Application of Exponential Evolutionary Programming to Security Constrained Economic Dispatch with FACTS Devices

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Abstract: This study presents an algorithm for solving Security Constrained Economic Dispatch (SCED) problem with Flexible AC Transmission Systems (FACTS) through the application of Evolutionary Programming (EP). The problem is decomposed into the optimal setting of FACTS parameters subproblem and the OPF with fixed FACTS parameters subproblem. These two subproblems are solved by Exponential Evolutionary Programming (EEP). Two types of FACTS devices are used: Thyristor-Controlled Series Capacitor (TCSC) and Thyristor-Controlled Phase Shifting (TCPS). The proposed approaches have been implemented on an adapted IEEE 30 bus system. The simulation results indicate are compared and discussed to show the performance of the EP technique.

Key words: Security constrained economic dispatch, optimal power flow, flexible AC transmission systems, exponential evolutionary programming

INTRODUCTION

The Flexible AC Transmission Systems (FACTS) devices are integrated in power systems to control power flow, increase transmission line capability to its thermal limit and improve the security of transmission systems (Hingorani and Gyugyi, 1999). In addition to controlling the power flow in specific lines, FACTS devices could be used to minimize the total generator fuel cost in Optimal Power Flow (OPF) problem. For example, the linear programming based security constrained OPF method (Ge and Chung, 1999) has been proposed to solve OPF with FACTS devices. Load equivalent method (Chung et al., 2000) has been proposed to solve OPF with FACTS devices. Meanwhile, several heuristic methods including local search and Genetic Algorithms (GA) were proposed to determine the optimal parameters of FACTS devices when the power flow control in specific lines is not required (Chung and Li, 2000). Orsakul and Bhaskar (2001) have used TS/SA approach to optimal power flow with FACTS devices. Gerbex (2001) have used GA to set the optimal value of multi type FACTS devices in a power system. Nevertheless, the obtained results were far from the optimal solutions. Lai and Ma (1997) have used evolutionary program to solve the power flow problem in FACTS. Yang et al. (1996) have used the EP based algorithm for solving Economic Dispatch (ED) problem with non smooth fuel cost functions. Wong and Yuryevich (1998) have developed a hybrid EP and sequential quadratic programming, to solve the ED problem with non smooth fuel cost function. However, the works mentioned above, each parent generates an offspring with Gaussian mutation and better individuals among parents and offspring are selected as a population of the next generation. Gaussian probability distribution has finite variance therefore it has shortest flat tails comparing with other distribution. Due to the characteristics of probability distribution, global optimum solutions is not guaranteed.

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In this study, Thyristor-Controlled Series Capacitor (TCSC) and Thyristor-Controlled Phase Shifting (TCPs) are integrated in OPF by using the reactance model and the injected power model, respectively. For OPF control, TCSC and TCPs are used to minimize the total generator fuel cost subject to power balance constraint, real and reactive power generation limits, voltage limits, transmission line limits and FACTS parameters limits. The proposed method solves the optimal settings of FACTS parameters in the first subproblem and conventional OPF subproblem. It is tested and compared to the GA and Hybrid TS/SA on the modified IEEE 30 bus system with TCSC and TCPs at the fixed locations.

MATERIALS AND METHODS

OPF With Facts Devices

A Static model of TCSC and TCPs are used in this study. TCSC can be seen as a series reactance with control parameter Xc. Figure 1 shows the model of TCSC. It is integrated in the OPF problem by modifying the line data. A new line reactance (X_{new}) is given as follows:

\[ X_{\text{new}} = X_i - X_o \]  

(1)

The power flow equations of the line with a new line reactance can be derived as follows:

\[ P_t = V_i^2 G_o - V_i V_j G_{ij} \cos(\delta_{ij}) - V_i V_j B_{ij} \sin(\delta_{ij}) \]  

(2)

\[ Q_t = -V_i^2 B_o - V_i V_j G_{ij} \sin(\delta_{ij}) + V_i V_j B_{ij} \cos(\delta_{ij}) \]  

(3)

\[ P_j = V_j^2 G_o - V_i V_j G_{ij} \cos(\delta_{ij}) + V_i V_j B_{ij} \sin(\delta_{ij}) \]  

(4)

\[ Q_j = -V_j^2 B_o + V_i V_j G_{ij} \sin(\delta_{ij}) + V_i V_j B_{ij} \cos(\delta_{ij}) \]  

(5)

