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# An optimal controller for FACTS devices based on fuzzy rules and bees algorithm

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ABSTRACT

Power systems including a collection of dynamic interconnected subsystems and devices. The control systems must have the capability of coordinating all sub-controllers under diverse operating conditions and limits. In the last decades, to cope with the increasing need for electric power, more and more FACTS devices are employed to enhance the transmission capability of the existing transmission system. As a result, the stability margin of power systems has decreased as the complexity of power systems has increased dramatically. This paper introduces the design and analysis of a nonlinear variable-gain ANFIS controller for a flexible ac transmission systems (FACTS) device such as the unified power flow controller (UPFC) to improve the transient stability efficiency of power systems. In ANFIS training, the radius vector of clusters has a high effect on the efficiency of ANFIS. For his reason in this paper, the bees algorithm is suggested in finding the optimum radius vector. Computer simulation results confirm the superior performance of this hybrid controller.



## 1. Introduction

With the deregulation and privatization of electricity supply, power systems are operating much near to their stability boundaries than ever before. The implementation of Flexible AC Transmission Systems (FACTS) devices to improve the power system stability has been widely recognized in the past (Hingorani et al., 2000; Handschin et al., 2003). As a result, the stability margin of power systems has reduced as the complexity of power systems has increased sizable. Therefore, new devices in power system control which can enhance the dynamic operation and transient stability of power systems present an even more formidable trouble.

Transient stability and voltage setting are two important criterion in power system performance. The turbulence of power systems may not just cause the system losing synchronism but also result in short-term voltage distortion. This need to the control system to have the capability to suppress the potential instability and poorly damped power angle fluctuations that can be hazardous for the system stability, and to compensate the voltage distortion that can harm both utility and customer devices.

For several decades, power system stabilizers (PSSs) have been one of the dominant common controls applied to damp out fluctuations and to offset the negative damping of the automatic voltage setting. The main figure of PSSs is to present a modulating signal acting through the stimulation system to add to rotor fluctuations damping. But, during some operating situations, this device may not produce sufficient damping, especially to inter-area states (Lei et al., 2001) and, hence, other impressive superseded are needed in addition to PSSs. In recent years, FACTS technology is appear as an interesting method to help in alleviating several power system operating problems, such as inter-area fluctuations and controlling voltages at critical nodes.

Amongst the all FACTS devices for transient stability improvement, the unified power flow controller (UPFC) is the dominant versatile one (Laifa and Boudour, 2010; Noroozian et al., 1997; Noroozian and Adersson, 1994; Dai et al., 2009). The UPFC is a solid-state controller based on high-power electronics equipment to control active power and reactive power flows in a transmission system. The UPFC comprises a series voltage-source converter and a parallel voltage- fount converter, each of which may be simulated as a controllable voltage fount. This is realized by connecting a voltage- fount converter through a transformer in series with the transmission line and other one in parallel at the same point of connection through a same transformer. The parallel branch of the UPFC produces the necessary voltage support to the connected bus and changes active power from the bus with the series-connected voltage fount. The power balance between the series and the parallel converters is a prerequisite to maintain a constant voltage through the dc capacitor contacted between the two mentioned converters. As the series branch of the UPFC infusion a voltage of variable amplitude and phase angle, it can change active power with the transmission line and, therefore, enhances the power flow ability of the line and its transient and small-signal stability boundaries. The parallel branch, however, can independently exchange non-active power with the transmission system.

Many control approaches for controlling the amplitude and phase angle of the series-voltage fount and the parallel-reactive current amplitude have been introduced recently (Noroozian et al., 1997; Noroozian and Adersson, 1994; Dai et al., 2009; Huang et al., 2000; Ramasubramanian et al., 2012). The infusion voltage can be divided into two parts, which are in phase (real voltage) and the quadrature (reactive voltage) with the line current. Controlling the quadrature part of the series voltage can impressively control the just active power through the transmission line.

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In the same strategy, by controlling the part of the voltage in phase with the line current, which may be measured territorially, one can control the reactive power flow through the transmission line. The active and reactive power references are achieved from the steady-state power flow essentials.

