# Unified Power Flow Controller Design based on Shuffled Frog Leaping Algorithm

Mojtaba Shirvani [1], Pejman Shakeri [2], Elahe Behzadipour [3], Iman Baghbani[4]

[1,2,3,4]Department of Electrical Engineering, Boroujen Branch, Islamic Azad University, Boroujen, Iran
mo_shirvani@yahoo.com

**Abstract:** This paper presents the application of Unified Power Flow Controller (UPFC) to enhance damping of Low Frequency Oscillations (LFO) at a Single-Machine Infinite-Bus (SMIB) power system installed with UPFC. Since UPFC is considered to mitigate LFO, therefore a supplementary damping controller based UPFC like power system stabilizer is designed to reach the defined purpose. Optimization methods such as Shuffled Frog Leaping algorithm (SLFA) and Genetic Algorithms (GA) are considered to design UPFC supplementary stabilizer controller. To show effectiveness and also comparing these two methods, the proposed methods are simulated under different operating conditions. Several linear time-domain simulation tests visibly show the validity of proposed methods in damping of power system oscillations. Also Simulation results emphasis on the better performance of SLFA in comparison with GA method.

[Mojtaba Shirvani, Pejman Shakeri, Elahe Behzadipour, Iman Baghbani. **Unified Power Flow Controller Design based on Shuffled Frog Leaping Algorithm.** Life Sci J 2012;9(2):1071-1076] (ISSN:1097-8135). http://www.lifesciencesite.com. 158

**Keywords:** Flexible AC Transmission Systems, Unified Power Flow Controller, Low Frequency Oscillations, Shuffled Frog Leaping algorithm, Genetic Algorithms.

## 1. Introduction

The rapid development of the high-power electronics industry has made Flexible AC Transmission System (FACTS) devices viable and attractive for utility applications. FACTS devices have been shown to be effective in controlling power flow and damping power system oscillations. In recent years, new types of FACTS devices have been investigated that may be used to increase power system operation flexibility and controllability, to enhance system stability and to achieve better utilization of existing power systems (Hingorani and Gyugyi 2000). UPFC is one of the most complex FACTS devices in a power system today. It is primarily used for independent control of real and reactive power in transmission lines for flexible, reliable and economic operation and loading of power systems. Until recently all three parameters that affect real and reactive power flows on the line, i.e., line impedance, voltage magnitudes at the terminals of the line, and power angle, were controlled separately using either mechanical or other FACTS devices. But UPFC allows simultaneous or independent control of all these three parameters, with possible switching from one control scheme to another in real time. Also, the UPFC can be used for voltage support and transient stability improvement by damping of low frequency power system oscillations (Faried and Billinton 2009; Jiang et al. 2010). Low Frequency Oscillations (LFO) in electric power system occur frequently due to disturbances such as changes in loading conditions or a loss of a transmission line or a generating unit. These oscillations need to be controlled to maintain system stability. Many in the past have presented lead-Lag type UPFC damping controllers (Guo and Crow 2009; Zarghami et al. 2010). They are designed for a specific operating condition using linear models. More advanced control schemes such as Particle-Swarm method, Fuzzy logic and genetic algorithms (Taher and Hematti 2008) offer better dynamic performances than fixed parameter controllers.

The objective of this paper is to investigate the ability of optimization methods such as Genetic Algorithms (GA) and Shuffled Frog Leaping algorithm (SLFA) for UPFC supplementary stabilizer controller design. A Sigel Machine Infinite Bus (SMIB) power system installed with a UPFC is considered as case study and a UPFC based stabilizer controller whose parameters are tuned using SLFA and GA is considered as power system stabilizer. Different load conditions are considered to show effectiveness of the proposed methods and also comparing the performance of these two methods. Simulation results show the validity of proposed methods in LFO damping.