Where:

\[ G_{ij} = R_{ij} / (R_{ij}^2 + X_{ji}^2) \quad B_{ij} = X_{ji} / (R_{ij}^2 + X_{ji}^2) \]  

(6)

\[ \delta_{ij} \text{ is the voltage angle difference between bus } i \text{ and } j. \]

TCPs can be modeled by a phase shifting transformer with control parameter \( \sigma_p \). Figure 2 shows the model of TCPs. The power flow equations of the line can be derived as follows:

\[ P_t = V_i^2 G_o / K^2 - (V_i / K) (G_{ij} \cos(\delta) + B_{ij} \sin(\delta)) \]  

(7)

![Fig. 1: Model of TCSC](image)

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Fig. 2: Model of TCPSC

Fig. 3: Injected power model of TCPS

\[ Q_{in} = -V_i^2B_i/K^2 - \left( V_iV_j/k \right) \left( G_i \sin(\delta) - B_i \cos(\delta) \right) \]  \hspace{1cm} (8)

\[ P_{in} = V_i^2G_i - \left( V_iV_j/k \right) \left( G_j \cos(\delta) - B_j \sin(\delta) \right) \]  \hspace{1cm} (9)

\[ Q_{in} = -V_i^2B_i + \left( V_iV_j/k \right) \left( G_i \sin(\delta) + B_i \cos(\delta) \right) \]  \hspace{1cm} (10)

Where:
- \( k = \cos(\alpha_p) \)
- \( \delta = \delta_i + \alpha_p \)

The injected power is used to model TCPS as shown in Fig. 3. The injected real and reactive power flow TCPS at bus and bus are as follows:

\[ P_{in} = -V_i^2G_i - V_iV_jG_j \sin(\delta_j) + V_iV_jB_j \cos(\delta_j) \]  \hspace{1cm} (11)

\[ Q_{in} = V_i^2B_i + V_iV_jG_j \cos(\delta_j) + V_iV_jB_j \sin(\delta_j) \]  \hspace{1cm} (12)

\[ P_{in} = -V_iV_jG_j \sin(\delta_j) - V_iV_jB_j \cos(\delta_j) \]  \hspace{1cm} (13)

\[ Q_{in} = -V_iV_jG_j \cos(\delta_j) - V_iV_jB_j \sin(\delta_j) \]  \hspace{1cm} (14)

Where:
- \( t = \tan(\alpha_p) \)

**Problem formulation**

The SCED problem with FACTS devices can be formulated as:

\[ \min \sum_{i=1}^{N} F_i(P_i) = \min \sum_{i=1}^{N} a_iP_i^2 + b_iP_i + c_i \]  \hspace{1cm} (15)

where, \( a_i, b_i, \) and \( c_i \) are cost coefficients of generator \( i \) and \( P_i \) is the power generated by the \( i \)th unit, \( F_i(P_i) \) is the generation cost function for \( P_i \) generation at bus \( i \), \( N \) is number of bus, subject to
• The power balance constraints

\[ P_i = \sum_{m} P_m + \sum_{m} P_i(\alpha_i) - \sum_{j} \sum_{k} V_j Y_{jk} (X_k) \cos(\theta_j(X_k) - \delta_k) \]  

(16)

where, \( P_d \) is the system load demand, \( P_i(\alpha_i) \) is the total injected power demand at bus \( i \) (MW), \( V_j \) is the voltage magnitude at bus \( j \), \( Y_{jk} \) is the magnitude of the \( ij \)th element in \( Y_{mto} \) with TCSC included, \( \theta_j(X_k) \) is the angle of the \( ij \)th element in \( Y_{mto} \) with TCSC included, \( \alpha_i \) is the phase shift angle of TCPS number \( i \), \( NP \) is the set of TCPS indices.

• The inequality constraint on real power generation at bus \( i \)

\[ P^{\min}_{i} \leq P_i \leq P^{\max}_{i} \]  

(17)

where, \( P^{\min}_{i} \) and \( P^{\max}_{i} \) are, respectively minimum and maximum values of real power generation allowed at generator bus \( i \).