The PI corrector used for control of FACTS devices (Huang et al., 2000) toil from the inadequacies of providing sufficient control and transient stability improvement over a widespread bound of power system operating situations. A radial basis FACTS function neural network (RBFNN) control plane has also been proposed for the UPFC to damp the electromechanical fluctuations of the power system (Ramasubramanian et al., 2012). Linearized power system patterns with UPFCs have been introduced in Wang (2000) and Ramírez and Coronado (2002) to provide control signal vectors to damp out inter-area fluctuations. Since these controllers are extracted from a small-signal patterns scheme at a given operating position, they don't have optimal values usually. Besides the nonlinear inherent of the power system performance necessitates the spread of a nonlinear linear or nonlinear controller. The fuzzy-logic (Limyingcharoen et al., 1998) technique, on the other hand, supply a model-free way for UPFC control and may be powerful over the entire boundary of power system performance. In addition, the fuzzy-logic way permits the knowledge from experiences to be incorporated to the control model as a set of oral rules, fuzzy motor, constant parameters and membership functions. The fuzzy method, which is used in the drafting of a FACTS corrector, uses oral rules for both antecedent and consequent components. This controller is not able to supply a widespread variation of the control gains as may be required for the performance of the UPFC as an impedance amends, phase-angle corrector, or a voltage setting. Instead, a Takagi–Sugeno (TS)-model fuzzy controller, which supply a widespread change of the control gains and could use either both a linear consequent rule base or a nonlinear one based on the power or voltage fault, and its integral operator or its derivative operator. A last type of this controller (Shaheen et al., 2010) is introduced to be very powerful for a wide variety of nonlinear control applications. Both the series and parallel power flow correctors of the UPFC using TS fuzzy control supply very good damping and dynamic operation enhancement in case of power systems subjected to a variety of transient disarray. In fuzzy operating part, adaptive neuro-fuzzy inference system (ANFIS) is used. The applied system uses fuzzy rules for UPFC control. Neuro-fuzzy method uses a heuristic learning algorithm whose high performance has been proved in many articles and books (Avci et al., 2007; Hosoz et al., 2011; Keleş et al., 2011; Lau et al., 2010). Therefore, proposed system has a strong inference engine containing fuzzy rules that can identify hidden relations in the case unrecognized by the man specialist. In ANFIS training process, the radius vector of clusters has high effect on operation of fuzzy motor. Thus in this paper, bees algorithm (BA) is suggested to select the optimal radius vector. Several case studies are presented in the simulation results section.

The rest of this paper is organized as follow. Section two describes the UPFC model and formulation. Section three presents the ANFIS concept and its connections. Section four describes the bees algorithm optimization technique. Section five presents proposed method and some simulation results and finally section six conclude the paper.

## 2. UPFC structure

A Unified Power Flow Controller (or UPFC) is an electrical device for supply fast-acting reactive power compensation on high-voltage electricity transmission system. It applies a double pair of three-phase controllable bridges to supply current that is infusion into a transmission line by a series transformer. The corrector can control real and non-real power flows in a transmission system. The UPFC applies solid state parts, which supply functional flexibility, generally not attainable by conventional thyristor controlled devices. The UPFC is a combination of a static synchronous compensator (STATCOM) and a static synchronous series compensator (SSSC) coupled by a common DC voltage connector. The UPFC permits a secondary but important function such as stability control to suppress power system fluctuations enhance the transient stability of power system. The UPFC consists of double voltage source converters; series and parallel converter, which are connected to each other with a common dc connector. Series converter or Static Synchronous Series Compensator (SSSC) is used to add controlled voltage amplitude and phase angle in series with the line, while parallel converter or Static Synchronous Compensator (STATCOM) is used to supply reactive power to the ac system, besides that, it will supply the dc power needed for both inverter. Each of the branches include of a transformer and power electronic device converter. These two voltage original converters shared a common dc capacitor (Hingorani and Gyugyi, 2000; Xu and Agelidis, 2002). The energy reserving ability of this dc capacitor is common small. Thus, real power drawn by the parallel converter should be equal hence to the real power provided by the series converter. The reactive power in the parallel or series converter can be selected independently, giving greater flexibility to the power flow control. The coupling transformer is applied to link the equipment to the system.

The UPFC scheme is presented in the Fig. 1 that shows the scheme of the UPFC; the Generator G is connected with the nodes m and n and the converters are connected by transformer. It consists the impedances of the converter such as series impedance Zse, load impedance ZL, parallel capacitors impedance Zsh and Generator side impedance ZG, generally we have four impedance. Also we have series transformers and infinite bus. The converters are connected with the DC link capacitor Cdc with voltage Vdc capacity that illustrated in Fig. 1. These can be incorporated to the UPFC power flow formulations, which are needed to find the power system clue values like equality and inequality limits. It can done due to the outage of generators presented in the power system, because the utilization side requires demand satisfaction at all seconds. The disturbed values are defined in the following lines.

