



Iranian Association of  
Electrical and Electronics  
Engineers

## Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864

P-ISSN: 2717-414X

Homepage: <https://jaree.scu.ac.ir/>



### Research Article

## Optimization of PSS and UPFC Controllers to Enhance Stability by Using a Combination of Fuzzy Algorithm and Shuffled Frog Leaping Algorithm

Mohammad Abedini<sup>1</sup> , and Mahyar Abasi<sup>\*2,3</sup>

<sup>1</sup> Department of Electrical Engineering, Faculty of Engineering, Ayatollah Boroujerdi University, Boroujerd, Iran

<sup>2</sup> Department of Electrical Engineering, Faculty of Engineering, Arak University, Arak 38156-8-8349, Iran.

<sup>3</sup> Research Institute of Renewable Energy, Arak University, Arak 38156-8-8349, Iran.

\* Corresponding Author: [m-abasi@araku.ac.ir](mailto:m-abasi@araku.ac.ir)

**Abstract:** Maintaining power system stability can be challenging due to low-frequency fluctuations. Traditionally, power system stabilizers (PSS) and unified power flow controllers (UPFC) have been used to address this issue. This paper proposes a novel approach that leverages both PSS and UPFC simultaneously, controlled by an optimized fuzzy logic system. The proposed fuzzy controller aims to enhance the efficiency of both PSS and UPFC, ultimately boosting system damping. The controller takes two key inputs: changes in angular speed and power angle. To dynamically adjust its response to changing system conditions, a shuffled frog leaping algorithm optimizes the fuzzy controller's gains. To assess the effectiveness of the controller, simulations are conducted across three different loading levels for the studied system. The results are presented for each stage and demonstrate a significant reduction in overshoot and improved overall system damping. Our method achieves a remarkable 43% enhancement in damping compared to PSS, a 45% improvement over UPFC alone, and a staggering 48% advantage over the hybrid PSS-UPFC approach.

**Keywords:** metaheuristic, optimization, stabilizer, damping.

### Article history

Received 21 January 2024; Revised 15 April 2024; Accepted 12 August 2024; Published online 5 November 2024.

© 20xx Published by Shahid Chamran University of Ahvaz & Iranian Association of Electrical and Electronics Engineers (IAEEE)

### How to cite this article

M. Abedini, and M. Abasi, "Optimization of PSS and UPFC Controllers to Enhance Stability by Using a Combination of Fuzzy Algorithm and Shuffled Frog Leaping Algorithm," *J. Appl. Res. Electr. Eng.*, Vol. 3, No. 1, pp. 168-177, 2024. DOI: [10.22055/jaree.2024.45910.1104](https://doi.org/10.22055/jaree.2024.45910.1104)



## 1. INTRODUCTION

Nowadays, with the expansion of power systems and with the increase of power transmission, dynamic and transient stability are of special importance for safe operation [1]. To preserve the system's security, the power system is expected to have normal condition, during which the magnitude of voltage and range of frequency are maintained in the allowed range. Stability control of electrical power systems examines if the synchronism of generation units is established in the case a significant perturbation is added to the system. Power system stabilizers (PSS) have widespread applications, such as being adopted as complementary controllers to improve stability. In addition, flexible alternating current transmission systems (FACTS) are suitable options for transient stability improvement in almost a short time [2-4]. Among all FACTS devices, unified power flow controllers (UPFCs) are of special attention, which present maximum flexibility and can be used for voltage control, series compensations, and phase shift. UPFCs can

quickly control active and reactive power flow on a line. Normally, a UPFC follows two control objectives, known as primary and supplementary controls. The purpose of the former is to supervise and control active and reactive power flows independently so that bus voltages can be controlled during the power system operation. Among the most common control methods for UPFC is the one based on vector control. This design allows active and reactive power to be controlled separately, where the balanced three-phase system is converted to the synchronous rotating reference frame. Also, proportional-integral (PI), fuzzy, and neural controls have been introduced in this field [5-6]. On the other side, supplementary control is beneficial only in the case the system encounters major disturbances. This complementary control strategy concerns improving the transient stability on the line, which is traditionally expressed using the Lyapunov stability method based on an energy function [7]. Although developments in improving control methods have been presented, they need to provide complete power system models and dynamic models of the UPFC. In the following,

the related literature is reviewed. In case a power oscillation damping (POD) controller is used in the control design, FACTS can improve stability by boosting the damping to the inter-area modes [8-10]. In [11] introduced a design method based on the particle swarm optimization (PSO) algorithm, which aimed to coordinate thyristor-controlled series compensator (TCSC) and PSS in power systems that contain several generation units. In [12] adopted the genetic algorithm (GA) to determine the UPFC installation location along with adjusting the PSS parameters so that the system damping reaches the maximum possible value. In [13] presented a hybrid method for damping power fluctuations in the power system; the method consisted of offline and online stages that simultaneously adjusted the parameters of the UPFC and PSS controllers using the PSO. In [14] suggested adjusting controllers by adopting optimal control theory for different conditions and the studies were implemented using a two-area symmetric system. PI controllers propose widespread applications in load frequency control, even though they suffer from many problems due to changes in the operating point of the system as well as network regulatory parameters [15-16]. Many articles have also discussed the design of the optimal performance of PSS in the power system, some of which use pole displacement techniques. Some other studies utilized artificial intelligence techniques [17-18]. In [19] the fuzzy algorithm was used to adjust PSS parameters to boost system stability. In [20], to coordinate between UPFC and PSS, the eigenvalue method was used to identify the largest real value of the system and minimize its value. The purpose was to reduce the fluctuations of the power system when applying a disturbance to the system. In [21], a genetic algorithm was incorporated to coordinate PSS and UPFC to optimize electromechanical modes, thus improving system damping. In [22], a neural network with single-neuron layers was developed with a radial function to optimize the performance of the PSS and UPFC. Then the GA was used to optimize the network weights and applied to a four-machine network. Methods based on robust control have also been proposed to overcome system uncertainty and increase damping with UPFC [23], [24].

By proposing a variable structure controller and deriving the appropriate control law in terms of fuzzy logic for UPFC and PSS, as well as using the shuffled frog leaping algorithm (SFLA) to adjust the proposed gain coefficients in the fuzzy controller in the single-machine power network, the present study attempts to reduce low-frequency fluctuations in a faster time during a disturbance. Fig. 1 shows the structure of the developed control scheme. Accordingly, the output of the fuzzy system provides the required control signal for PSS and UPFC; in addition, the gains designed in the fuzzy controller for PSS and UPFC are optimized by the SFLA to enhance the system damping. The contributions of this study are described as follows:

- Designing fuzzy controllers for PSS and FACTS;
- Optimizing the parameters of the proposed fuzzy controller;
- Minimization of the objective function of speed changes to reduce fluctuations and improve system damping; and
- Comparing the proposed controller at three different levels of system loading with conventional controllers and showing the high capability of the proposed system.

