



# Asian Journal of Scientific Research

ISSN 1992-1454

**science**  
alert  
<http://www.scialert.net>

**ANSI***net*  
an open access publisher  
<http://ansinet.com>

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

<sup>1</sup>J. Jayakumar and <sup>2</sup>K. Thanushkodi

<sup>1</sup>Faculty of Electrical Engineering, Karunya University, Coimbatore-14, India

<sup>2</sup>Faculty of Electrical Engineering, Anna University, Coimbatore, India

---

**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 indicates 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). Ongsakul and Bhasaputra (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.

---

**Corresponding Author:** J. Jayakumar, Faculty of Electrical Engineering, Karunya University, Coimbatore-641114, Tamil Nadu, India Tel: 91+0422-2614392 Fax: 91+0422-2614614

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  $X_s$ . 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:

$$X_{new} = X_{ij} - X_s \tag{1}$$

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

$$P_{ij} = V_i^2 G_{ij} - V_i V_j G_{ij} \cos(\delta_{ij}) - V_i V_j B_{ij} \sin(\delta_{ij}) \tag{2}$$

$$Q_{ij} = -V_i^2 B_{ij} - V_i V_j G_{ij} \sin(\delta_{ij}) + V_i V_j B_{ij} \cos(\delta_{ij}) \tag{3}$$

$$P_{ji} = V_j^2 G_{ij} - V_i V_j G_{ij} \cos(\delta_{ij}) + V_i V_j B_{ij} \sin(\delta_{ij}) \tag{4}$$

$$Q_{ji} = -V_j^2 B_{ij} + V_i V_j G_{ij} \sin(\delta_{ij}) + V_i V_j B_{ij} \cos(\delta_{ij}) \tag{5}$$

Where:

$$G_{ij} = R_{ij} / (R_{ij}^2 + X_{new}^2), B_{ij} = X_{new} / (R_{ij}^2 + X_{new}^2) \tag{6}$$

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

TCPS can be modeled by a phase shifting transformer with control parameter  $\alpha_p$ . Figure 2 shows the model of TCPS. The power flow equations of the line can be derived as follows.

$$P_{ij} = V_i^2 G_{ij} / K^2 - (V_i V_j / k) (G_{ij} \cos(\delta) + B_{ij} \sin(\delta)) \tag{7}$$

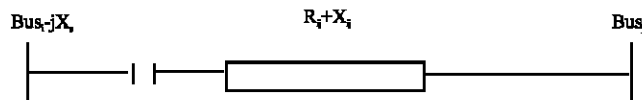


Fig. 1: Model of TCSC

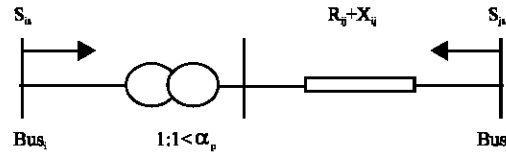


Fig. 2: Model of TCPS

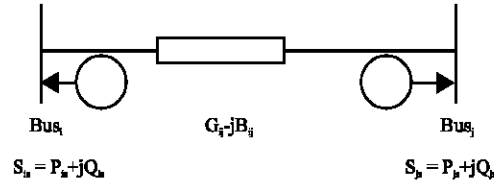


Fig. 3: Injected power model of TCPS

$$Q_{ij} = -V_i^2 B_{ij} / K^2 - (V_i V_j / k) (G_{ij} \sin(\delta) - B_{ij} \cos(\delta)) \quad (8)$$

$$P_{ji} = V_j^2 G_{ij} - (V_i V_j / k) (G_{ij} \cos(\delta) - B_{ij} \sin(\delta)) \quad (9)$$

$$Q_{ji} = -V_j^2 B_{ij} + (V_i V_j / k) (G_{ij} \sin(\delta) + B_{ij} \cos(\delta)) \quad (10)$$

Where:

$$k = \cos(\alpha_p)$$

$$\delta = \delta_{ij} + \alpha_p$$

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:

$$P_{is} = -V_i^2 t^2 G_{ij} - V_i V_j t G_{ij} \sin(\delta_{ij}) + V_i V_j B_{ij} \cos(\delta_{ij}) \quad (11)$$

$$Q_{is} = V_i^2 t^2 B_{ij} + V_i V_j t G_{ij} \cos(\delta_{ij}) + V_i V_j B_{ij} \sin(\delta_{ij}) \quad (12)$$

$$P_{js} = -V_i V_j t G_{ij} \sin(\delta_{ij}) - V_i V_j B_{ij} \cos(\delta_{ij}) \quad (13)$$

$$Q_{js} = -V_i V_j t G_{ij} \cos(\delta_{ij}) - V_i V_j B_{ij} \sin(\delta_{ij}) \quad (14)$$

