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Adaptive FACTS Transient Controller Design using ANFIS Technology

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Abstract

Adaptive Network based Fuzzy Inference System (ANFIS) approach adaptively actives transient stability controller for series FACTS devices during large disturbances in the large power system. Using the training data set, which is obtained by simulating over a wide range of operating situations and disturbance conditions, the parameters of the proposed controller are optimized using the ANFIS technology. The performance of the proposed controller can verified for the large power system under different disturbances. Simulation results validate the effectiveness of the proposed control strategy. Moreover, the approach is easy to realize and implement in real power systems.

Keywords: POD: power oscillation damping, FACTS: Flexible AC Transmission System, ANFIS: Adaptive network based Fuzzy Inference System.

Introduction

This paper deals with the development of adaptive FACTS transient controller using Adaptive Network based Fuzzy Inference System (ANFIS) technology. The approach adaptively switches between the transient stability controller and POD controller for series FACTS devices in large power systems. The designed controller using ANFIS technology adaptively activates the transient stability controller for series FACTS devices during large disturbances. Traditionally, the switching mechanism between FACTS transient controller and POD controller is achieved using a pre-set fixed switching time [1]. However, the optimal switching time is varied with different disturbances and different operating conditions. Moreover, the switching time cannot be automatically adjusted to different situations.

Switching strategy for FACTS transient controller

FACTS controller focuses mainly on the following three control objectives [1]:. Steady-state power flow control, transient stability control for improving the first swing stability, and power oscillation damping control to damp the power system oscillations. The comprehensive control scheme is shown in Figure 1 [1]. In this paper, the active power flow through the FACTS device is used as an input for the comprehensive control scheme.

The FACTS transient controller and POD controller achieve different control objectives in different situations. Conventionally, in order to enhance transient stability and damp the subsequent oscillations, a switching control strategy is always used between these two different controllers [1]. The switching control strategy is as follows:

- Following a large disturbance, the transient controller acts first to maintain the transient stability of power systems.
- After the pre-set switching time period T_0, the control is then transferred to the power flow and POD controller. During the post-fault oscillations, due to the large integral time constant of $T_{I\text{-}s}$, the POD controller has the most influence.

The pre-set switching time T_0 should be reasonably chosen within the transient period. Practically, the exact switching time is determined by trial and error using transient simulation results. This so determined switching time is physically fixed according to one particular fault sequence. However, power systems may have different disturbances and different operating conditions and therefore this pre-set switching time T_0 may not be suitable for all those situations.

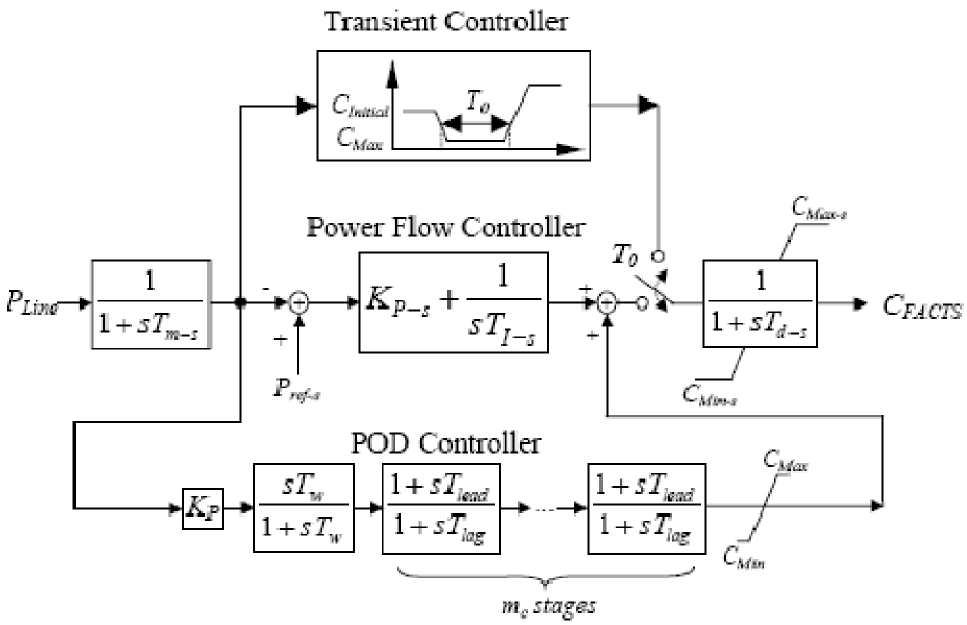


Figure 1: FACTS comprehensive control scheme.