The power system commonly contributes to the satisfaction of total lack of the utilities. Here, the system provides must satisfy the total lack of the loads and power loss of the transmission system lines. It is denoted as the equality limits or power balance situation of the power system. The generators introduced in the system get outage; it may enhance the power loss and affect the dynamic stability performance. The needed power balance situation is shown in Eq. 1.

$$\sum_{i=1}^{N_G} P_G^i = P_D + \sum_{j=1}^{N_G}\left(P_L^j + jQ_L^j\right) \tag{1}$$

where $P_G^i$ is the power generated in the ith node, $P_D$, the lack, $P_L^j$ and $Q_L^j$, the active and reactive power losses of the jth node, which are computed by the:

$$P_L^j = |V_i||V_j||Y_{ij}|\sum_{n=1}^{N}\cos(\alpha_{ij} - \delta_i - \delta_j) \tag{2}$$

$$Q_L^j = |V_i||V_j||Y_{ij}|\sum_{n=1}^{N}\sin(\alpha_{ij} - \delta_i - \delta_j) \tag{3}$$

here $V_i$ and $V_j$ are the voltage value of the nodes i and j, $Y_{ij}$, the node admittance value matrix, $\alpha_{ij}$, the angle between the nodes i and j, $\delta_i$ and $\delta_j$, the load angles values of i and j nodes. Also power system dynamic performance stability mainly imagined the voltage profile of every bus. The stable power flow require the voltage at each node at the boundary of 0.95–1.05 pu. The change in voltage is shown in the Eq. 4.

$$\Delta \mathrm{V_i} = \frac{1}{\sqrt{\mathrm{l}}}\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{l}}\left(V_i^k\right)^2} \tag{4}$$

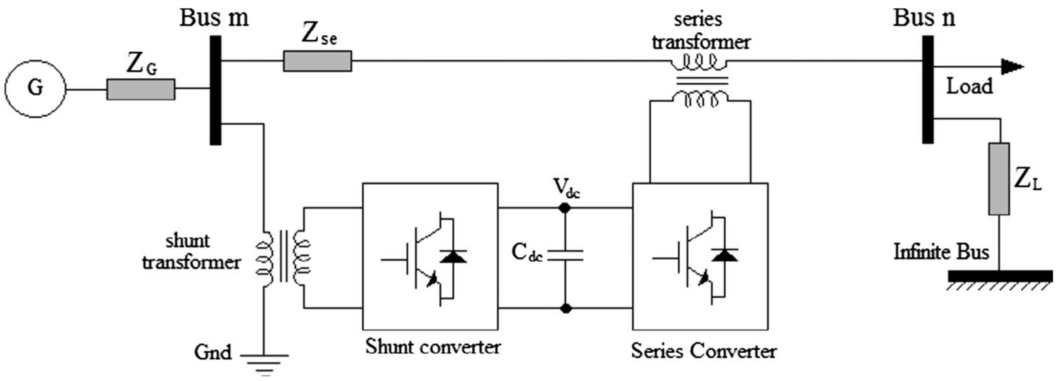


**Fig. 1.** Scheme of the UPFC.

Each synchronous generator in a single-machine infinite-bus system or a multi machine power system is modeled as a third order model equipped with a simple automatic voltage regulator (AVR) for excitation control. Also, a PSS is used for correcting the local modal fluctuations, as said in previous lines. In the system for highlighting the powerfulness of UPFC control, we used no speed governor. Also no damper winding is schemed, because the goal is investigating the operation of UPFC controllers. The dynamics formulation of each synchronous machine is described below:

$$\omega = \omega_0 + p\delta, \mathrm{p} = \frac{\mathrm{d}}{\mathrm{dt}} \text{(differentialoperator)}$$
$$\mathrm{p}\omega = \frac{\pi f}{H}(P_m - P_e)$$
$$pE_q^{/} = \frac{\left(E_{fd0}+\Delta E_{fd}-E_q^{/}-\left(x_d-x_d^{/}\right)\right)}{\tau_{d0}^{/}} \tag{5}$$
$$p\Delta E_{fd} = \frac{K_e(V_{ref}-V_t+u)}{\tau_e} - \frac{\Delta E_{fd}}{\tau_e}$$
$$and - 6.0 \leq E_{fd} \leq 6.0$$
$$\mathrm{P_e} = E_q^{/} i_q + (x_q - x_q^{/}) i_d i_q$$

In the above equation, control $u$ is achieved from the PSS control loop as:

$$u = K_\delta\left(\frac{s.t_q}{1+s.t_q}\right).\left\{\frac{(1+s.t_1)}{(1+s.t_2)}\right\}\Delta\omega \tag{6}$$

The algebraic formulation for both single and multi-machine power systems are simple after incorporating two controllable loads $Y_s$ and $Y_r$ for the UPFC. For the multi machine case, just the generator nodes are retained at last for transient stability investigation. The next section presents the fuzzy logic base controller for generating a widespread change of nonlinear gains for controlling the phase $V_{cp}$ and quadrature $V_{cr}$ part of the UPFC.