## 2. System under Study

Fig. 1 shows a SMIB power system installed with UPFC (Hingorani and Gyugyi 2000). The UPFC is installed in one of the two parallel transmission lines. This configuration (comprising two parallel transmission lines) permits to control of real and reactive power flow through a line. The static excitation system, model type IEEE – ST1A, has been considered. The UPFC is assumed to be based on Pulse Width Modulation (PWM) converters.

## 3. Dynamic model of the system

### 3.1. Linear dynamic model

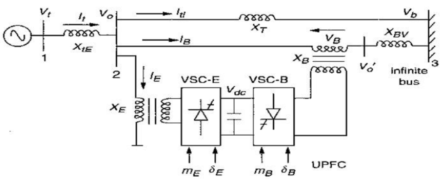


Figure 1. A Single Machine power system installed with UPFC in one of the lines

A non-linear dynamic model of the system is derived by disregarding the resistances of all components of the system (generator, transformers, transmission lines and converters) and the transients of the transmission lines and transformers of the UPFC (Wang, 2000). A linear dynamic model is obtained by linearizing the nonlinear dynamic model around nominal operating condition. The linear model of the system is given as (1).

$$\begin{cases} \Delta\dot{\delta} = w_0 \Delta w \\ \Delta\dot{\omega} = (-\Delta P_e - D\Delta\Delta)/M \\ \Delta\dot{E}_q^{/} = (-\Delta E_q + \Delta E_{fd})/T_{do}^{/} \\ \Delta\dot{E}_{fd} = -\frac{1}{T_A}\Delta E_{fd} - \frac{K_A}{T_A}\Delta V \\ \Delta\dot{v}_{dc} = K_7\Delta\delta + K_8\Delta E_q^{/} - K_9\Delta v_{dc} + K_{ce}\Delta m_E + K_{c\delta\delta}\Delta\delta_E \\ \quad + K_{cb}\Delta m_B + K_{c\delta\delta}\Delta\delta_B \end{cases} \quad (1)$$

Where

$$\Delta P_e = K_1\Delta\delta + K_2\Delta E_q^{/} + K_{pd}\Delta v_{dc} + K_{pe}\Delta m_E + K_{p\delta\delta}\Delta\delta_E + K_{pb}\Delta m_B + K_{p\delta\delta}\Delta\delta_B$$

$$\Delta E_q = K_4\Delta\delta + K_3\Delta E_q^{/} + K_{qd}\Delta v_{dc} + K_{qe}\Delta m_E + K_{q\delta\delta}\Delta\delta_E + K_{qb}\Delta m_B + K_{q\delta\delta}\Delta\delta_B$$

$$\Delta V_t = K_5\Delta\delta + K_6\Delta E_q^{/} + K_{vd}\Delta v_{dc} + K_{ve}\Delta m_E + K_{v\delta\delta}\Delta\delta_E + K_{vb}\Delta m_B + K_{v\delta\delta}\Delta\delta_B$$

Fig. 2 shows the transfer function model of the system including UPFC. The model has numerous constants denoted by $K_{ij}$. These constants are function of the system parameters and the initial operating condition. Also the control vector U in Fig. 2 is defined as (2).

$$U = [\Delta m_E \quad \Delta\delta_E \quad \Delta m_B \quad \Delta\delta_B]^T \quad (2)$$

Where:

$\Delta m_B$: Deviation in pulse width modulation index $m_B$ of series inverter. By controlling $m_B$, the magnitude of series- injected voltage can be controlled.

$\Delta\delta_B$ : Deviation in phase angle of series injected voltage.

$\Delta m_E$ : Deviation in pulse width modulation index $m_E$ of shunt inverter. By controlling $m_E$, the output voltage of the shunt converter is controlled.

$\Delta\delta_E$: Deviation in phase angle of the shunt inverter voltage.

The series and shunt converters are controlled in a coordinated manner to ensure that the real power output of the shunt converter is equal to the power input to the series converter. The fact that the DC-voltage remains constant ensures that this equality is maintained.