## 2. CONTROL SYSTEM MODELING

Here, models of the PSS, UPFC, and dynamic modeling of a power system are introduced.

### 2.1. Power System Stabilizer

The PSS enhances the system's dynamic behavior by introducing supplementary signals to the excitation system. The PSS typically receives data such as motor speed, frequency, and generator output power, and effectively improves the dynamic behavior by reducing its fluctuations [25]. PSS has three blocks: phase compensator block, signal effect removal block, and gain block. The phase compensator block gives the most suitable phase-lead characteristic for phase-lag compensation of the system between the excitation input and the electric torque of the generator. Fig. 2 demonstrates the PSS structure based on the phase lag-lead controller.

### 2.2. Modeling the UPFC

UPFC is a device placed between two buses known as sending and receiving ends of the UPFC. This device consists of two interconnected voltage source converters via a DC link (refer to Fig. 3). This damping controller produces electric torque and the speed derivative to compensate the damping torque. The control parameters of the UPFC are  $m_B$ ,  $m_E$ ,  $\delta_B$ , and  $\delta_E$  which help to produce the damping torque. Parameters  $m$  and  $\delta$  respectively indicate the amplitude modulation coefficient and the initial angle of the reference signal of individual converters. In this article,  $\delta_E$  was adopted for generating the control signal. The structure of UPFC for the damping controller is also similar to the phase lag-lead controller of the PSS.

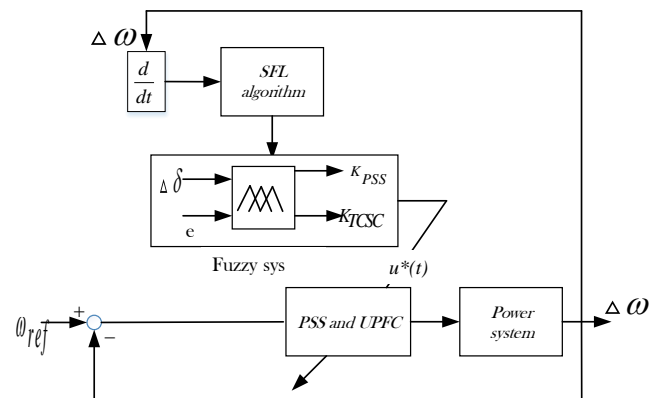


Fig. 1: Structure of the developed control design using a fuzzy controller

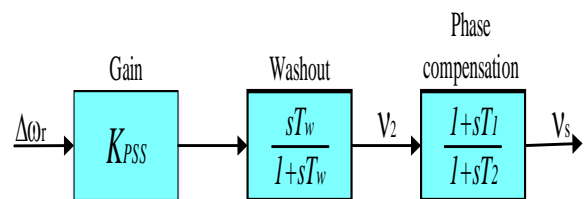


Fig. 2: Structure of the PSS

### 2.3. Modeling the Power System

Equations (1)-(7) describe the dynamic behavior of the studied system with a UPFC (Fig. 3) in the state space form related to the single-machine system [26]:

$$\dot{\delta}_i = \omega_i - \omega_0 \quad (1)$$

$$\dot{\omega}_i = \frac{1}{M_i} (P_{mi} - P_{ei} - D_i(\omega_i - \omega_0))/\omega_0 \quad (2)$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}} [-E_{fdi} - (X'_{di} - X_{di})I_{di} - E_{qi} - E'_{qi} + E'_{qi}] + \dot{E}'_{qi} \quad (3)$$

$$\dot{E}'_{fdi} = \frac{1}{T_{Ai}} (-E_{fdi} + K_{Ai}(V_{refi} - V_{Ti})) \quad (4)$$

$$E_q = -r_a I_d + \frac{\dot{E}'_{qi}}{\omega_0} + E'_d + X'_q I_q \quad (5)$$

$$E_q = -r_a I_d + \frac{\dot{E}'_{qi}}{\omega_0} + E'_q + X''_d I_d \quad (6)$$

$$T_e = E'_d I_d + E'_q I_q + (X'_q - X''_d) I_d I_q \quad (7)$$

Therefore, state space equations of the system may be rewritten as Eq. (8):

$$\begin{bmatrix} \dot{\Delta\delta} \\ \dot{\Delta\omega} \\ \dot{\Delta E}'_q \\ \dot{\Delta E}'_{qe} \end{bmatrix} = A \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E'_q \\ \Delta E'_{qe} \end{bmatrix} + B \Delta V_{dc} + C \begin{bmatrix} \Delta m_E \\ \Delta\delta_E \\ \Delta m_B \\ \Delta\delta_R \end{bmatrix} \quad (8)$$

where A, B, and C are given as Eqs. (9)-(11):

$$A = \begin{bmatrix} 0 & \omega_b & 0 & 0 & 0 \\ \frac{K_1}{M} & -\frac{D}{M} & \frac{K_2}{M} & 0 & \frac{K_{pd}}{M} \\ \frac{K_5}{T'_{do}} & 0 & \frac{K_3}{T'_{do}} & \frac{1}{T'_{do}} & \frac{K_{pd}}{T'_{do}} \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & -\frac{K_A K_{vd}}{T_A} \\ K_7 & 0 & K_8 & 0 & K_9 \end{bmatrix} \quad (9)$$

$$B = \begin{bmatrix} 0 \\ -\frac{K_{pd}}{M} \\ -\frac{K_{qd}}{T'_{do}} \\ -\frac{K_A K_{vd}}{T_A} \end{bmatrix} \quad (10)$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & -\frac{K_{pe}}{M} & -\frac{K_{p\delta e}}{M} & -\frac{K_{pb}}{M} & -\frac{K_{p\delta b}}{M} \\ 0 & -\frac{K_{qe}}{T'_{do}} & -\frac{K_{q\delta e}}{T'_{do}} & -\frac{K_{qb}}{T'_{do}} & -\frac{K_{q\delta b}}{T'_{do}} \\ \frac{K_A}{T_A} & -\frac{K_A K_{ve}}{T_A} & -\frac{K_A K_{v\delta e}}{T_A} & -\frac{K_A K_{vd}}{T_A} & -\frac{K_A K_{v\delta b}}{T_A} \\ 0 & k_{ce} & k_{c\delta e} & k_{cb} & k_{c\delta b} \end{bmatrix} \quad (11)$$

Coefficients  $K_{pu}$ ,  $K_{vu}$ ,  $K_{qu}$ , and  $K_{cu}$  are defined in Eqs. (12)-(14):

$$K_{pu} = [K_{pe} K_{p\delta e} K_{pb} K_{p\delta b}] \quad (12)$$

$$K_{vu} = [K_{ve} K_{v\delta e} K_{vd} K_{v\delta b}] \quad (13)$$

$$K_{qu} = [K_{qe} K_{q\delta e} K_{qb} K_{q\delta b}] \quad (14)$$

All coefficients  $K_1$  to  $K_9$  and coefficients  $K_{pu}$ ,  $K_{vu}$ ,  $K_{qu}$ , and  $K_{cu}$  are linearized constants.