## 3. Adaptive network based fuzzy inference system (ANFIS)

The adaptive network based fuzzy inference system or ANFIS introduces an effective artificial neural network approach for the solution of function approximation cases. Data extraction procedures for the synthesis of ANFIS systems are usually based on clustering a training dataset of numerical samples of the vague function to be learned. Since introduction, ANFIS systems have been successfully applied to detection cases, rule-based process system controls, pattern recognition and identification problems and the like of these. ANFIS structure is a multilayer feed-forward network in which each node does a special function on input signal vectors and has a set of parameters pertaining to this node. Similar to ANN, ANFIS is capable of mapping unknown input dataset to their output datasets by training the rules from previously seen dataset. Here a fuzzy inference system comprises of the fuzzy model proposed by Takagi and Sugeno (1993) to systemize a systematic method to provide fuzzy rules from an input dataset- output data set.

In this section we briefly describe the ANFIS structure. For this purpose and for simplicity, we assumed that the fuzzy inference system under consideration has double inputs and just one output. The rule base include two fuzzy if-then rules of Takagi and Sugeno'stype (Takagi and Sugeno, 1983) as defined as follows:

$If$ x is A and y is B then z is f(x, y)

In the above relation, $A$ and $B$ are the fuzzy variable sets in the antecedents and $z = \mathrm{f}(\mathrm{x}, \mathrm{y})$ is a crisp function in the consequent. f(x, y) is commonly a polynomial or free degree for the input variables X and Y. However, it may be any other function, if it can approximately define the output of the system through the fuzzy territory as determined by the antecedent. If f(x, y) has constant value, a zero order Sugeno fuzzy model is built, which can be supposed to be a special model of Mamdani fuzzy inference system (Mamdani and Assilian, 1975) where each rule consequent is specified by a fuzzy singleton. If f(x, y) is taken to be a first order polynomial a first order Sugeno fuzzy model is built. For a first order two-rule Sugeno fuzzy inference system Mamdani fuzzy inference system, the two rules can be described as follow:

Rule 1: $If$ x is $\mathrm{A_1}$ and y is $\mathrm{B_1}$ then $\mathrm{f_1} = \mathrm{p_1x} + \mathrm{q_1y} + \mathrm{r_1}$
Rule 2: $If$ x is $\mathrm{A_2}$ and y is $\mathrm{B_2}$ then $\mathrm{f_1} = \mathrm{p_2x} + \mathrm{q_2y} + \mathrm{r_2}$

Here type-3 fuzzy inference system introduced by Takagi and Sugeno (1993) is applied. In this inference system the output of each rule is a linear composition of input variables and their sum by a constant term value. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure can be seen in Fig. 2.

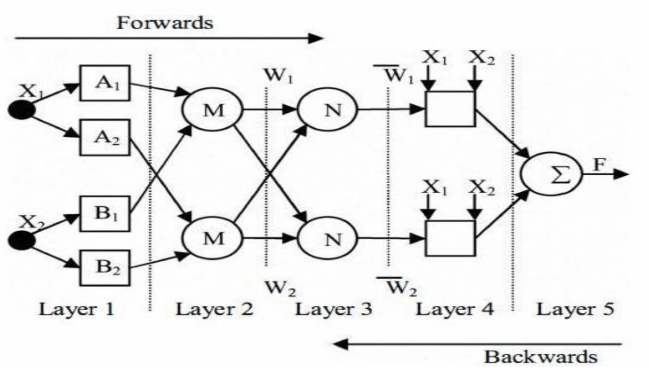


**Fig. 2.** ANFIS structure.

The role of each layer in the above structure is presented below:

*Layer 1*: In this layer, every node i has this relation:

$$O_i^1 = \mu_{A_i}(x) \tag{7}$$

here $x$ is the input to node $i$, and $A_i$ the linguistic variable linked with this node function and $\mu_{A_i}$ is the membership function of $A_i$ that defined before. But commonly $\mu_{A_i}(x)$ is selected as

$$\mu_{A_i}(x) = \frac{1}{1+[({x-c_i}/{a_i})^2]^{b_i}} \tag{8}$$

or

$$\mu_{A_i}(x) = \exp\left\{-(\frac{x-c_i}{a_i})^2\right\} \tag{9}$$

where $x$ is the input and $\{a_i, b_i, c_i\}$ is the premise parameter set.