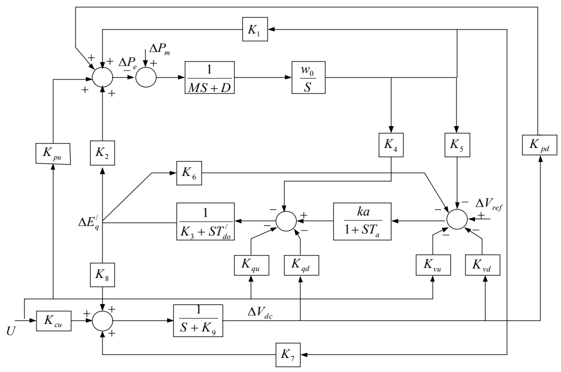

Figure 2. Transfer function model of the system including UPFC

It should be noted that $K_{pu}$ , $K_{qu}$ , $K_{vu}$ and $K_{cu}$ in Fig. 2 are the row vectors and defined as follow:

$$K_{pu} = [K_{pe} \quad K_{p\delta e} \quad K_{pb} \quad K_{p\delta b}]$$
$$K_{qu} = [K_{qe} \quad K_{q\delta e} \quad K_{qb} \quad K_{q\delta b}]$$
$$K_{vu} = [K_{ve} \quad K_{v\delta e} \quad K_{vb} \quad K_{v\delta b}]$$
$$K_{cu} = [K_{ce} \quad K_{c\delta e} \quad K_{cb} \quad K_{c\delta b}]$$

### 3.2. State-space model

The dynamic model of the system in state-space form is as (3).

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \Delta\dot{E}_q' \\ \Delta\dot{E}_{fd} \\ \Delta\dot{V}_{dc} \end{bmatrix} = \begin{bmatrix} 0 & w_0 & 0 & 0 & 0 \\ -\frac{K_1}{M} & 0 & -\frac{K_2}{M} & 0 & -\frac{K_{pd}}{M} \\ -\frac{K_4}{T_{do}'} & 0 & -\frac{K_3}{T_{do}'} & \frac{1}{T_{do}'} & -\frac{K_{qd}}{T_{do}'} \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & -\frac{K_A K_{vd}}{T_A} \\ K_7 & 0 & K_8 & 0 & -K_9 \end{bmatrix} \times \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E_q' \\ \Delta E_{fd} \\ \Delta v_{dc} \end{bmatrix} \quad (3)$$

$$+ \begin{bmatrix} 0 & 0 & 0 & 0 \\ -\frac{K_{pe}}{M} & -\frac{K_{p\delta e}}{M} & -\frac{K_{pb}}{M} & -\frac{K_{p\delta b}}{M} \\ -\frac{K_{qe}}{T_{do}'} & -\frac{K_{q\delta e}}{T_{do}'} & -\frac{K_{qb}}{T_{do}'} & -\frac{K_{q\delta b}}{T_{do}'} \\ -\frac{K_A K_{vc}}{T_A} & -\frac{K_A K_{v\delta e}}{T_A} & -\frac{K_A K_{vb}}{T_A} & -\frac{K_A K_{v\delta b}}{T_A} \\ Kce & K_{c\delta e} & K_{cb} & K_{c\delta b} \end{bmatrix} \times \begin{bmatrix} \Delta m_E \\ \Delta\delta_E \\ \Delta m_B \\ \Delta\delta_B \end{bmatrix}$$

In this research the power system oscillation-damping controller are considered for UPFC.

## 4. Analysis

For the nominal operating condition the eigenvalues of the system are obtained using state-space model of the system presented in (3) and these eigenvalues are shown in Table 1. It is clearly seen that the system is unstable and needs to power system stabilizer (damping controller) for stability.

Stabilizer controllers design themselves have been a topic of interest for decades, especially in form of Power System Stabilizers (PSS) (Taher and Hematti 2008; Guo and Crow 2009; Zarghami et al. 2010). But PSS cannot control power transmission and also cannot support power system stability under large disturbances like 3-phase fault at terminals of generator (Mahran et al. 1992). For these problems, in this paper a stabilizer controller based UPFC is provided to mitigate power system oscillations. Two optimization methods such as SLFA and GA are considered for tuning stabilizer controller parameters. In the next section an introduction about SLFA is presented.