Fuzzy adaptive switching controller

In this study, the fuzzy-logic approach is used to switch the FACTS transient stability controller adaptively under different operating situations and fault sequences. The fuzzy adaptive switching controller design procedure involves the following steps:

1. Determination of the structure of fuzzy adaptive switching controller
2. Use ANFIS for training of the fuzzy adaptive switching controller
3. Non-linear simulation for verifying the performance of the proposed controller

Structure of the fuzzy adaptive switching controller

As stated in Chapter 2, the reason for choosing fuzzy-logic controller is that fuzzy-logic is one of the most successful approaches for utilizing the qualitative knowledge of a system to design a controller. Particularly, in this study, in order to handle the uncertainties of fault sequences and different operating conditions, fuzzy-logic controller is an appropriate approach for the non-linear adaptive control of FACTS transient controller [6,7].

As stated above, the objective is to achieve a good transient behavior and damping performance for the considered system. Therefore, the switching controller must have the following functions:

- Using only local signals, the controller must switch adaptively, i.e. as a time-variant switch, between the FACTS transient controller and POD controller.
- Moreover, the controller must also react robustly under different situations without knowing fault sequences in the system.

Therefore, the fuzzy adaptive switching controller may have two control loops as shown in Figure 2, the controller consists of fuzzy-logic loop and protection loop.

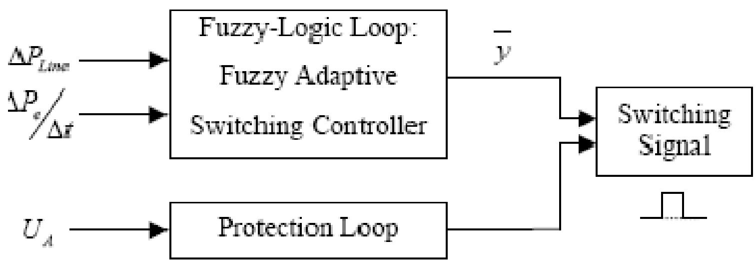


Figure 2: fuzzy adaptive switching controllers.

The three inputs to the fuzzy adaptive switching controller are: ΔP_{Line}, $\Delta P_e/\Delta t$ and U_A. Here U_A is the FACTS terminal voltage magnitude.: ΔP_{Line}, and $\Delta P_e/\Delta t$ are defined as Follows:

$$\Delta P_{Line} = P_{Line}^{(ns+1)} - P_{Line}^{(0)}$$

$$\frac{\Delta P_e}{\Delta t} = \frac{P_{Line}^{(ns+1)} - P_{Line}^{(ns)}}{\Delta t} \tag{1}$$

Where

ΔP_{Line} Active power difference flow through FACTS device

$P_{Line}^{(0)}$ The initial (pre-fault) active power transferred through the FACTS device

$P_{Line}^{(ns)}, P_{Line}^{(ns+1)}$ The active power transferred through the FACTS device at the time ns and $(ns+1)$

Δt: The time step between two sample points

The output $\bar{y}$ the switching signal for the adaptive switching between FACTS transient controller and POD controller. The statement of the function is as follows:

If $\bar{y}$ =1, then FACTS transient controller should be employed. Otherwise, if $\bar{y}$ = 0, then FACTS POD controller should be employed.

Fuzzy-logic loop

Similar to the conventional fuzzy-logic controller this fuzzy-logic loop also involves fuzzification, inference and defuzzification.

Fuzzification

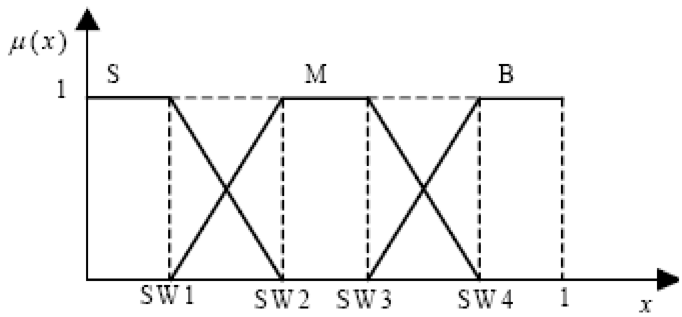


Figure 3: Membership functions.

The fuzzification is a process whereby the input variables are mapped onto fuzzy variables (linguistic variables). Each fuzzified variable has a certain membership function. The inputs are fuzzified using three fuzzy sets: B (big), M (medium) and S (small), as shown in Figure 3.

Inference

Fuzzy inference system involves fuzzy rules for determining output decisions. The fuzzified input variables are mapped onto the output variables using these fuzzy rules.

In this paper, the Sugeno fuzzy inference system is employed, because it is able to combine transparency of the rules and the accuracy of the predictions concomitantly

[3,4]. The outputs of the inference system are linear membership functions and the first order Sugeno fuzzy model is given as:

$$\text{if } x \text{ is } A_1 \text{ and } y \text{ is } A_2 \text{ then } f_i = p_{ci}x + q_{ci}y + r_{ci} \tag{2}$$

where x and y represent the ΔP_{Line} and the $\Delta Pe/\Delta t$ defined in Equation 1 respectively. A_1 and A_2 are fuzzy sets in the antecedent, while p_{ci}, q_{ci} and r_{ci} are the consequent parameters S_2 [4]. Conventionally, the fuzzy inference system is always obtained from the system operation and operator knowledge. Here in this study, in order to achieve high accuracy, the fuzzy inference system is trained using the ANFIS technology.