*Layer 2*: In this layer each node is a constant node which computes the firing strength $w_i$ of a rule. The output of each node in this layer is the generate of all the input signals to it and is given by

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \mathrm{i} = 1{,}2 \tag{10}$$

*Layer 3*: Every node in this layer is a fixed node. Each *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of firing strengths of all the rules. The output from the *i*th node is the normalized firing strength given by

$$O_i^3 = \overline{w} = \frac{w_i}{w_1+w_2}, \mathrm{i} = 1{,}2 \tag{11}$$

*Layer 4*: Every node in this layer is an adaptive node with a node function described by

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(\mathrm{p_i x + q_i y + r_i}) \tag{12}$$

here $\overline{w_i}$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.

*Layer 5*: This layer comprises of just one constant node that computes the overall output as the adding of all input vector signals, i.e.,

$$O_i^5 = overall\mathrm{output} = \sum_\mathrm{i} \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{13}$$

More details regarding the extracting the initial fuzzy model can be found in (Chiu, 1994; 1996; Buragohain and Mahanta, 2008).

## 4. Bees algorithm

In soft computing science and operations research, the Bees Algorithm optimization is a population-based search algorithm which was introduced in 2005 (Pham.et al., 2006). It imitation the source of food foraging behavior of honey bee colonies. In basic version of the bees algorithm, the algorithm does a model of neighborhood probe combined with global probe, and maybe applied for both combinatorial optimization and continuous optimization. The just term for the application of the Bees Algorithm is that some measure of topological distance between the solutions is determined. The forcefulness and top abilities of the Bees Algorithm have been proven and studied in a number of literatures.

A collection of honey bees may extend itself over long interval (over than 14 km) and in multiple aims concurrently to harvest ambrosia or pollen from several food sources (flower patches). A small fraction of the colony constantly quests the environment looking for new flower patches. These scout bees move chance fully in the area surrounding the apiary, evaluating the profitability (net energy yield) of the food sources encountered. When they return to the apiary, the scouts deposit the food harvested. Those bees that found a better profitable food origin go to an environment in the apiary called the "dance floor", and perform a ritual known as the waggle dance. Through the waggle dance a scout bee shares the position of its discovery to idle onlookers, which join in the exploitation of the flower meadow. Since the length of the dance is proportional to the scout's rating of the food source, more foragers get recruited to harvest the best rated flower meadows. After frolicking, the scout come back to the food origin it found to collect more nectars. In this process that they are evaluated as fitness, better food origin will be advertised by the scouts as they return to the apiary. Recruited foragers may waggle dance as well, enhancing the recruitment for highly rewarding flower patches. Thanks to this autocatalytic process, the bee collection is capable to rapidly return the focus of the foraging effort on the main profitable flower meadows.

The pseudo code of bees algorithm is shown in Fig. 3. The algorithm needs a number of parameters to be determined, such as: number of scout bees (*n*), number of sites defined out of n searched sites (*m*), number of best directions out of m selected sites (*e*), number of bees recruited for best e directions (*nep*), number of bees recruited for the other (*m-e*) selected sites (*nsp*), initial size of patches (*ngh*) which consists directions and its neighborhood and stopping bet. The algorithm starts with the n scout bees being generated accidently in the search boundary. The fitnesses of the directions investigated by the scout bees are computed in next sage. In next stage (step 4), bees that have the best fitnesses are selected as "selected bees" and directions discovered by them are chosen for neighborhood search space. In next stage (steps 5 and 6), the algorithm leads searches in the neighborhood of the chosen directions, assigning more bees to search near to the best e directions. The bees may be chosen directly according to the fitnesses associated with the directions they are discover. Consequently, the fitness values are applied to assign the probability of the bees being chosen. Searches in the neighborhood of the best e directions which represent more promising outs are made more accuracy by recruiting more bees to pursuit them than the other chosen bees. Together with scouting, this differential recruitment is a key performance of the Bees Algorithm optimization.

Nevertheless, in stage 6, for each inset just the bee with the highest fitness will be chosen to build the next bee generation. In fact, there is no such a restriction in real world and nature. This restriction is introduced here to reduce the number of points to be explored in the optimization procedure. In next stage, i.e., step 7, the remaining bees in the population are determined accidently about the search space boundary scouting for new potential solutions to be explored by detail and closely. These stages are repeated and repeated until a stopping index is achieved. At the end of each iteration, the collection of all bees will have two components to its new generation representatives from each determined patch and other scout bees determined to lead random probes (Pham.et al., 2006).