Table 1. Eigen-values of the closed-loop system without damping controller

| |
|---|
| -15.3583 |
| -5.9138 |
| 0.7542 + 3.3055i |
| 0.7542 - 3.3055i |
| -0.7669 |

## 5. SFLA Overview

Over the last decades there has been a growing concern in algorithms inspired by the observation of natural phenomenon. It has been shown by many researches that these algorithms are good alternative tools to solve complex computational problems.

The SFLA is a meta-heuristic optimization method inspired from the memetic evolution of a group of frogs when searching for food (Huynh 2008). SFLA, originally developed in determining the optimal discrete pipe sizes for new pipe networks and for existing network expansions. Due to the advantages of the SFLA, it is being researched and utilized in different subjects by researchers around the world, since 2003 (Ebrahimi et al. 2011).

The SFL algorithm is a memetic meta-heuristic method that is derived from a virtual population of frogs in which individual frogs represent a set of possible solutions. Each frog is distributed to a different subset of the whole population described as memeplexes. The different memeplexes are considered as different culture of frogs that are located at different places in the solution space (i.e. global search). Each culture of frogs performs simultaneously an independent deep local search using a particle swarm optimization like method. To ensure global exploration, after a defined number of memeplex evolution steps (i.e. local search iterations), information is passed between memeplexes in a shuffling process. Shuffling improves frog ideas quality after being infected by the frogs from different memeplexes, ensure that the cultural evolution towards any particular interest is free from bias. In addition, to improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions. After this, local search and shuffling processes (global relocation) continue until defined convergence criteria are satisfied. The flowchart of the SFLA is illustrated in Fig. 3.

The SFLA begins with an initial population of "*P*" frogs $F=\{X_1,X_2,...,X_n\}$ created randomly within the feasible space Ω. For S-dimensional problems (S variables), the position of the $i^{th}$ frog is represented as $X_i=[x_{i1},x_{i2},...,x_{is}]^T$. A fitness function is defined to evaluate the frog's position. Afterward the performance of each frog is computed based on its position. The frogs are sorted in a descending order according to their fitness. Then, the entire population is divided into *m* memeplexes, each of which consisting of *n* frogs (i.e. $P=n\times m$). The division is done with the first frog goes to the first memeplex, the second frog goes to the second memeplex, frog *m* goes to the $m^{th}$ memeplex, and the $(m + 1)^{th}$ frog back to the first memeplex, and so on. The local search block of Fig. 3 is shown in Fig. 4.

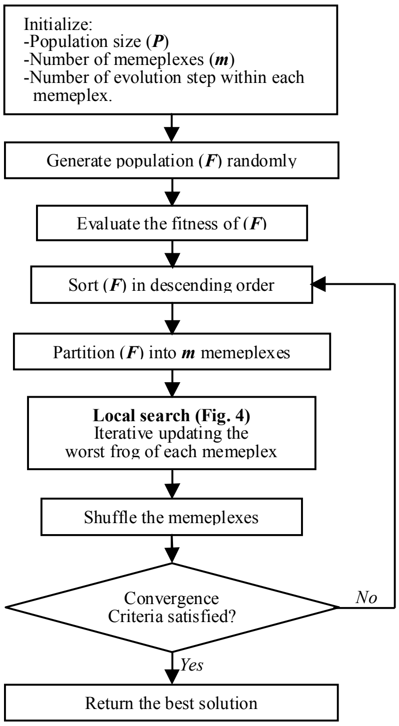


Figure 3. General principle of SFLA (Ebrahimi et al., 2011)