• The power flow equation of the power network is given by

\[ g(V, \phi) = \begin{cases} P(V, \phi) - P^{\max}_{i} \\ Q(V, \phi) - Q^{\max}_{i} \\ P_{\phi}(V, \phi) - P^{\max}_{\phi} \end{cases} \]  

(18)

Where:
\( P \) and \( Q \) = Calculated real and reactive power for PQ bus \( i \)
\( P^{\max}_{i} \) and \( Q^{\max}_{i} \) = Specified real and reactive power for PQ bus \( i \)
\( P_{\phi} \) and \( P^{\max}_{\phi} \) = Calculated and specified real power for PV bus \( m \)
\( V \) and \( \phi \) = Voltage magnitude and phase angles at different buses

• The inequality constraint on reactive power generation \( Q \) at each PV bus

\[ Q^{\min}_{i} \leq Q_i \leq Q^{\max}_{i} \]  

(19)

where, \( Q^{\min}_{i} \) and \( Q^{\max}_{i} \) are, respectively minimum and maximum value of reactive power at PV bus.

• The inequality constraint on voltage magnitude \( V \) of each PQ bus

\[ V^{\min}_{i} \leq V_i \leq V^{\max}_{i} \]  

(20)

where, \( V^{\min}_{i} \) and \( V^{\max}_{i} \) are, respectively minimum and maximum voltage at bus \( i \).

• The inequality constraint on phase angle of voltage at all the buses \( i \)

\[ \phi^{\min}_{i} \leq \phi_i \leq \phi^{\max}_{i} \]  

(21)
where, \( \phi_i^{\text{min}} \) and \( \phi_i^{\text{max}} \) are, respectively minimum and maximum voltage angles allowed at bus \( i \)

- MVA flow limit on transmission line

\[
\text{MVA}_i \leq \text{MVA}_i^{\text{max}}
\]

(22)

where, \( \text{MVA}_i^{\text{max}} \) is the maximum rating of transmission line connecting bus \( i \) and \( k \).

- TCSC reactance limit

\[
0 \leq X_a \leq X_a^{\text{max}}
\]

(23)

where, \( X_a \) is the reactance of TCSC number \( i \) and \( X_a^{\text{max}} \) is maximum reactance of TCSC.

- TCPS phase shift angle limit

\[
0 \leq \alpha_i \leq \alpha_i^{\text{max}}
\]

(24)

where, \( \alpha_i \) is the phase shift angle of TCPS number \( i \) and \( \alpha_i^{\text{max}} \) maximum phase shift angle.

**New OPF Formulation**

The FACTS devices parameters in Eq. 15 are additional control variables that cannot be solved by the conventional OPF because these parameters will change the admittance matrix. Therefore, the OPF with FACTS devices problem is decomposed into two subproblems. The first subproblem is optimal setting of FACTS parameters and the second subproblem is OPF with fixed FACTS parameters.

**Optimal Setting of FACTS Parameters Subproblem**

The proposed EEP method is used to determine the optimal setting of FACTS parameters, minimizing the generator fuel cost within power flow security limits. FACTS devices control variable in Eq. 16 will be fixed in the conventional OPF subproblem, which is solved by EEP. The results from EEP OPF are used to evaluate the quality of FACTS parameters.

**Opf with Fixed FACTS Parameters Subproblem**

The OPF with fixed FACTS parameters subproblem is expressed as:

\[
\min \sum_{i=1}^{N} F(P_i) = \min \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i
\]

(25)

Subject to:

\[
P_i = \sum_{i=1}^{N} P_i + \sum_{i=1}^{N} \sum_{i=1}^{N} V_i V_j (X_i) \cos(\delta_i - \delta_j)
\]

(26)

\[
P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}}
\]

(27)
\[ Q^{**} \leq Q \leq Q^{**} \]  
(28)

\[ V_{i}^{**} \leq V_{i} \leq V_{i}^{**} \]  
(29)

\[ \text{MVA}^{**} \leq \text{MVA}^{**} \]  
(30)

where, \( \sigma \) is the fixed \( \sigma \) obtained from the first subproblem and \( X'_{i} \) is fixed \( X \) obtained from the first subproblem.

**EXPONENTIAL EVOLUTIONARY PROGRAMMING**

**Overview**

The conventional EP employing the Gaussian mutation operator is called as Classical Evolutionary Programming (CEP). The EP using Cauchy mutation operator is called as Fast Evolutionary Programming (FEP) as it converges faster than CEP.

Cauchy mutation is more likely to generate an offspring further away from its parent than Gaussian mutation due to its long flat tails. It is expected to have a higher probability of escaping from a local optimum, especially when the basin of attraction of the local optimum or the plateau is large relative to the mean step size.