*1. Generate the solution population in search space randomly.*
*2. Compute the fitness of the generated population.*
*3. While (stopping criterion is not met) //Forming new population.*
*4. Select sites for neighborhood search.*
*5. Recruit bees for determined directions (more bees for the best e sites) and compute fitnesses.*
*6. Select the fittest bee from each site.*
*7. Determine remaining bees to search randomly and compute their fitnesses.*
*8. End While*

**Fig. 3.** Pseudo code.

## 5. Proposed method

It can be seen that from papers and studies, regardless of the type, fuzzy controllers are only classical nonlinear controllers and may provide sufficient outcome when constructed in its true way. Compared with the existing types of many systems, a last type of a nonlinear variable- gain proportional and derivative type controller using the Takagi- Sugeno (TS) control rule structure has been introduced. The simplified Takagi–Sugeno (TS) rules are shown to parameterize the features of the gain changes, and therefore an infinitely large number of gain change features may be generated. For control the amplitude and phase angle of the series-converter voltage origin, the next steps is defined: the real or reactive power fluctuant are fuzzified by two incoming fuzzy sets with the name of P (positive) and N (negative), and the membership functions defined as follow:

$$\mu_P(x_i) = \begin{cases} 0 & x_i < -L \\ \frac{x_i+L}{2L} & -\mathrm{L} \le x_i \le L \\ 1 & x_i > \mathrm{L} \end{cases} \quad (14)$$

here $x_i(k)$ define fault at the $k$th sampling instant formulated by:

$$x_1(k) = e(k) = P_{ref} - P(k) \text{or} \mathrm{Q}_{\mathrm{ref}} - Q(k) \text{and} x_2(k) = \int e(k)$$

For the negative set we will have:

$$\mu_N(x_i) = \begin{cases} 1 & x_i < -L \\ \frac{-x_i+L}{2L} & -\mathrm{L} \le x_i \le L \\ 0 & x_i > \mathrm{L} \end{cases} \quad (15)$$

The membership functions for the fault and integration of fault can be seen in Fig. 4.

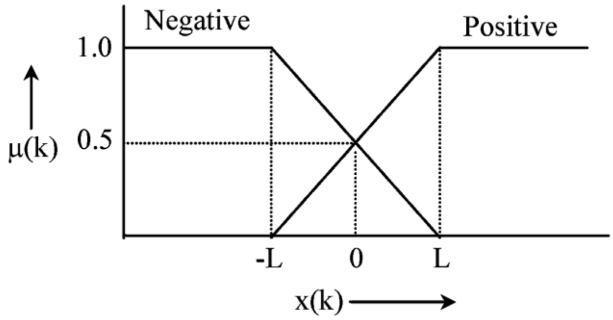


**Fig. 4.** Membership function.

In the Takagi-Sugeno fuzzy controller we have four fuzzy rule that given below:

$R_1$: If $\mathrm{e(k)}$ is positiveand $\int \mathrm{e(k)}$ is positive, then $\mathrm{u}_1(k) = K_1(a_1 e(k) + a_2 \int e(k) + a_3(\int e(k).\,|e(k)|))$

$R_2$: If $\mathrm{e(k)}$ is positiveand $\int \mathrm{e(k)}$ is negative, then $\mathrm{u}_2(k) = K_2 u_1(k)$

$R_3$: If $\mathrm{e(k)}$ is negative, and $\int \mathrm{e(k)}$ is positive, then $\mathrm{u}_3(k) = K_3 u_1(k)$

$R_4$: If $\mathrm{e(k)}$ is negative, and $\int \mathrm{e(k)}$ is negative, then $\mathrm{u}_4(k) = K_4 u_1(k)$

In these rule $u_1, u_2, u_3, and\ u_4$ denote the output of the TS fuzzy controller respectively. If we have use Zadeh's rules for the AND operation and the general defuzzifier, we will have following equation:

$$u(k) = \frac{\sum_{j=1}^{4}(\mu_j)^{\alpha} u_j(k)}{\sum_{j=1}^{4}(\mu_j)^{\alpha}} \quad (16)$$

But, for $\alpha = 1$, we get the centroid defuzzifer with $u(k)$ as below:

$$u(k) = a.\,e(k) + b \int e(k) + c.\,(|e(k)|.\int e(k)) \quad (17)$$

where

$$\begin{aligned} a &= a_1 K(x_1, x_2) \\ b &= a_2 K(x_1, x_2) \\ c &= a_3 K(x_1, x_2) \end{aligned} \quad (18)$$

and

$$K(x_1, x_2) = \frac{K_1(\mu_1 + K_2\mu_2 + K_3\mu_3 + K_4\mu_4)}{(\mu_1 + \mu_2 + \mu_3 + \mu_4)} \quad (19)$$

Consequently, the proportional and integral gains at any arbitrary instant will depends on fault and its integration. If the maximum values of fault and its relative integration are $L_1$ and $L_2$, respectively, then we will have:

$$\begin{aligned} &K(0,0) = \frac{K_1(1+K_2+K_3+K_4)}{4} \\ &K(L_1, L_2) = K_1,\ \mathrm{K}(L_1, -L_2) = \mathrm{K}_1 K_2 \\ &\mathrm{K}(-L_1, L_2) = \mathrm{K}_1 K_3,\ \mathrm{K}(-L_1, -L_2) = \mathrm{K}_1 K_4 \end{aligned} \quad (20)$$