According to Fig. 4., during memeplex evolution, the position of frog $i^{th}$ ($D_i$) is adjusted according to the different between the frog with the worst fitness ($X_w$) and the frog with the best fitness ($X_b$) as shown in (4). Then, the worst frog $X_w$ leaps toward the best frog $X_b$ and the position of the worst frog is updated based on the leaping rule, as shown in (5).

$$\text{Position change } (D_i) = rand() \times (X_b - X_w) \qquad (4)$$

$$X_w(new) = X_w + D, (\|D\| < D_{\max}) \qquad (5)$$

where *rand ()* is a random number in the rang [0,1] and $D_{max}$ is the maximum allowed change of frog's position in one jump. If this repositioning process produces a frog with better fitness, it replaces the worst frog, otherwise, the calculation in (4) and (5) are repeated with respect to the global best frog ($X_g$), (i.e. $X_g$ replaces $X_b$). If no improvement becomes possible in this case, then a new frog within the feasible space is randomly generated to replace the worst frog. Based on Fig. 3., the evolution process is continued until the termination criterion is met. The termination criterion could be the number of iterations or when a frog of optimum fitness is found (Huynh 2008).

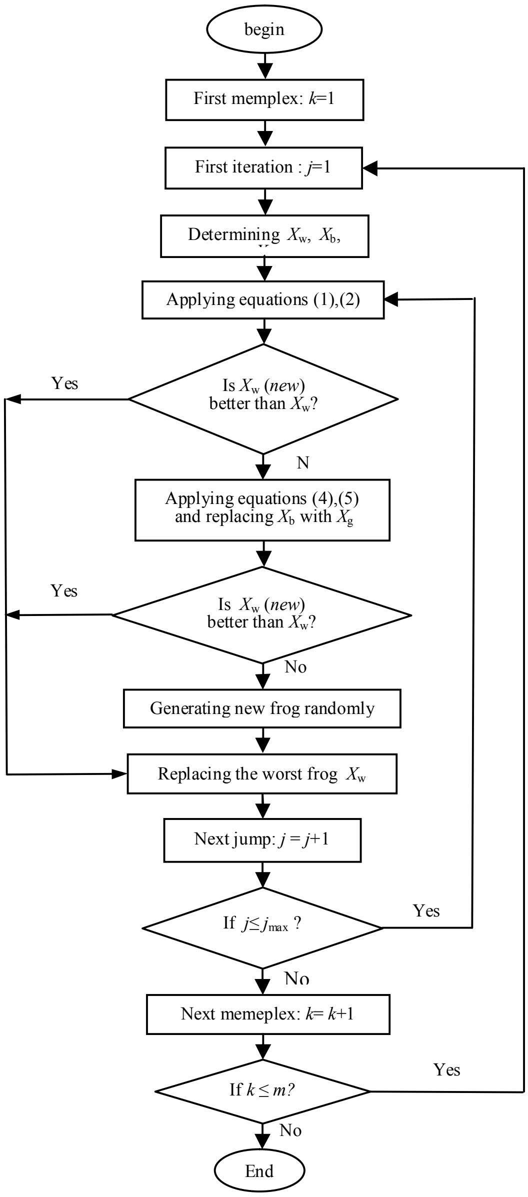


Figure 4. Local search block of Figure 3 (Huynh, 2008).

To compute the fitness value for each frog, firstly, the values of the $I_{pi}$ variables are extracted by decoding the frog information. In this study the fitness index is considered as (6). In fact, the performance index is the Integral of the Time multiplied Absolute value of the Error (*ITAE*).

$$\text{ITAE} = \int_0^t t|\Delta\omega|dt \qquad (6)$$

Where, $\Delta\omega$ is the frequency deviation, $\Delta V_{DC}$ is the deviation of DC voltage and parameter "t" in ITAE is the simulation time.

Based on Fig. 3 the local search and shuffling processes (global relocation) continue until the last iteration is met. In this paper, the number of iteration is set to be 50.