Fig. 4 provides a linearized model of control model of the system under study, based on which the proposed fuzzy controller is suggested for damping the system.

### 3. FUZZY THEORY

The fuzzy theory was first introduced by Zadeh in an article titled ‘‘Fuzzy Sets’’. A decade later, Mamdani and Asilian defined a basic framework for a fuzzy controller and used the fuzzy controller in a steam engine [27]. In 1978, Holmblad and Ostergaard adopted the first fuzzy controller for a complete industrial process [27].

A fuzzy controller has one or more non-fuzzy input signals and one non-fuzzy output signal. To create the desired output signal, in general, the controller has the following parts:

- Fuzzy rules base
- Fuzzy inference engine
- Fuzzifier and de-fuzzifier

A fuzzy rule base is formed from a set of fuzzy *if-then* rules. In a fuzzy inference engine, the principles of fuzzy logic are used to combine *if-then* rules in the fuzzy rule base to map from the fuzzy set A in U to the fuzzy set B in V. The fuzzifier acts as an intermediary between the input environment, which is in the form of real numbers, and the fuzzy inference engine. The de-fuzzifier is a mapping of the fuzzy set of the output of the fuzzy inference engine to a definite point. So, a de-fuzzifier identifies the point that represents the output fuzzy set most properly.

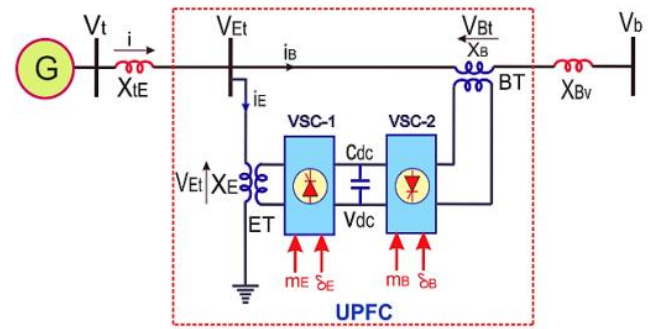


Fig. 3: A single-machine power system with a UPFC [31].

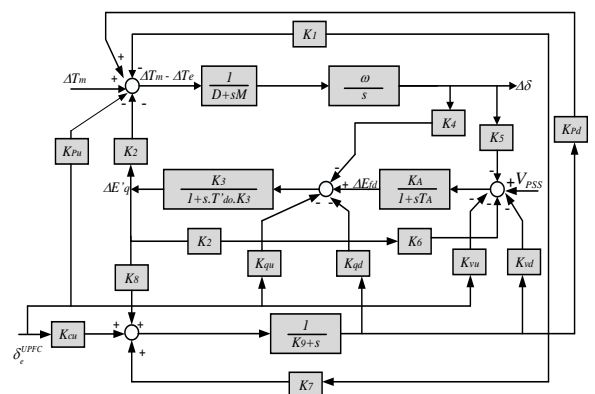


Fig. 4: Block diagram of the power system with a UPFC

### 3.1. Fuzzy theory for designing the PSS controller

In this part, the PSS controller is designed to boost power system damping based on fuzzy logic. Angular velocity changes and power angular changes are considered as fuzzy inputs. The fuzzy system output is also applied to the excitation system ( $V_{PSS}$ ), which is shown in Fig. 4. As seen in Fig. 5., two constant parameters are used in the input and one constant parameter in the fuzzy system output, which will be optimized by the SFLA in Section 4.

### 3.2. Fuzzy theory for the design of the UPFC controller

A similar method to the design of the PSS fuzzy controller has been used for UPFC. Angular velocity changes and power angular changes are considered as fuzzy inputs. The fuzzy system output is fed into the converter angle ( $\delta_e^{UPFC}$ ), according to Fig. 6.

According to Fig. 6, two constant parameters are used in the input and one constant parameter in the fuzzy system output, which will be optimized by the SFLA in Section 4.

### 3.3. Step 2: Fuzzification rules

This part forms the foundation and main logic of the control action, where the whole data needed for the control operation is stored in the form of fuzzy rules. For example, if the output value is significantly dissimilar to the desired value, the fuzzy part applies more control value in a different direction. The fuzzy control rules that are necessary to generate the control signals of  $\delta_e^{UPFC}$  and  $V_{PSS}$  are given in Tables 1 and 2, which will be applied to the studied system according to Fig. 4. It should be noted that the fuzzy functions used for  $\omega$  and  $\Delta\delta$  are triangular.

### 3.4. Step 3: Fuzzy inference method

Normally, Mamdani and Takagi Sugeno methods are mainly utilized in control applications. The former is used in this section, because it is a very powerful method at the same time. Using the Mamdani method, Eq. (15) is written:

$$\mu_{R_i}(\omega, \Delta\delta) = \mu_{A_i}(\omega) \times \mu_{B_i}(\Delta\delta) \quad (15)$$

where  $\omega$  and  $\Delta\delta$  represent the speed and changes of the speed. Also,  $u$  is the output value.  $\mu_{A_i}(\omega)$  and  $\mu_{B_i}(\Delta\delta)$  are the fuzzified value of the speed and the rate of change of speed.

As shown in Tables 1 and 2, the labels NB, NM, NS, ZR, PS, PM, and PB represent the membership function values in this fuzzy system. These terms correspond to negative big, negative medium, negative small, zero, positive small, positive medium, and positive big, respectively. Tables 1 and 2 present the fuzzy rule base, derived from human experience. The rules employ the following format: 'If input variable 1 ( $\omega$ ) is  $A_i$  and input variable 2 ( $\Delta\delta$ ) is  $B_i$ , then the output variable ( $u$ ) is  $C_i$ . In this rule format, ' $A_i$ ' and ' $B_i$ ' represent the membership function values for the corresponding input variables ( $\omega$  and  $\Delta\delta$ ). The output ' $C_i$ ' translates these fuzzy values into control signals that are sent to both the PSS and UPFC.

