find this starting solution.

4.5. Operating Cost Calculation

Once a trial solution is obtained, the corresponding total operating cost is determined. Since the production cost is quadratic function, the Economic Load Dispatch (ELD) is solved using a quadratic programming routine. The start up cost is then calculated for the given schedule.

4.6. 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
- The tie line constraints are satisfied

4.7. Tabu List (TL)

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 [17]. 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.

![Flowchart](https://example.com/flowchart)

**Fig. 2. Flowchart for TS general algorithm**
4.8. Aspiration Criteria
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”[17].

5. Evolutionary Programming
5.1. Introduction
EP is a mutation-based evolutionary algorithm applied to discrete search spaces. D. Fogel (Fogel, 1988) [6][7] extended the initial work of his father L. Fogel (Fogel, 1962) [6][7] for applications involving real-parameter optimization problems. Real-parameter EP is similar in principle to evolution strategy (ES), in that normally distributed mutations are performed in both algorithms. Both algorithms encode mutation strength (or variance of the normal distribution) for each decision variable and a self-adapting rule is used to update the mutation strengths. Several variants of EP have been suggested (Fogel, 1992).

5.2. Evolutionary Strategies
For the case of evolutionary strategies, Fogel remarks “evolution the chromosome, the individual, the species, and the ecosystem” [6][7] can be categorized by several levels of hierarchy: the gene, the chromosome, the individual, the species, and the ecosystem” [6][7]. Thus, while genetic algorithms stress models of genetic operators, ES emphasize mutational transformation that maintains behavioural linkage between each parent and its offspring at the level of the individual. ES are a joint development of Bienert Rechenberg and schwetel. The first applications were experimental and addressed some optimization problems in hydrodynamics.

5.3. EP General Algorithm
Evolutionary programming is conducted as a sequence of operations and is given below. The flowchart for EP general algorithm [7] is shown in Fig. 3.

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

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

3. Each $s_i$, $i = 1,\ldots,m$, is altered and assigned to $s_{i+m}$ such that $s_{i+m} = s_i + N(0,\beta)\mathcal{N}(s_i) + z_j$, $j = 1,\ldots,k$. $N(0,\beta)\mathcal{N}(s_i) + z_j$ represents a Gaussian random variable with mean $\mu$ and variance $\sigma^2$. $\beta$ is a constant of proportionality to scale $\mathcal{N}(s_i)$, and $z_j$ amount of variance.

4. Each $s_{i+m}$, $i = 1,\ldots,m$, is assigned a fitness score $(s_{i+m}) = G(F(s_{i+m}),v_{i+m})\mathcal{N}(s_i)$ if there are more than $m$ solutions attaining a value $\mathcal{N}(s_i)$, and $z_j$ amount of variance.

5. For each $s_i, i = 1,\ldots,2m$, a value $w_i$ is assigned according to $w_i \sim \mathcal{U}(0,1)$. $\mathcal{U}([0,1])$ denotes the uniform distribution.

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

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

6. EVOLUTIONARY PROGRAMMING-BASED TABU SEARCH FOR MAUCP
6.1. Tabu Search
1. Take the parent as the initial feasible solution.
2. Take demand as control parameter and generate the trial solution.
3. Check for the stopping criterion.
4. If false, decrement system peak demand, and go to step 2.
5. If true, generate the optimal solution, and calculate the total operating cost.

6.2. EP-Based TS

In the EPTS technique for solving MAUCP, initial operating schedule status in terms of maximum real power generation of each unit is given as input. As we that TS is used to improve any given status by avoiding entrapment in local minima, the offspring obtained from the EP algorithm is given as input to TS, and the refined status is obtained. In addition, evolutionary strategy selects the final status.

1. Get the unit data, tie-line data, load demand profile for n areas and number of iterations to be carried out.
2. Generate population of parents (N) by adjusting the existing solution to the given demand to the form of state variables.
3. Unit down time makes a random recommitment.
4. Check for constraint in the new schedule by TS. If the constraints are not met, then repair the schedule as 6.3.
5. Perform ELD and calculate total production cost for each parent.
6. Add the Gaussian random variable to each state variable and, hence, creation of offspring. This will further undergo some repair operations as given in section 6.4. Following these, the new schedules are checked in order to verify that all constraints are met.
7. Improve the status of the evolved offspring, and verify the constraints by TS.
8. Formulate the rank for the entire population.
9. Select the best N number of population for next iteration.
10. Has the iteration count been reached? If yes, go to step 11, else go to step 2.
11. Select the best population by evolutionary strategy.
12. Check for n areas are completed. If yes go to step 13, else go to step 1.
13. Export power from lower operating cost areas to higher operating cost areas by following tie-line constraints.
14. Print the commitment schedule of n areas and tie-line flows.