This TS fuzzy controller is a very nonlinear variable-gain controller, and the factors $k_1, k_2, k_3, and\ k_4$ provide a widespread fluctuant of the controller gains. If the fuzzy controller apply all the 3 factors $a_1, a_2, and\ a_3$, it is named as a nonlinear rules (NLR) controller, and if it uses $a_1\ and\ a_2$ only, it is named as a linear rule (LR) controller.

We want to create a variable-gain PI controller by a TS fuzzy structure, the classical PI controller is created at first. $V_{\mathrm{cp}}\ and\ V_{\mathrm{cr}}$ are then achieved from the PI controller using the following equations

$$\begin{aligned} V_{cp} &= (\mathrm{K}_{\mathrm{PP}}.\,\Delta Q + K_{iP} \int \Delta Q) \\ \mathrm{V}_{\mathrm{cr}} &= (\mathrm{K}_{\mathrm{Pr}}.\,\Delta P + K_{ir} \int \Delta P) \end{aligned} \quad (21)$$

In Fig. 5 the classical PI control scheme is illustrated. The gains of the PI controller will be optimized using taking the $ITAE\left(\int_0^{t_{sim}} t|e(t)|dt\right)$ fitness function. The ITAE of the system at a special operating criteria is computed for vast values of $P$ and $I$ parameters. The balanced proportional and integral parameters are those for which ITAE is least. $K_{pp}$ and $K_{ip}$ are balanced by taking $\Delta Q$ as the fault, and the fault $\Delta P$ balance$K_{pr}$ and $K_{ir}$.

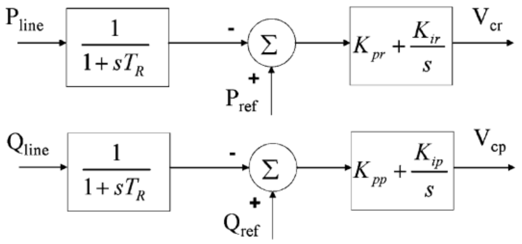


**Fig. 5.** Classical PI control structure.

The TS fuzzy controller is shown in Fig. 6. In this system the fuzzy rules achieved using ANFIS and the radius vector of ANFIS is selected by bees algorithm optimization technique.

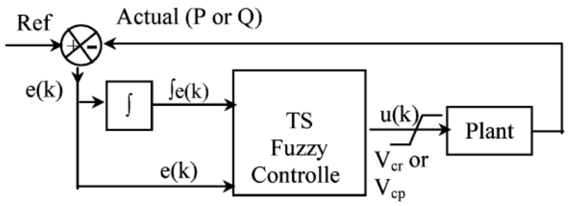


**Fig. 6.** Proposed method.

## 6. Simulation results

This section shows some simulation results and for this purpose we used the single-machine infinite-bus system as shown in Fig. 7. Large disturbances are created by initiating a three-phase error close to the infinite bus on the transmission line of power system. The classical PI controller is balanced at a low power level with $P = 0.8\ p.u., Q = 0.8\ p.u.$ The presented controller gains and relative power system parameters and constants are noted in the Tables 1 and 2 respectively.

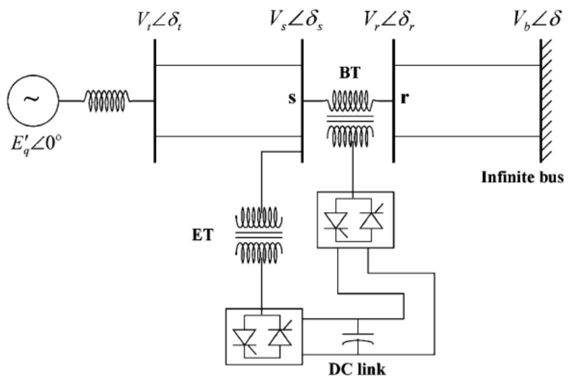


**Fig. 7.** Single-machine infinite-bus power system scheme.

**Table 1**
Power system parameters and constants.

| Single-Machine Infinite-Bus Data | | UPFC data in per units | |
|---|---|---|---|
| $x_d$ | 20 | $V_{dcbase}$ | 31.113 $Kv$ |
| $x_q$ | 1.9 | $MVA_{base}$ | 100 |
| $x'_d$ | 0.25 | C | 5500 $\mu f$ |
| $\tau'_{do}$ | 6s | $V_{cpmax}$ | 0.2 |
| H | 4s | $V_{crmax}$ | 0.2 |
| $x_e$ | 0.3 | $V_{cpmin}$ | -0.2 |
| $x_e$ | 30 | $V_{crmin}$ | -0.2 |
| $\tau_e$ | 0.05s | $X_{se}$ | 0.0006 |