### 3.5. Step 4: fuzzy to crisp transformation

The transformation of the fuzzy central average value to the crisp value is used here. In this way, the output value is given as Eq. (16):

$$\mu(\omega, \Delta\delta) = \frac{\sum_{i=1}^n u_i' \min(\mu_{A_i}(\omega), \mu_{B_i}(\Delta\delta))}{\sum_{i=1}^n \min(\mu_{A_i}(\omega), \mu_{B_i}(\Delta\delta))} \quad (16)$$

where  $u_i'$  indicates the central value of the fuzzy output. The fuzzy logic output is used for the excitation system signal in PSS and also for the converter angle in UPFC. The signals are changed instantaneously using fuzzy logic according to Eqs. (17) and (18):

$$V_{PSS} = V_{PSSo} + \Delta U_{PSS} \quad (17)$$

$$\delta_e^{UPFC} = \delta_e^{UPFCo} + \Delta U_{UPFC} \quad (18)$$

$V_{PSSo}$  and  $\delta_e^{UPFCo}$  are the initial values related to the PSS and UPFC signals.  $\Delta U_{PSS}$  and  $\Delta U_{UPFC}$  are the output of the fuzzy section.

### 4. SHUFFLED FROG LEAPING ALGORITHM (SFLA)

The SFLA can be categorized as a metaheuristic optimization method, which mimics the mimetic evolution of a group of frogs as they search for a location with the maximum food. In metaheuristic algorithms, the objective function has a conscious process and the decision space is intelligently discovered [28].

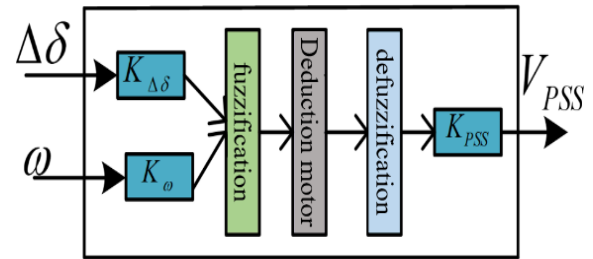


Fig. 5: Block diagram of the fuzzy controller for the PSS.

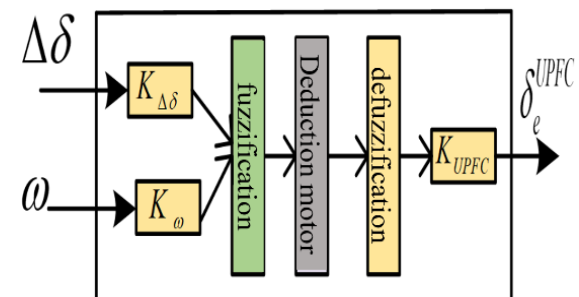


Fig. 6: Block diagram of the UPFC's fuzzy controller.

**Table 1:** Fuzzy rules needed in the UPFC controller.

$\omega$	$\Delta\delta$						
	NB	NM	NS	Z	PS	PM	PB
NB	NH	NH	NH	NS	PM	PS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NM	NM	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PM	PB	PB	PB

**Table 2:** Fuzzy rules needed in the PSS controller.

$\omega$	$\Delta\delta$						
	NB	NM	NS	Z	PS	PM	PB
NB	NH	NH	NH	NB	NM	NS	Z
NM	NB	NB	NM	NM	NS	Z	PS
NS	NB	NM	NS	NS	Z	PS	PM
Z	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PM	PM	PB
PM	NS	Z	PS	PM	PM	PB	PB
PB	Z	PS	PM	PB	PB	PB	PB

**4.1. Structure of the SFLA**

SFLA has both certainty and random strategy elements in finding the optimal solution. The certainty strategy allows the algorithm to effectively use the shallow information of the solution to guide a heuristic search such as the PSO algorithm. Random elements guarantee the flexibility and strength of the search pattern in the proposed method. The steps of the SFLA are given below.

**Step 1:** an initial population containing  $N$  solutions to the problem  $P = \{X_1, X_2, \dots, X_n\}$  is generated. A solution to the problem for primary gains in the controller of Figs. 5 and 6 are considered as follows.

$$X_i = [K_{\Delta\delta}^{PSS}, K_{\omega}^{PSS}, K_{PSS}, K_{\Delta\delta}^{UPFC}, K_{\omega}^{UPFC}, K_{UPFC}]^T$$

**Step 2:** using the fitness function defined in Eq. (19), each of the solutions to the problem is evaluated and the solutions are sorted in descending order as per their fitness values.

$$J = \int_0^T t |\Delta\omega| dt \tag{19}$$

The objective function is introduced to improve the system damping.

**Step 3:** the whole population is divided into  $m$  equal parts, and each of these sub-parts is called a Memplex. In each memplex,  $n$  solutions of the problem are placed ( $n = \frac{N}{m}$ ); the solution with the highest fitness value is placed in the first memplex, the second solution is placed in the second memplex, the  $m^{th}$  solution is placed in the  $m^{th}$  memplex, and the  $(m + 1)^{th}$  solution is placed again in the first memplex. This process continues until all the solutions are distributed.

**Step 4:** Since the frogs' preference is centered around a specific frog that may be the local optimum, it is not always desirable to use the best frog; therefore, a subset of memplexes called sub-memplexes is considered. In each of the memplexes, the solutions with the worst and the best degree of fitness are specified and denoted by  $X_w$  and  $X_b$ , respectively. Also, the solution with the best amount of

fitness among the entire population is also defined by  $X_g$ . During the evolution process of memplexes, the worst solution moves towards the best solution. Fig. 7 shows the evolution of memplexes.

**Step 5:** the new position of the worse solution is calculated using the leaping law of frogs in the SFLA, as Eqs. (20)-(21):

$$D = rc(x_b - x_w) + w \tag{20}$$

$$x_w^{new} = \begin{cases} x_w + D & \|D\| \leq D_{max} \\ x_w + \frac{D}{\sqrt{D^T D}} D_{max} & \|D\| > D_{max} \end{cases} \tag{21}$$

where  $r$  is a random number between 0 and 1,  $C$  is a fixed number between 1 and 2,  $r$  is a random number between -1 and 1,  $D$  shows the maximum allowed leap distance, and  $w$  represents the maximum allowed movement and penetration.

**Step 6:** update the worst solution using Eq. (22):

$$if : f(x_w^{new}) < f(x_w) \quad then \quad x_w = x_w^{new} \tag{22}$$

Otherwise,  $X_b$  is replaced by  $X_g$ , and  $x_w^{new}$  is recalculated from Eq. (21). If there is still no improvement in the solution,  $X_w$  is deleted and a new solution is randomly replaced.

**Step 7:** This stage is called the combination process, where the population of memplexes are combined with each other. Then, return to Step 2.