## 6. Stabilizer controller design using SLFA

In this section the parameters of the proposed stabilizer controller are tuned using SLFA. Four control parameters of the UPFC ($m_E$, $\delta_E$, $m_B$ and $\delta_B$) can be modulated in order to produce the damping torque. The parameter $m_E$ is modulated to output of damping controller and speed deviation $\Delta\omega$ is also considered as input of damping controller. The parameters of supplementary stabilizer controller are as follow:

$K_{DC}$: the damping controller gain

$T_W$: the parameter of washout block

$T_1$ and $T_2$: the parameters of compensation block

The optimum values of $T_1$ and $T_2$ which minimize an array of different performance indexes are accurately computed using SLFA and $T_W$ is considered equal to 10.

To compute the optimum parameter values, a 0.1 step change in mechanical torque ($\Delta Tm$) is assumed and the performance index is minimized using SLFA.

The first step to implement the SFL is generating the initial population (*N* frogs) where *N* is considered to be 20. The number of memeplex is considered to be 2 and the number of evaluation for local search is set to 2. Also $D_{max}$ is chosen as *inf*. To find the best value for the solution, the algorithms are run for 10 independent runs under different random seeds. The optimum values of $T_1$ and $T_2$, resulting from minimizing the performance index is presented in Table 2. Also in order to show effectiveness of SLFA, the parameters of stabilizer controller are tuned using the other optimization method, GA. In GA case, the performance index is considered as SLFA case and the optimal parameters of stabilizer controller are obtained as shown in Table 3.

Table 2. Optimum values of stabilizer controller parameters using SLFA

| | |
|---|---|
| $T_1$ | 0.2187 |
| $T_2$ | 0.01 |

Table 3. Optimum values of stabilizer controller parameters using GA

| | |
|---|---|
| $T_1$ | 0.251 |
| $T_2$ | 0.1 |

## 7. Simulation results

In this section, the designed SLFA and GA based stabilizer controllers are applied to damping LFO in the under study system. In order to study and analysis system performance under system uncertainties (controller robustness), two operating conditions are considered as follow:

Case 1: Nominal operating condition

Case 2: Heavy operating condition

SLFA and GA stabilizer controllers have been designed for the nominal operating condition. In order to demonstrate the robustness performance of the proposed method, The *ITAE* is calculated following 10% step change in the reference mechanical torque *($\Delta P_m$)* at all operating conditions (Nominal and Heavy) and results are shown at Table 4. Following step change, the SLFA based stabilizer has better performance than the GA based stabilizer at all operating conditions.

Also for case 1 the simulation result is shown in Fig. 5. The simulation result shows that applying the supplementary control signal greatly enhances the damping of the generator angle oscillations and therefore the system becomes more stable. The SLFA stabilizer performs better than the GA controller. For case 2, the simulation result is shown in Fig. 6. Under this condition, while the performance of GA supplementary controller becomes poor, the SLFA controller has a stable and robust performance. It can be concluded that the SLFA supplementary controller have suitable parameter adaptation in comparing with the GA supplementary controller when operating condition changes.

Table 4. The *ITAE* following 10% step change in the reference mechanical torque *($\Delta P_m$)* at all operating conditions

| | The calculated ITAE | |
|---|---|---|
| | SLFA Stabilizer | GA Stabilizer |
| Nominal operating condition | 0.0016 | 0.0020 |
| Heavy operating condition | 0.0018 | 0.0022 |

## 8. Conclusions

In this paper Genetic Algorithms and Shuffled Frog Leaping algorithm have been successfully applied to design stabilizer controller based UPFC. A Single Machine Infinite Bus power system installed with a UPFC with various load conditions has been assumed to demonstrate the methods. Simulation results demonstrated that the designed controllers capable to guarantee the robust stability and robust performance under a different load conditions. Also, simulation results show that the SLFA has an excellent capability in power system oscillations damping and power system stability enhancement under small disturbances in comparison with GA method.