The EP that uses the double exponential mutation operators is called as Exponential EP (EEP) as it has higher convergence rate compared to CEP and FEP (Narihisa and Kohmoto, 2006). Considering the shape of the three fundamental one-dimensional distributions shown in Fig. 4, Cauchy distribution has the longest flat tails and Gaussian distribution has the shortest flat tails. In other words, the shape of double exponential distribution has the middle long flat tails among three distributions. This fact can be expected that double exponential distribution may have the both merits of Gaussian and Cauchy distribution. Due to the characteristics of probability distributions, global optimum solutions with less time is guaranteed.

**Double Exponential Probability Distribution**

The one-dimensional probability density function of double exponential probability distribution for parameter \( \lambda \) is given as:

![Double Exponential Probability Distribution](image)

*Fig. 4: Distribution of N(0,1), C(0,1) and E(0,1)*
\[ f(x) = \left( \frac{\lambda}{2} \right) \exp[-\lambda|x|], \quad -\infty < x < \infty, \quad \lambda > 0 \]  

(31)

The mean value of the probability density function \( x \) is 0 and the variance \( \text{var}(x) \) is \( 2/\lambda \). The distribution is shown in Fig. 4. Clearly, this distribution is symmetric and the variance can be controlled by the parameter \( \lambda \). This plays an important role at the evolving process in EP computations. The parameter \( \lambda \) should be small at early stage of evolution for the sake of global search and should be large at final stage of evolution for the sake of local search. This appropriate value of \( \lambda \) is essentially problem-dependent. Random number generation based on double exponential probability distribution using uniform random number \( y \) (0 ≤ \( y \) ≤ 1) as:

\[
x = \begin{cases} 
\frac{1}{\lambda} \ln(2y) & \text{if } y \leq 1/2 \\
-\frac{1}{\lambda} \ln(2(1 - y)) & \text{if } y > 1/2 
\end{cases}
\]  

(32)

The double exponential probability distribution based random number is \( \mathcal{E}(0, \lambda) \), which has the mean value of \( \bar{x} = 0 \) and the parameter \( \lambda \).

Therefore,

\[ \mathcal{E}(0, \lambda) = (1/\lambda)\mathcal{E}(0, 1). \]

**IMPLEMENTATION OF EXPONENTIAL EVOLUTIONARY PROGRAMMING TO SCED**

Evolutionary programming is a probabilistic, global search technique that starts with a population of randomly generated candidate solutions and evolves towards better solutions over a number of generations or iterations. The main stages of this technique include initialization, mutation and competition and selection. The major steps involved in the evolutionary programming approach are explained as:

**Initialization**

The initial population comprises combinations of only the candidate dispatch solutions which satisfy all the constraints. It consists of \( [X_n, \alpha_j] \), \( j = 1, 2, \ldots, I \). Where, \( I \) is number of trial parent individuals. The elements of a parent are reactance of TCSC and phase shift angle of TCPS randomly chosen by a random number ranging over \( [0, X_{\alpha}^{\text{max}}] \) and \( [0, \alpha^{\text{max}}] \).

**Creation of Offspring (Mutation)**

Using double exponential mutation, an offspring is created by:

\[ X_{n'} = X_n + \sigma_{i} \mathcal{E}(0, \lambda) \text{ for } i = 1, 2, 3 \ldots NS \]  

(33)

\[ \alpha_{i} = \alpha_{i} + \sigma_{\alpha} \mathcal{E}(0, \lambda) \text{ for } i = 1, 2, 3 \ldots NP \]  

(34)

where, \( \mathcal{E}(0, \lambda) \) is a double exponential random number with parameter \( \lambda \) and is generated anew for each value of \( i \). \( NS \) is the set of TCSC indices.

The standard deviation is given by the expression

\[ \sigma_{\alpha} = \left( \beta_{\alpha} / \alpha_{\text{max}} \right) X_{\alpha}^{\text{max}} - X_{\alpha}^{\text{max}} \]  

(35)
\[
\sigma_m = (\beta_f / f_{max})(\sigma_{lim} - \sigma_{lim}) \tag{36}
\]

where, \(\beta\) is the scaling factor which has to be tuned during the process of search for the optimum around the initial points, \(f\) the fitness value of the jth individual and \(f_{max}\) is the maximum fitness among the 1 parents. Mutation results in creation of 1 offspring individuals. The parent individuals are candidate dispatch solutions which satisfy all constraints. However, after mutation, the elements of offspring \(P_i\) may violate constraint Eq. 16. This violation is corrected as follows:

\[
\begin{align*}
\sigma'_i &= \begin{cases} 
0, & \text{if } \sigma'_i < 0 \\
\sigma_{lim}, & \text{if } \sigma'_i > \sigma_{lim}
\end{cases} \\
X'_i &= \begin{cases} 
0, & \text{if } X'_i < 0 \\
X_{lim}, & \text{if } X'_i > X_{lim}
\end{cases}
\end{align*} \tag{37}
\]