**Step 8:** As soon as the specified number of iterations is met, the optimization process is completed.

**5. SIMULATION**

Simulations of all samples were performed on a single-machine IEEE standard system (Fig. 3). Table 3 lists the information of the standard single-machine network under study along with the UPFC. Also, the number of memplexes is 7 and the population of each memplex is 15. The number of iterations is 100. To evaluate the efficacy of the controller designed in this study, its response was assessed using PSS and UPFC damping controllers independently and at different load percentages. Table 4 summarizes the results in the presence of a three-phase fault occurring at  $t = 0.5$  s with different network loading conditions. In addition to the objective function of Eq. (19), the index given in Eq. (23) was also used when comparing different controllers:

$$F = (100 \times OS)^2 + (500 \times US)^2 + TS^2 \tag{23}$$

where  $OS$  is the overshoot of the system,  $US$  is the undershoot, and  $TS$  is the settling time of the machine speed deviation.

**Table 3:** Standard single-machine network information

Generator	$M = 8, D = 0, T'_{do} = 5.044, X_q = 0.6, X_d = 1, X'_d = 0.3$
Excitation	$K_A = 10, T_A = 0.05$
Transmission line	$X_{LE} = 0.1, X_{BV} = 0.5$
Operating condition	$Pe = 0.8, V_i = 1, V_b = 1$
UPFC Transformers	$X_E = 0.1, X_B = 0.1$
Parameters of DC link	$V_{DC} = 2, CDC = 1$

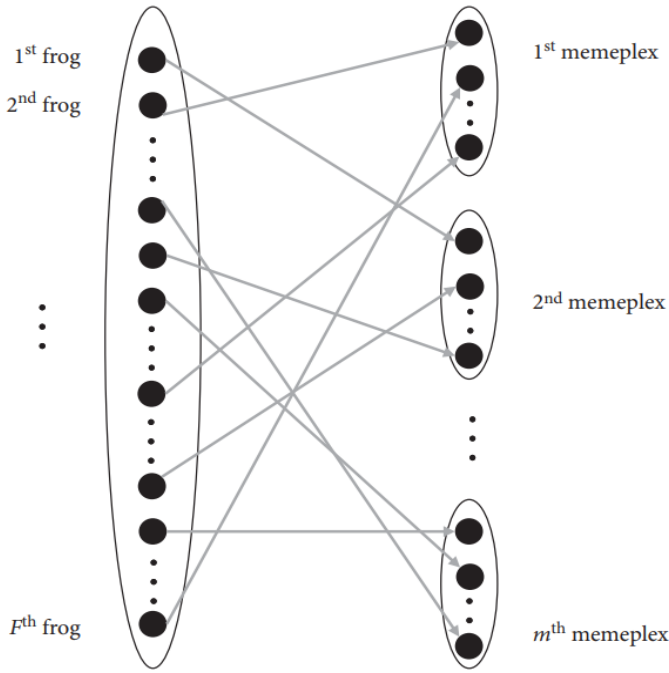


Fig. 7: Leaping process in the SFLA [30].

Table 4: A comparison between the performance of different controllers in network load conditions

Controller	80%		100%		110%	
	F	J	F	J	F	J
PSS	0.0126	14.02	0.0159	15.17	0.0170	16.76
UPFC	0.0143	14.25	0.0167	15.26	0.0184	16.89
Proposed	0.0126	6.05	0.0146	8.43	0.0158	10.61
PSS&UPFC-PID	0.0159	14.85	0.0172	16.37	0.0193	17.055

Table 3 shows that the optimized fuzzy controller based on the SFLA performs better in comparison with the traditional PID controller, and this demonstrates the capability of the proposed method. In addition, in Table 4, a comparison between the proposed method based on the optimized fuzzy with conventional methods such as PID and reference [29] has been made in terms of the generator angle performance, which shows that the proposed controller has a lower generator angle during the loading conditions of the studied system. Table 5 shows the performance of the suggested controller when only the fuzzy combination of PSS and UPFC is used, which shows that it will not perform well without optimization. It can be seen from Tables 4 and 5 that the use of UPFC alone can even have a negative effect on the generator oscillation, which is due to the UPFC's attempt to keep the line power constant after a fault occurs in the network. Fig. 8 shows the convergence of the optimization problem using the SFLA method. As is observed in the figure, the objective function converged after 50 iterations, which shows the optimal performance of the SFLA in finding the fuzzy controller coefficients.

The response of different controllers considering different load levels of 80%, 100%, and 110% are shown in Figs. 9 to 14. Fig. 9 compares the speed response of four controllers, including the proposed method in which the parameters of the fuzzy controller are optimized with the SFLA; the fuzzy controller; the conventional control

including only PID; and finally, when no controller is applied to the single-machine system. After disturbing the input mechanical power of the generator, the generator speed fluctuates and these fluctuations are comparable for these four controllers in Fig. 9 for the capacity equivalent to 80% of the nominal load, which show that the optimized fuzzy controller gives the best response with suitable settling time and damping.

Fig. 10 shows the changes in the system voltage for 80% of the rated load, where the proposed fuzzy optimized controller (PSS and UPFC) with overshoot of less than 0.5% and without undershoot was able to reach a stable state. On the other hand, the graph has higher overshoot and undershoot for the fuzzy controller. The conventional PID controller has also reached a steady state after several overshoots and undershoots.

Table 5: A comparison between the performance of different controllers in terms of network loading according to the generator angle ( $\delta^\circ$ )

Controller	80%	100%	110%
PSS	-----	55.01	69.83
UPFC	42.79	58.74	70.65
PSS&UPFC-PID	40.52	53.91	67.52
PSS&UPFC-Fuzzy	42.86	54.19	68.42
Ref [29]	39.72	52.45	66.61
The proposed controller	38.16	51.39	64.17

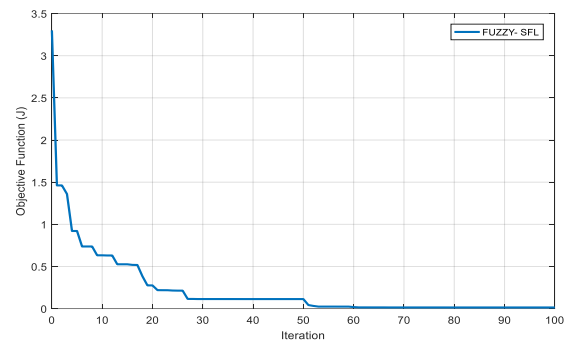


Fig. 8: Convergence curve of the SFLA for minimization of the proposed objective function