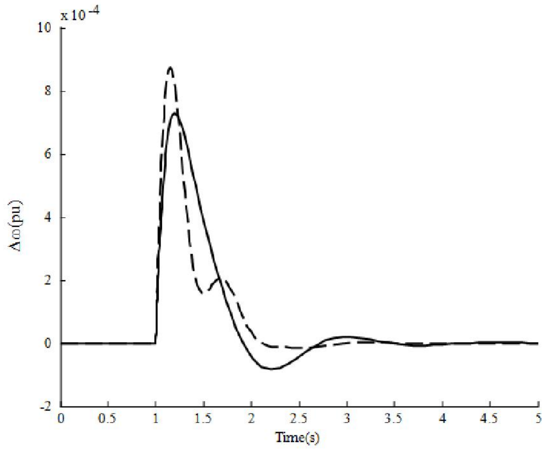


Figure 5. Dynamic response Δω for case 1

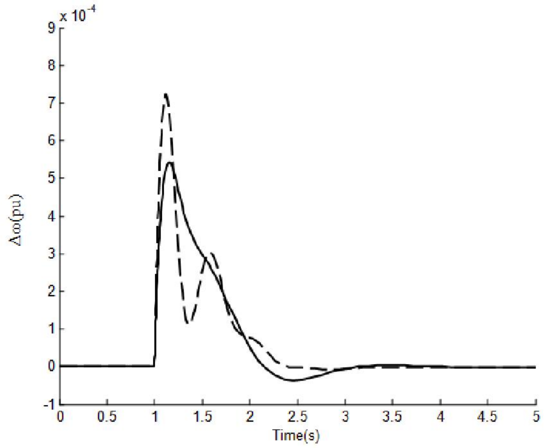


Figure 6. Dynamic response Δω for case 2

**Corresponding Author:**
Mojtaba Shirvani
Department of Electrical Engineering,
Boroujen Branch, Islamic Azad University,
Boroujen, Iran.
E-mail: mo_shirvani@yahoo.com

**References**

1. Ebrahimi J, Hosseinian SH, Gharehpetian GB. Unit Commitment Problem Solution Using Shuffled Frog Leaping Algorithm, IEEE Transactions on Power Systems, 2011, 26(2), pp. 573–581.
2. Faried SO, Billinton R. Probabilistic technique for sizing FACTS devices for steady-state voltage profile enhancement, IET generation, transmission & distributed, 2009; 3(4), pp. 385 – 392.
3. Guo J, Crow ML. An improved UPFC control for oscillation damping, IEEE Transactions on Power systems, 2009; 25(1), pp. 288 – 296.
4. Hingorani NG, Gyugyi L. Understanding FACTS, IEEE Press, 2000.
5. Huynh TH. A Modified Shuffled Frog Leaping Algorithm for Optimal Tuning of Multivariable PID Controllers, IEEE International Conference on Industrial Technology, 2008.
6. Jiang S, Gole AM, Annakkage UD, Jacobson DA. Damping Performance Analysis of IPFC and UPFC Controllers Using Validated Small-Signal Models, IEEE Transactions on Power Delivery, 2010; 26(1), pp. 446-454.
7. Mahran AR, Hogg BW, El-sayed ML. Co-ordinate control of synchronous generator excitation and static var compensator, IEEE Transactions on Energy conversion, 1992; 7(4), pp. 615-622.
8. Taher SA, Hematti R. Optimal supplementary controller designs using GA for UPFC in order to LFO damping, International Journal of Soft Computing, 2008; 3(5), PP. 382-389.
9. Wang HF. A unified model for the analysis of FACTS devices in damping power system oscillation Part III: Unified Power Flow Controller, IEEE Transactions on Power Delivery, 2000; 15(3), pp. 978-983.
10. Zarghami M, Crow ML, Sarangapani J, Yilu Liu, Atcitty S. A novel approach to inter-area oscillations damping by UPFC utilizing ultra-capacitors, IEEE Transactions on Power Systems, 2010; 25(1), pp. 404 – 412.

5/27/2012