However, after mutation, the elements of offspring \(P_i\) may violate constraint Eq. 16. This violation is corrected as follows:

In the case of SCED problems, the objective function given by Eq. 1 is augmented by a term for the violation of line limits as:

\[
\min \sum_{i=1}^{N} F(P_i) + k_i (MVA_{\text{lim}} - MVA_{\text{actual}}) \tag{38}
\]

where, \(k_i\) is a penalty coefficient.

The second term in Eq. 38 are equal to zero during initialization and they get non-zero value after mutation only if \(MVA_i\) violate their minimum and maximum limits. The initial population and their offspring created by mutation form a combined population of 2I individuals.

**Competition and Selection**

The 2I individuals compete with each other for selection. Fitness function value is calculated for all the 2I individuals. The fitness function values are arranged in ascending order. First I fitness functions and the corresponding I individuals are selected as parents for next generation.

Steps 2 and 3 are repeated until there is no appreciable improvement. The same procedure is repeated for the second subproblem.

**Parameter Selection**

The final printed size of an au The total number of function evaluations is fixed at 50 and population size is kept 50. The scaling factor \(\beta\) is taken as 0.02 for 30 bus system and 0.04 for 10 bus system. The distribution control parameter \(\lambda\) is discretely increased from 0.01 to 2.5 for 10 bus system and 0.1 to 2.5 for 30 bus system, respectively. Selection of \(\beta\) and \(\lambda\) are problem dependent.

**RESULTS AND DISCUSSION**

The algorithm discussed earlier has been tested on an adapted IEEE 30-bus systems (Somasundaram and Kuppusamy, 2005) to assess the performance of the proposed algorithm. The algorithms for solving the examples were implemented on Matlab 6.5 platform. Their solutions are compared in the tables and graphs are plotted to show their relative convergence characteristics. The parameters of EEF approach are set as scaling factor \(\beta\) is self adaptive population size is 50 and maximum number of iterations is 50. The results are also compared with solutions of earlier methods such as genetic algorithm, TS/SA algorithm that were previously reported (Ongsakul and Bhasaputra, 2001).
For the example considered in this study, line security constraint violations can be taken into account by including additional terms with a penalty coefficient in Eq. 31.

**Example IEEE 30-Bus System**

The algorithm discussed earlier has been tested on adapted IEEE 30-bus (Somasundaram and K uppusamy, 2005) systems to assess the performance of the proposed algorithm. The objective function is the total fuel cost and the fuel cost curve of the units are represented by quadratic cost functions. The adapted IEEE 30-bus system consists of 6 generators, 41 lines and a total demand of 283.4 MW. The fuel cost coefficient and the generator data, load data, line data, transformer data and shunt capacitor data for the system can be found in (Somasundaram and Kuppusamy, 2005). Near optimal placements of TCSC and TCPS on the IEEE 30 bus system are guided by the loss sensitivity index (Paredavichat and Srivastava, 1997). In the experiments, the reactance limit of TCSC in pu is \(0 < x_{sc} < 0.02\) and phase shifting angle of TCPS in radian is \(0 < \phi < 0.1\).

There are four case studies. Case 1 is OPF with TCSC at line 3-4; Case 2 is OPF with TCSC and TCPS at line 3-4; Case 3 is OPF with two TCSC at line 3-4 and line 19-20 and TCPS at line 3-4; Case 4 is OPF with two TCSC at line 3-4 and line 19-20 and two TCPS at line 3-4 and line 5-7.

Table 1 and 2 shows the solutions and the times for convergence obtained by EEP technique. It is shown from the Table 1 and 2 that, in all the cases the proposed method gives better solutions compared with the solutions obtained by TS/SA Ongsakul and Bhasaputra (2002). Their convergence characteristics are shown in Fig. 5.