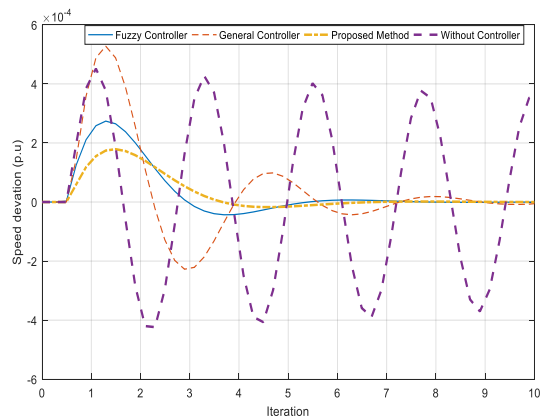
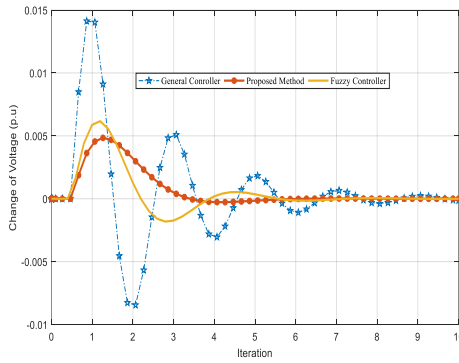


Fig. 9: Comparison of the response of speed changes of three controllers for UPFC and PSS in 80% of the rated load.

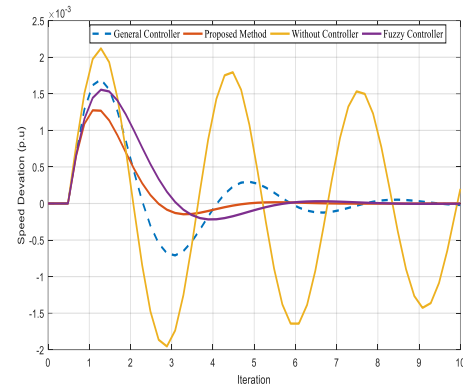


**Fig. 10:** Generator voltage deviation to show the performance of three controllers at 80% of the rated load

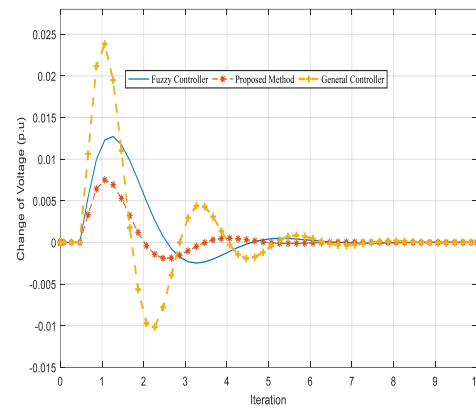
In Figs. 11 and 12, the diagram of speed deviation and voltage changes of the studied system at rated load is displayed. At rated load, the suggested controller has a faster damping response and a shorter settling time. In Fig. 11, the system lacks any controller and the excitation system lacks PSS. By sorting the linearized state equations of the system that were extracted in Section 2, they were implemented in the MATLAB software under normal load conditions and the outputs were displayed. After disturbing the mechanical power input of the generator, the generator speed fluctuates and the fluctuations are not dampened. Even though the PID controller has been able to reduce the magnitude of oscillations, the number of overshoots and undershoots is high. However, the fuzzy controller has reached the damping state after almost two oscillations, and finally, the optimized fuzzy control has been able to show a fast-damping response.

In Figs. 13 and 14, for a 10% increase in rated load, the time response of generator speed changes along with voltage changes for the three state controllers are shown. It can be seen from Fig. 13 that the optimized fuzzy controller responded well to the changes and was able to dampen the response, while the other two controllers reached the damping mode after several oscillations. If the PSS and UPFC controls are not used, the system remains unstable. Fig. 14 shows that the voltage deviation is fixed after approximately three seconds.

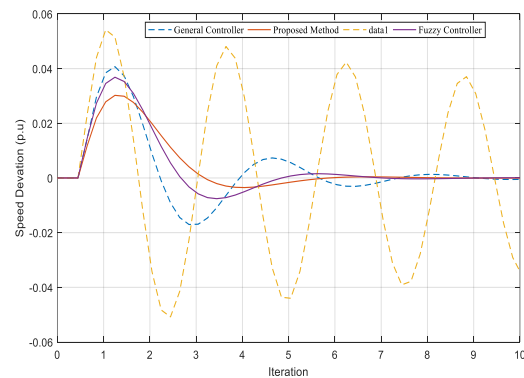
The simplest method among the three used controllers is the PID controller, which is designed by the phase compensation method considering the state of the system poles. By installing these controllers, it is possible to obtain feedback from the speed changes and damp the system by applying changes to the PSS and UPFC inputs. Nonetheless, the results showed that the settling time of the system as well as the overshoot in this method is more compared to the fuzzy and optimized fuzzy methods. The comparison between these two methods in the design of the controller also shows that using the optimized gains in the fuzzy method, the damping speed of the system and the magnitude of oscillations have decreased. It should be noted that the simultaneous use of both PSS and UPFC controllers will have a significant impact on the system performance after a disturbance appears in the system, while the absence of these controllers, as shown in Figs. 9, 11, and 13, causes system instability. Fig. 15 depicts the output of the fuzzy signals based on the inputs used for the UPFC controller.



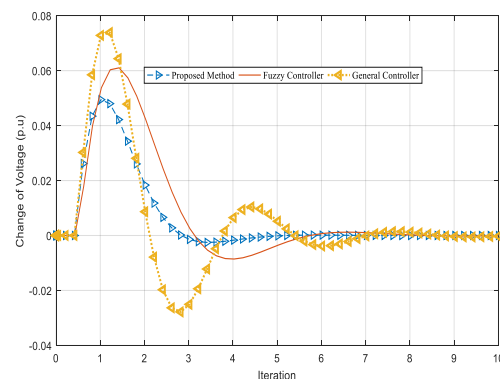
**Fig. 11:** Comparison of the response of speed changes of three controllers for UPFC and PSS in the rated load mode



**Fig. 12:** Generator voltage deviation to show the performance of three controllers at the rated load



**Fig. 13:** Comparison of the speed changes response of three controllers for UPFC and PSS at 110% of the nominal load



**Fig. 14:** Generator voltage deviation to show performance of three controllers at 110% of the rated load

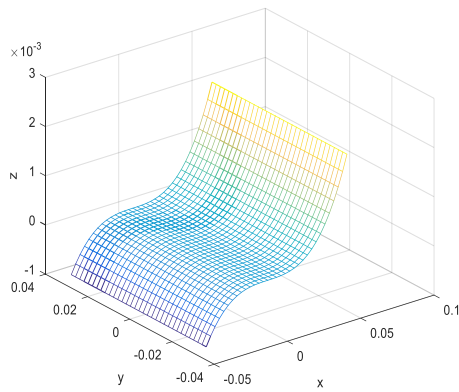


Fig. 15: Optimized fuzzy controller output for input  $\delta_e^{UPFC}$

## 6. DISCUSSION AND RESULTS

This section explores how varying SFLA parameters influence the optimization of the proposed objective function.