6.3. Repair mechanism

A repair mechanism to restore the feasibility of the constraints is applied and described as follows [13]

- Pick at random one of the OFF units at one of the violated hours.
- Apply the rules in section IV.3 to switch the selected units from OFF to ON keeping the feasibility of the down time constraints.

Fig. 3 Flowchart for EP-TS algorithm for MAUCP
• Check for the reserve constraints at this hour. Otherwise repeat the process at the same hour for another unit.

6.4. Making Offspring Feasible
While solving the constrained optimization problem, there are various techniques to repair an infeasible solution [8] [11]. In this paper, we have chosen the technique, which evolves 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 “curling force” to estimate the feasible schedules. Before the best solution is selected by evolutionary strategy, the trial is made to correct the unwanted mutations.

6.5. Implementation
Software program were developed using MATLAB software package, and the test problem was simulated for ten independent trials using EPTS. The training and identification part as implemented in the EPTS technique is employed here and considered as a process involving random recommitment, constraint verification, and offspring creation.

7. Numerical Results
There are two test systems considered for case studies. The first test system consists of four areas, and each area has 26 thermal generating units [1] and second test system consists of four areas, and each area has 7 unit NTPC system. Units have quadratic cost functions, and exponential start up cost functions. Generating unit characteristics like the minimum up/down times, initial conditions and generation limits of units in every area, The cost functions of units given in the four area [1] are taken for analysis. Load demand profile for each area is different and is given in Fig. 4. The tie line flow pattern at 11 am and 4 pm are shown in Fig. 5 and Fig. 6 respectively. The total operating cost in pu comparison between DP, EP, TS and EPTS method is shown in Table 3. Comparison of total operating cost in each area by DP, EP, TS and EPTS method is shown in Fig. 3. The comparison of total operating cost in each area of 7 unit and 26 unit systems are shown in Fig. 7 and Fig. 8 respectively. The proposed algorithm quickly reaches smallest total operating cost compared to DP, EP, TS and EPTS method, which indicates that the proposed algorithm could determine the appropriate schedule within a reasonable computation time. It is noted that cost in one iteration may be lower than that of the previous iteration, indicating that our optimization rules always comply with the equal incremental cost criterion for dispatching power generation among thermal units.

![Fig. 4. Load demand profile of area1, area 2, area 3 and area 4](image)

![Table 1. Hourly operating cost of each area of EP-TS method for 7 unit (NTPS)](table)
Table 2. Hourly operating cost of each area of EP-TS method for 26 unit system

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<th>Area 2 (26 unit)</th>
<th>Area 3 (26 unit)</th>
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</table>

Fig. 5. Tie line flow pattern at 11 am of EP-TS method for 26 unit system

Fig. 6. Tie line flow pattern at 4 pm of EP-TS method for 26 unit system

Table 3. Comparison of cost for 7 Unit (NTPS) and 26 Unit system

<table>
<thead>
<tr>
<th>System</th>
<th>Method</th>
<th>Total Operating Cost (pu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7 unit</td>
<td>DP[7]</td>
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<td>EP[7]</td>
<td>0.96623</td>
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<tr>
<td></td>
<td>PSO[7]</td>
<td>0.95478</td>
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<tr>
<td></td>
<td>SA[7]</td>
<td>0.95129</td>
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<td></td>
<td>EPS[7]</td>
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<tr>
<td></td>
<td>EPSA[7]</td>
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<tr>
<td></td>
<td>EPTS</td>
<td>0.91247</td>
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<tr>
<td>26 unit</td>
<td>DP[7]</td>
<td>1.00000</td>
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<tr>
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<tr>
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<td>PSO[7]</td>
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<tr>
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<td>SA[7]</td>
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<td>EPSA[7]</td>
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</tbody>
</table>
8. Conclusions
This paper presents EPTS method for solving multi area unit commitment problem with import and export constraints. In comparison with the results produced by the technique DP, EP, PSO, SA, EPSS and EPS method obviously proposed method displays satisfactory performance. Test results have demonstrated that the proposed method of solving multi area unit commitment problem with import and export constraints reduces the total operating cost of the plant. An effective tie line constraint checking procedure is implemented in this paper. This method provides more accurate solution for multi area unit commitment problem with import and export constraints.

References