Where:

$$t = \tan(\alpha_p)$$

**Problem formulation**

The SCED problem with FACTS devices can be formulated as:

$$\min \sum_{i=1}^N F_i(P_i) = \min \sum_{i=1}^N a_i P_i^2 + b_i P_i + c_i \quad (15)$$

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

$$P_D = \sum_{i=1}^N P_i + \sum_{i=1}^{NP} P_i(\alpha_i) - \sum_{i=1}^N \sum_{j=1}^N V_i V_j Y_{ij}(X_s) \cos(\theta_{ij}(X_s) - \delta_j) \quad (16)$$

where,  $P_D$  is the system load demand,  $P_i(\alpha_i)$  is the total injected power demand at bus  $i$  (MW),  $V_i$  is the voltage magnitude at bus  $i$ ,  $V_j$  is the voltage magnitude at bus  $j$ ,  $Y_{ij}(X_s)$  is the magnitude of the  $ij$ th element in  $Y_{bus}$  with TCSC included,  $\theta_{ij}(X_s)$  is the angle of the  $ij$ th element in  $Y_{bus}$  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  $i$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (17)$$

where,  $P_i^{\min}$  and  $P_i^{\max}$  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

$$g(V, \phi) = \begin{cases} P_i(V, \phi) - P_i^{\text{net}} \\ Q_i(V, \phi) - Q_i^{\text{net}} \\ P_m(V, \phi) - P_m^{\text{net}} \end{cases} \quad (18)$$

Where:

- $P_i$  and  $Q_i$  = Calculated real and reactive power for PQ bus  $i$
- $P_i^{\text{net}}$  and  $Q_i^{\text{net}}$  = Specified real and reactive power for PQ bus  $i$
- $P_m$  and  $P_m^{\text{net}}$  = 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  $Q_i$  at each PV bus

$$Q_i^{\min} \leq Q_i \leq Q_i^{\max} \quad (19)$$

where,  $Q_i^{\min}$  and  $Q_i^{\max}$  are, respectively minimum and maximum value of reactive power at PV bus.

- The inequality constraint on voltage magnitude  $V$  of each PQ bus

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (20)$$

where,  $V_i^{\min}$  and  $V_i^{\max}$  are, respectively minimum and maximum voltage at bus  $i$

- The inequality constraint on phase angle of voltage at all the buses  $i$

$$\phi_i^{\min} \leq \phi_i \leq \phi_i^{\max} \quad (21)$$

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

- MVA flow limit on transmission line

$$MVA_{ik} \leq MVA_{ik}^{\max} \quad (22)$$

where,  $MVA_{ik}^{\max}$  is the maximum rating of transmission line connecting bus i and k.

- TCSC reactance limit

$$0 \leq X_{si} \leq X_{si}^{\max} \quad (23)$$

where,  $X_{si}$  is the reactance of TCSC number i and  $X_{si}^{\max}$  is maximum reactance of TCSC.

- TCPS phase shift angle limit

$$0 \leq \alpha_i \leq \alpha_i^{\max} \quad (24)$$

where,  $\alpha_i$  is the phase shift angle of TCPS number i and  $\alpha_i^{\max}$  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 in 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:

$$\min \sum_{i=1}^N F_i(P_i) = \min \sum_{i=1}^N a_i P_i^2 + b_i P_i + c_i \quad (25)$$

Subject to:

$$P_D = \sum_{i=1}^N P_i + \sum_{i=1}^{NP} P_i(\alpha_i) - \sum_{i=1}^N \sum_{j=1}^N V_i V_j Y_{ij}(X_s') \cos(\theta_{ij}(X_s') - \delta_{ij}) \quad (26)$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (27)$$

$$Q_i^{\min} \leq Q_i \leq Q_i^{\max} \tag{28}$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{29}$$

$$MVA_{ik} \leq MVA_{ik}^{\max} \tag{30}$$

where,  $\alpha_i$  is the fixed  $\alpha_i$  obtained from the first subproblem and  $X_s$  is fixed  $X_s$  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:

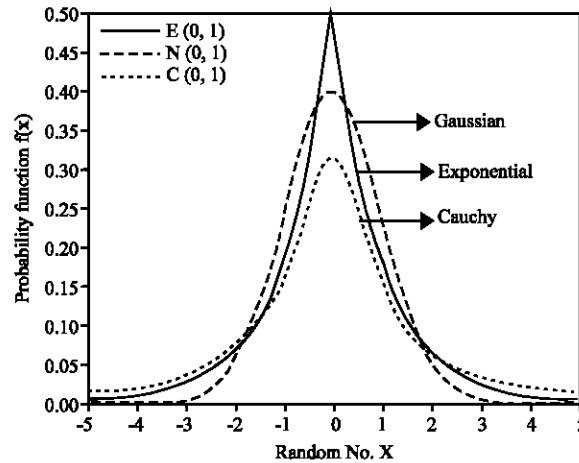


Fig. 4: Distribution of N(0,1), C(0,1) and E(0,1)

$$f(x) = (\lambda/2)\exp[-\lambda|x|], -\infty < x < \infty, \lambda > 0 \quad (31)$$

The mean value of the probability density function  $\bar{x}$  is 0 and the variance 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  $y$  ( $0 \leq y \leq 1$ ) as:

$$x = \begin{cases} (1/\lambda)\ln(2y) & y \leq 1/2 \\ -(1/\lambda)\ln(2(1-y)) & y > 1/2 \end{cases} \quad (32)$$

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

Therefore,

$$E(0, \lambda) = (1/\lambda)E(0, 1).$$

### 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  $[X_s, \alpha_j]$ ,  $j = 1, 2, \dots, I$ . 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  $[0, X_s^{max}]$  and  $[0, \alpha_i^{max}]$ .

#### Creation of Offspring (Mutation)

Using double exponential mutation, an offspring is created by:

$$X'_s = X_s + \sigma_s E_i(0, \lambda) \text{ for } i = 1, 2, 3 \dots NS \quad (33)$$

$$\alpha'_i = \alpha_i + \sigma_{\alpha} E_i(0, \lambda) \text{ for } i = 1, 2, 3 \dots NP \quad (34)$$

where,  $E_i(0, \lambda)$  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

$$\sigma_s = (\beta f_j / f_{max})(X_s^{max} - X_s^{min}) \quad (35)$$



$$\sigma_{\alpha_i} = (\beta f_j / f_{\max}) (\alpha_i^{\max} - \alpha_i^{\min}) \quad (36)$$

where,  $\beta$  is the scaling factor which has to be tuned during the process of search for the optimum around the initial points,  $f_j$  the fitness value of the  $j$ th individual and  $f_{\max}$  is the maximum fitness among the  $I$  parents. Mutation results in creation of  $I$  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:

$$\alpha_i' = \begin{cases} 0, & \text{if } \alpha_i' < 0 \\ \alpha_i^{\max}, & \text{if } \alpha_i' > \alpha_i^{\max} \end{cases} \quad (37)$$

$$X_{si}' = \begin{cases} 0, & \text{if } X_{si}' < 0 \\ X_{si}^{\max}, & \text{if } X_{si}' > X_{si}^{\max} \end{cases}$$

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:

$$\min \sum_{i=1}^N F_i(P_i) + k_i (MVA_{ik}' - MVA_{ik}^{\lim}) \quad (38)$$

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  $MVA_{ik}'$  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 Kuppasamy, 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 EEP 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 Kuppusamy, 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 (Preedavichat and Srivastava, 1997). In the experiments, the reactance limit of TCSC in pu is  $0 \leq X_{TCSC} \leq 0.02$  and phase shifting angle of TCPS in radian is  $0 \leq \alpha_i \leq 0.1$ .

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 compare with the solutions obtained by TS/SA Ongsakul and Bhasaputra (2002). Their convergence characteristics are shown in Fig. 5.

Table 1: Simulation results of cases 1-2 best solutions (demand 283.4 MW)

Generation unit	Case 1		Case 2	
	TS/SA	EEP	TS/SA	EEP
P <sub>1</sub> (MW)	192.6018	174.8485	192.5105	176.4877
P <sub>2</sub> (MW)	48.4147	49.4959	48.3951	48.3994
P <sub>3</sub> (MW)	19.5561	21.7994	19.5506	21.5867
P <sub>4</sub> (MW)	11.6615	22.7605	11.6204	22.0219
P <sub>5</sub> (MW)	10.0000	11.8692	10.0000	12.3781
P <sub>6</sub> (MW)	12.0000	12.0128	12.0000	12.0017
Injected power by TVPS (MW) (line 3-4)	-	-	-	1.3557
Total (MW)	294.2341	292.7863	294.0766	292.8755
P <sub>Loss</sub> (MW)	10.8341	93.3630	10.6766	10.8312
Total cost (\$/h)	804.6497	802.3999	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 cases 3-4 best solutions (demand 283.4 MW)