### 6.1 Parameter Setting Problem:

We leverage research and experimentation to recommend appropriate Shuffled Frog Leaping Algorithm (SFLA) parameters based on the problem's characteristics, such as the number of variables and desired accuracy. Considering these factors, we have chosen to use 7 memplexes, each containing 15 frogs.

### 6.2 Convergence problem:

To address these convergence challenges, we implemented the following strategies:

- **Increased Population Diversity:** We experimented with a larger frog population (15 frogs) distributed across 7 memplexes. This improves diversity and enhances the likelihood of exploring the entire search space effectively.
- **Adaptive Leaping Distance:** Equation (20) details how we implemented an adaptive leaping distance mechanism. This allows each frog to dynamically adjust its search range based on the current iteration. This approach balances exploration in the early stages with exploitation later in the optimization process. The results demonstrate the effectiveness of these strategies. As shown in Figure 7, the SFLA algorithm achieves convergence after only 55 iterations.

### 6.3 Sensitivity to high dimensions:

The SFLA is well-suited for problems with large search spaces. However, its performance can suffer when dealing with high dimensionality. This is because the complexity of the search space increases exponentially with each added dimension, making exploration more challenging for SFLA. While some research suggests exploring alternative algorithms for very high dimensions [30], the proposed problem in this work has only 6 variables. This dimensionality falls within a range where SFLA can be effective (as shown in Figure 7). Therefore, the search space size and dimensionality of the proposed problem were well-suited for the application of SFLA in this work.

## 6.4 Current Landscape:

While fuzzy logic control is not yet the dominant approach for PSS and UPFC applications, research and development efforts are ongoing. Pilot projects and demonstrations are helping to establish the technology's potential. As the challenges are addressed and the benefits become more widely recognized, the use of optimized fuzzy logic control for power system stabilization is likely to become more feasible in practice.

## 6.5 Reaction Time Considerations

The SFLA optimization is performed offline (not in real-time) to determine optimal fuzzy controller gains, and then execution time is less critical. The gains can be pre-calculated and stored for real-time use by the fuzzy controller.

## 6.6 Gaps and Challenges of the Proposed Method

Integrating a new control system like this with existing protection and control infrastructure requires careful planning and testing. Regulatory considerations specific to each region might also need to be addressed. Also, the performance of the method might be highly dependent on the specific power system it's designed for. Further research might be needed to explore how well the approach generalizes to different power system configurations and operating conditions.

## 7. CONCLUSION

The paper presented a new control strategy that coordinated PSS and UPFC controllers by applying fuzzy rules. Moreover, SFLA was utilized to adjust the parameters of fuzzy functions to deal with sub-synchronous oscillation. An outstanding benefit of the proposed technique, in contrast to conventional controllers, is its ability to deliver a time-varying control signal continuously. This ensures that the system consistently adheres to the correct trajectory, and it can be implemented for non-linear systems without the need for mathematical modeling of the system. The simulation results including the optimized fuzzy controller showed its proper performance under different loading conditions of the system during a disturbance in the system. By introducing a combined index of the amounts of overshoot, undershoot, and settling time for the suggested fuzzy controller, this index showed up to 100% improvement compared to that obtained by conventional PID controllers. In addition, the first angle of the generator in different loading conditions was lower compared to other methods. For future works, other methods can be incorporated in optimizing the gains of the fuzzy controller, or the effect of adding the UPFC in a suitable place to boost the system damping can be investigated.

## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

**Mohammad Abedini:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Roles/Writing - original draft. **Mahyar Abasi:** Conceptualization, Supervision, Validation, Roles/Writing - original draft.

## DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent,



misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

#### REFERENCES

- [1] J. Ruan, Z. Shi, M. Yu, et al., "Simplified damping analysis and suppression method for low-frequency oscillation introduced by virtual synchronous generator", *Journal Power Electron*, vol. 21, no. 10, pp. 1600–1610, Oct. 2021.
- [2] P. Dey, S. Anulekha, M. Sourav, D. Bishwajit, B. Aniruddha, and M. Boonruang. "Improvement of Small-Signal Stability with the Incorporation of FACTS and PSS." In *2021 Control Applications in Modern Power System: Select Proceedings of EPREC 2020*, 2021, pp. 335-344.
- [3] S. Kumar, A. Kumar and G. Shankar, "Crow search algorithm based optimal dynamic performance control of SVC assisted SMIB system," *2018 20th National Power Systems Conference (NPSC)*, 2018, pp. 1-6.
- [4] N. Sahu, M. Singh, S. Ralhan, "Performance analysis of hybrid controller in SMIB system using metaheuristic optimization techniques under different design criteria", *Journal on Future Engineering & Technology*, vol. 16, no. 1, 2020.
- [5] E. Afzalan, and M. Joorabian, "Analysis of the simultaneous coordinated design of STATCOM-based damping stabilizers and PSS in a multimachine power system using the seeker optimization algorithm", *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 1003–1017.
- [6] L.-J. Cai, and I. Erlich, "Simultaneous coordinated tuning of PSS and FACTS damping controllers in large power systems," in *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 294-300, Feb. 2005
- [7] M. Chandhari, G. Andersson and I. A. Hiskens, "Control Lyapunov functions for controllable series devices," *2002 IEEE Power Engineering Society Winter Meeting. Conference Proceedings*, 2002, pp. 753.
- [8] L. F. B. Martins, P. B. de Araujo, E. de Vargas Fortes, and L. H. Macedo, "Design of the PI-UPFC-POD and PSS damping controllers using an artificial bee colony algorithm", *Journal of Control, Automation and Electrical Systems*, vol. 28, no. 6, pp. 762–773, 2017.
- [9] E. d. V. Fortes, L. H. Macedo, P. B. d. Araujo, and R. Romero, "A VNS algorithm for the design of supplementary damping controllers for small-signal stability analysis", *International Journal of Electrical Power & Energy Systems*, vol. 94, pp. 41–56, 2018.
- [10] E. de Vargas Fortes, P. B. de Araujo, and L. H. Macedo, "Coordinated tuning of the parameters of PI, PSS and POD controllers using a Specialized Chu-Beasley's Genetic Algorithm", *Electric Power Systems Research*, vol. 140, pp. 708–721, 2016.
- [11] H. Shayeghi, A. Safari, and H. A. Shayanfar, "PSS and TCSC damping controller coordinated design using PSO in multimachine power system", *Energy Conversion and Management*, vol. 51, no. 12, pp. 2930–2937, 2010.
- [12] L. H. Hassan, M. Moghavvemi, H. A. F. Almurib, and K. M. Muttaqi, "A coordinated design of PSSs and UPFCbased stabilizer using genetic algorithm", *IEEE Transactions on Industry Applications*, vol. 50, no. 5, pp. 2957– 2966, 2014.
- [13] M. Khaksar, A. Rezvani, and M. H. Moradi, "Simulation of novel hybrid method to improve dynamic responses with PSS and UPFC by fuzzy logic controller", *Neural Computing & Applications*, vol. 29, no. 3, pp. 837–853, 2016.
- [14] B. Mohandes, Y. L. Abdelmagid, and I. Boiko, "Development of PSS tuning rules using multi-objective optimization", *International Journal of Electrical Power & Energy Systems*, vol. 100, pp. 449–462, 2018.
- [15] M. Saini, M. R. Djalal and A. M. S. Yunus, "Optimal Coordination PID-PSS Control Based on Crazyness Particle Swarm Optimization in Sulselrabar System", *2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2022, pp. 695-699.
- [16] M. R. Djalal, M. Saini and A. S. Yunus, "Optimization Power System Stabilizer and Energy Storage Using Ant Colony Optimization" in *2021 International Seminar on Machine Learning Optimization and Data Science (ISMODE)*, 2022, pp. 120-124.
- [17] D. K. Sambariya and R. Prasad, "Design of PSS for SMIB system using robust fast output sampling feedback technique," *2013 7th International Conference on Intelligent Systems and Control (ISCO)*, 2013, pp. 166-171
- [18] M. Rais, M. R. Djalal, V. A. Tandirerung, R. Aminuddin, I. Syarif and Rosmiati, "Coordination PID-PSS Control Based on Ant Colony optimization In Sulselrabar System", *2022 2nd International Seminar on Machine Learning, Optimization, and Data Science (ISMODE)*, Jakarta, Indonesia, pp. 254-258,2022.
- [19] Tang K. S. Kim Fung Man, Guanrong Chen, and Sam Kwong, 2001, "An Optimal Fuzzy PID Controller", *IEEE Transactions on Industrial Electronics*, Vol. 48, No. 4, August 2001.
- [20] G. Shahgholian, H. Karimi, H. Mahmoodian, "Design a power system stabilizer based on fuzzy sliding mode control theory", *International Review on Modelling and Simulations*, vol. 5, no. 5, pp. 2191-2196, Oct. 2010.
- [21] W. Fang, H.W. Ngan, "Enhancing small signal power system stability by coordinating unified power flow controller with power system stabilizer", *Electric Power Systems Research*, Vol. 65, No. 2, pp.91-99, May 2003.
- [22] S. Mishra, "Neural-network-based adaptive UPFC for improving transient stability performance of power

- system", *IEEE Trans. Neural Networks*, vol. 17, pp. 461-470, 2006.
- [23] B.C. Pal, "Robust damping of interarea oscillations with unified power flow controller", *IEE Proceedings-Generation, Transmission and Distribution*, vol. no. 6, pp. 733-8. 2022.
- [24] H. Wang, "A unified model for the analysis of FACTS devices in damping power system oscillations. III. Unified power flow controller," in *IEEE Transactions on Power Delivery*, vol. 15, no. 3, pp. 978-983, July 2000.
- [25] M. Jokarzadeh, M. Abedini, A. Seifi, "Improving power system damping using a combination of optimal control theory and differential evolution algorithm", *ISA transactions*, vol. 90, pp. 169-77, July 2019.
- [26] Y. Zhang, S. Guan, Y. Zhang, "Single-Stage AC-AC Converter with Controllable Phase and Amplitude", *IEEE Transactions on Power Electronics*, vol. 34, no. 7, pp. 6991-7000, 2019.
- [27] J. C. Bezdec, *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, 1981.
- [28] H. Moayedi, DT. Bui, PT. Thi Ngo, "Shuffled Frog Leaping Algorithm and Wind-Driven Optimization Technique Modified with Multilayer Perceptron", *Applied Sciences*, vol. 10, no. 2, pp. 689, 2020.
- [29] T.K. Mok, Haoming Liu, Yixin Ni, Felix F. Wu, Ron Hui, "Tuning the fuzzy damping controller for UPFC through genetic algorithm with comparison to the gradient descent training", *International Journal of Electrical Power & Energy Systems*, vol. 27, no. 4, 2005.
- [30] X. Tao, H. Li, C. Mao, "Developing Shuffled Frog-Leaping Algorithm (SFLA) Method to Solve Power Load-Constrained TCRTO Problems in Civil Engineering", *Advances in Civil Engineering*, vol. 19, no. 2, 2019.
- [31] O. Muhammed Neda "Optimal coordinated design of PSS and UPFC-POD using DEO algorithm to enhance damping performance", *International Journal of Electrical and Computer Engineering (IJECE)* 2020; 10 (6) :611-621.

#### BIOGRAPHY



**Mohammad Abedini** was born in Boroujerd, Iran, in 1986. He received his B.Sc degree in electrical engineering from the Islamic Azad university of Borujerd, Borujerd, Iran in 2006. M.Sc. and Ph.D degrees in electrical engineering from Bu-Ali Sina University in 2008 and 2010, respectively. He is currently an associate professor at ayatollah Borujerdi university. His current research interest includes microgrids and distribution systems.



**Mahyar Abasi** was born in 1989 in Iran. He graduated with a Ph.D. in Electrical Power Engineering from Shahid Chamran University of Ahvaz, Ahvaz, Iran in 2021. He has published more than 60 journal and conference papers, more than 10 authored books, 11 industrial research projects and a patent in the field of power systems. In 2021, he was introduced as the top researcher of Khuzestan province, Iran, and in the years 2021 to 2023, he was successful in receiving 4 titles from the membership schemes of the National Elite Foundation in Iran. He is currently an assistant professor in the Electrical Engineering department of Arak University, Arak, Iran. His specialized interests are fault protection, detection, classification and location in HVAC and HVDC transmission lines, control of reactive power and FACTS devices, evaluation and improvement of power quality and power system studies.

#### Copyrights

© 2024 by the author(s). Licensee Shahid Chamran University of Ahvaz, Ahvaz, Iran. This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution –NonCommercial 4.0 International (CC BY-NC 4.0) License (<http://creativecommons.org/licenses/by-nc/4.0/>).