| Table 1: Simulation results of case 1-2 best solutions (demand 283.4 MW) |
|-----------------------------------------------|---------------|---------------|---------------|
| Generation unit | Case 1 | Case 2 | Case 2 |
| P1 (MW) | 192.6018 | 174.8485 | 192.5105 | 176.4877 |
| P2 (MW) | 48.4147 | 49.4959 | 48.3951 | 48.3994 |
| P4 (MW) | 11.6615 | 22.7665 | 11.6204 | 22.0219 |
| P5 (MW) | 10.6000 | 11.8692 | 10.0000 | 12.3791 |
| P6 (MW) | 12.0000 | 12.0128 | 12.0000 | 12.0017 |
| Injected power by | - | - | - |
| TVPS (MW) (line 3-4) | 1.4557 |
| Total (MW) | 294.2341 | 292.7863 | 294.0766 | 292.8755 |
| F1 (MW) | 10.8341 | 93.3630 | 10.6766 | 10.8312 |
| Total cost ($/h) | 804.6497 | 802.3989 | 804.1072 | 802.3702 |
| TCSC (pu) Line 3-4 | 0.0200 | 0.0200 |
| TCPS (rad) Line 3-4 | 0.0137 |

| Table 2: Simulation results of case 3-4 best solutions (demand 283.4 MW) |
|-----------------------------------------------|---------------|---------------|
| Generation unit | Case 3 | Case 4 | Case 4 |
| P1 (MW) | 192.5099 | 176.6412 | 192.4664 | 176.4136 |
| P2 (MW) | 48.3950 | 48.3999 | 48.3857 | 48.5633 |
| P3 (MW) | 19.5506 | 21.4811 | 19.5506 | 21.4066 |
| P4 (MW) | 11.622 | 22.2361 | 11.6020 | 22.1114 |
| P5 (MW) | 10.6000 | 12.1323 | 10.0000 | 12.3846 |
| P6 (MW) | 12.0000 | 12.0055 | 12.0000 | 12.0000 |
| Injected power by | - | 1.3495 | - | 1.4972 |
| TVPS (MW) (line 3-4) | - |
| Total (MW) | 294.1757 | 292.8891 | 294.0007 | 292.8795 |
| F1 (MW) | 10.6757 | 10.8386 | 10.6007 | 10.9767 |
| Total cost ($/h) | 804.1041 | 802.3670 | 803.8459 | 802.3663 |
| TCSC (pu) Line 3-4 | 0.0200 | 0.0200 | 0.0200 | 0.0200 |
| TCPS (rad) Line 3-4 | 0.0139 | 0.1365 | 0.0144 | 0.0663 |
| TCSC (pu) Line 3-4 | 0.0200 | 0.0200 | 0.0200 | 0.0200 |
| TCPS (rad) Line 3-4 | 0.0334 | 0.0665 |
Fig. 5: Convergence characteristics of EEP for SCED for 30 bus system

Table 3: Comparison of various methods from 20 runs for case 3

<table>
<thead>
<tr>
<th></th>
<th>TS/SA</th>
<th>EEP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worst</td>
<td>804.1074</td>
<td>802.3715</td>
</tr>
<tr>
<td>Average</td>
<td>804.1073</td>
<td>802.3706</td>
</tr>
<tr>
<td>Best</td>
<td>804.1072</td>
<td>802.3702</td>
</tr>
</tbody>
</table>

Table 3 shows the comparison of TS/SA and EEP methods from 20 run for case 2. It is seen from as more TCSC and TCPS are installed, the total generator fuel is further reduced from 804.7837 to 802.3661. But required CPU times of cases 2-5 increase since more computation are needed.

CONCLUSIONS

In this study, the EEP approach is effectively and successfully implemented to minimize the generator fuel cost in OPF control with TCSC and TCPS devices. The proposed EEP approach achieves better solutions than TS/SA on the modified IEEE 30 bus system with TCSC and TCPS fixed at given locations. Accordingly, the proposed EEP is potentially viable to OPF control due to generator fuel cost savings. Almost evolutionary programming that have been proposed till now commonly use Gaussian random number or Cauchy random number as the mutation of strategy parameter. The role of strategy parameter of evolutionary programming influences the search step size in solution search algorithm. Therefore, it must be small value within neighborhood of optimal solution. However, self-adaptive EP should obtain information concerning the convergence contribution of objective function for the sake of good solution. At this point of view, though almost EP algorithms use Gaussian random number in self-adaptation, it is expected that self-adaptation which uses double exponential random number can absorb the wide information concerning convergence contribution comparing with that of Gaussian random number. From the above mentioned reason, the performance of EEP is significantly better than TS/SA in terms of convergence rate and slightly better solutions. The experimental results show that EEP outperforms GA and TS/SA on applying to the function optimization problems. In the future, this EEP on applied to various types of optimization problems.

REFERENCES