Generation unit	Case 3		Case 4	
	TS/SA	EEP	TS/SA	EEP
P <sub>1</sub> (MW)	192.5099	176.6442	192.4664	176.4136
P <sub>2</sub> (MW)	48.3950	48.3999	48.3857	48.5633
P <sub>3</sub> (MW)	19.5506	21.4811	19.5506	21.4066
P <sub>4</sub> (MW)	11.62.2	22.2261	11.6202	22.1114
P <sub>5</sub> (MW)	10.0000	12.1323	10.0000	12.3846
P <sub>6</sub> (MW)	12.0000	12.0055	12.0000	12.0000
Injected power by TCPS (MW) (line 3-4)	-	1.3495	-	1.4972
Total (MW)	294.1757	292.8891	294.0007	292.8795
P <sub>Loss</sub> (MW)	10.6757	10.8386	10.6007	10.9767
Total cost (\$/h)	804.1041	802.3670	803.8459	802.3661
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

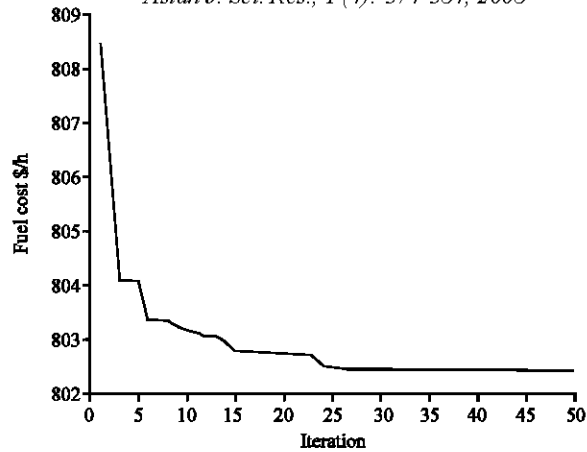


Fig. 5: Convergence characteristics of EEP for SCED for 30 bus system

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

	TS/SA	EEP
Worst	804.1074	802.3715
Average	804.1073	802.3706
Best	804.1072	802.3702

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

Chung, T.S., D. Qifeng and Z. Boming, 2000. Optimal active OPF with FACTS devices by an innovative load equivalent approach. IEEE. Power Eng. Rev., 20 (5): 63-66.  
 Chung, T.S. and Y.Z. Li, 2000. A hybrid GA approach for OPF with consideration of FACTS devices. IEEE. Power Eng. Rev., 20 (8): 54-57.

- Ge, S.Y. and T.S. Chung, 1999. Optimal active power flow incorporating power flow control needs in flexible AC systems. *IEEE. Trans. Power Syst.*, 14 (2): 738-744.
- Gerbex, S., 2001. Optimal location of multi type FACTS device in a power system by means of genetic algorithms. *IEEE. Trans. Power Syst.*, 16 (3): 531-544.
- Hingorani, N.G. and L. Gyugyi, 1999. *Understanding FACTS. Concepts and Technology of Flexible AC Transmission System.* IEEE Press, New York.
- Lai, L.L. and J.T. Ma, 1997. Application of evolutionary programming to reactive power planning-comparison with non linear programming approach. *IEEE. Trans. Power Syst.*, 12 (1): 198-206.
- Narihisa, H. and K. Kohmoto, 2006. Evolutionary programming with only using exponential mutation. *IEEE. Congress Evol. Comput.*, 16 (31): 552-559.
- Ongsakul, W. and P. Bhasaputra, 2001. Optimal power flow with FACTS devices by hybrid TS/SA approach. *Elect. Power Energy Syst.*, 24: 851-857.
- Preedavichat, P. and S.C. Srivastava, 1997. Optimal reactive power dispatch considering FACTS devices. *Proceeding of the 4th International Conference on Advances in Power system Control, Operation and Management (APSCOM)*, 2: 620-626.
- Somasundaram, P. and K. Kuppasamy, 2005. Application of evolutionary programming to security constrained economic dispatch. *Elect. Power Energy Syst.*, 27: 343-351.
- Wong, K.P. and J. Yuryevich, 1998. Evolutionary-programming-based algorithm for environmentally-constrained economic dispatch. *IEEE. Trans. Power Syst.*, 13 (2): 301-306.
- Yang, H.T., P.C. Yang and C.L. Huang, 1996. Evolutionary programming based economic dispatch for units with non-smooth fuel cost function. *IEEE. Trans. Power Syst.*, 11 (1): 112-118.