**Table 2**
Controller parameters and constants.

| Tuned PI controller Both P and Q controller | | Optimized ANFIS controller by bees algorithm | | | |
|---|---|---|---|---|---|
| | | P Controller | | Q Controller | |
| $K_p$ | 0.3 | $L_1$ | 1 | $L_1$ | 0.5 |
| $K_i$ | 2 | $L_2$ | 0.2 | $L_2$ | 0.1 |
| | | $a_3$ | 60 | $a_3$ | 5 |

The following error investigations are done for testing the performance of the proposed controller.

Case 1: The loading situations of the generator are at a power level $P = 0.8\ p.u., Q = 0.8\ p.u.$ and a three-phase error of 0.1-s throughout is investigated close the infinite bus. In this case, the response with real and reactive power flow control is shown in Fig. 8, from which it may be seen that the TS fuzzy (NLR) in addition TS fuzzy (LR) done much best compared with the classical PI controller.

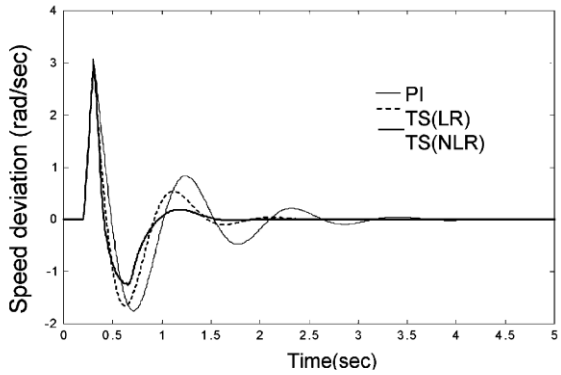


**Fig. 8.** Transient operation for a three-phase error close the infinite bus (P = 0.8 p.u., Q = 0.2 p.u.).

Case 2: To investigate the powerfulness of the proposed controller for higher loading situation, the power level is enhanced to $P = 1.2\ p.u., Q = 0.3\ p.u.$ The same condition, three-phase error occurs close the infinite bus at the high power level. Fig. 9 shows the transient reply of the power system with UPFC with TS (NLR), TS (LR) fuzzy control and the classical PI control. From the reply, it is can be seen that the first undershoot and the second overshoot are noticeably damped by the nonlinear consequent component in the rule base of the TS fuzzy controller TS (NLR) in comparison with the classical PI regulator in addition TS (LR) controller.

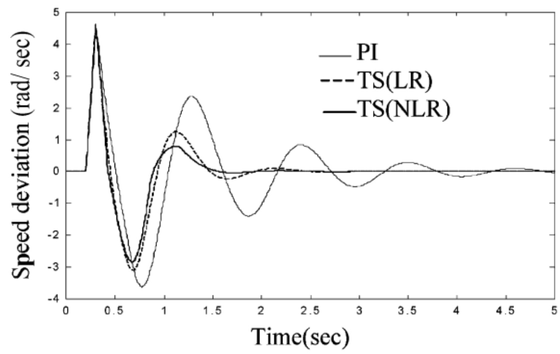


**Fig. 9.** Transient operation for a three-phase fault near the infinite bus (P =1.2 p.u., Q = 0.3 p.u.).

## 7. Conclusion

In this paper, we proposed a nonlinear variable-gain controller for the UPFC. Create of controller parameters is dealt with in great detail for enhancing the stability performance of a power system by a powerful type of the optimized TS ANFIS-control structure. The new fuzzy-logic-based control scheme provide a widespread fluctuant of the control gains, depending on the operating situations of the power system and, therefore, a high performance in comparison with the linear PI controllers applied in the UPFC. In the proposed TS ANFIS-control scheme, the rule consequent could be both a linear and a nonlinear function of input sets variable, and, therefore, a superb nonlinear variable- gain controller may be realized. The performance of the UPFC with the proposed optimized TS ANFIS-control scheme is tested vis-à-vis the classical PI control to support its superior performance in respect of transient stability improvement in a single-machine power system case. This controller or proposed method is found to be very powerful to error location and supply high transient stability performance enhancement over a wide range of operating fuzzy situations. Both inter-area and local modals of power system fluctuant are damped much rapidly by this proposed controller compared with the classical PI controller. Furthermore, the error clearing time is enhanced noticeably with this intelligent controller.

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