Defuzzification

The defuzzification process transforms the fuzzy results of the inference into a crisp output. In this work, the weighted average method is employed. Since the output of each rule is a linear combination of input variables, the final output is the weighted average of each rule's output [4]:

$$\bar{y} = \frac{\sum_{i=1}^{9} \beta_i f_i}{\sum_{i=1}^{9} \beta_i} = \frac{\sum_{i=1}^{9} \beta_i (p_{ci}x + q_{ci}y + r_{ci})}{\sum_{i=1}^{9} \beta_i} \tag{3}$$

Where β_i represents the firing strength of the i^{th} rule expressed as Equation 4 in the following section.

Protection loop

The function of the protection loop is to protect the FACTS devices under large disturbances. Its input is the FACTS terminal voltage magnitude U_A at any bus A. For instance, under large disturbances, if U_A has a large difference (more than ±15%) with the nominal voltage, the FACTS devices must be blocked from being damaged.

ANFIS training

ANFIS serves as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. In this paper, the ANFIS structure and the procedure for training will be discussed in detail. Furthermore, using ANFIS technology, both the membership functions and the inference system can be optimized.

ANFIS structure

ANFIS consists of an adaptive network, which contains nodes and directional links. The nodes are connected through the directional links. Moreover, part or all of the nodes are adaptive, which means each output of these nodes depends on the parameters pertaining to this node, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure [4].

Commonly, as shown in Figure 4, the ANFIS has five layers. In layer 1, each node generates membership grades of a linguistic label [2,4]. In this research, as shown in

Figure 3, the trapezoid functions are selected. The parameters in this layer are referred to as premise parameters *S1* and they can be trained using the ANFIS learning algorithm.

Every node in layer 2 is a fixed node and calculates the firing strength (the weight) of each rule via multiplication of the incoming signals:

$$\beta_i = \mu_{Aj}(x) \times \mu_{Bj}(y) \tag{4}$$

where μ_{Aj} and μ_{Bj} *(j=1~3)* represent the fuzzified rules and β_i *(i=1~9)* is the firing strength.

Nodes in layer 3 compute the normalized firing strength of each rule. The $i^{\,th}$ node calculates the ratio of the $i^{\,th}$rule's firing strength to the sum of all rules' firing strengths:

$$\overline{\beta_i} = \beta_i.\,(\textstyle\sum_{i=1}^{9}\beta_i)^{-1} \tag{5}$$

The nodes in layer 4 are adaptive nodes and the $i^{\,th}$node has the following output:

$$f_i = \overline{\beta}_i.\,(p_{ci}x + q_{ci}y + r_{ci}) \tag{6}$$

where

$\bar{\beta}_i$ is the output of layer 3.

$p_{ci}x, q_{ci}y\ and\ r_{ci}$ are referred to as the consequent parameter set *S2*. They can also be trained using ANFIS learning algorithm.

The node in layer 5 sums up all the incoming signals and its output is given by Equation 7.

$$\bar{y} = \textstyle\sum_{i=1}^{9}\overline{\beta}_i.\,(p_{ci}x + q_{ci}y + r_{ci}) \tag{7}$$

The detailed ANFIS structure is shown in Figure 4.

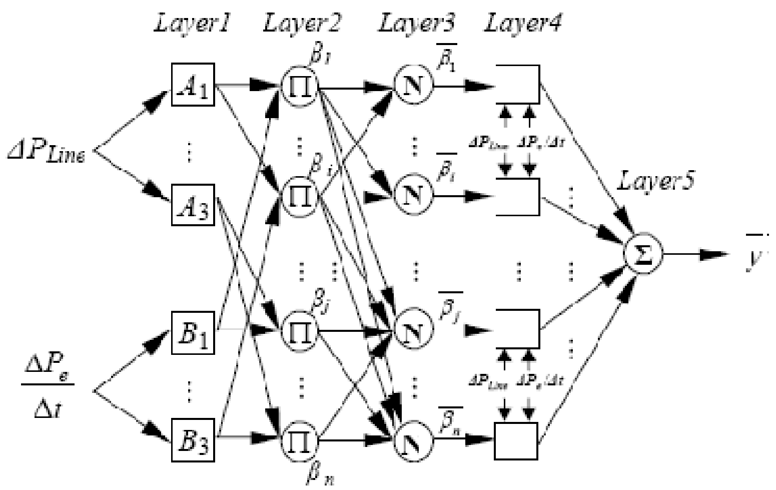


Figure 4: ANFIS structure.

Given the initial values of premise parameters *S1*, the overall output can be expressed as a linear combinations of the consequent parameters *S2*. Therefore the hybrid learning algorithm, which consists of forward pass and backward pass, can be applied for the training [2,4]. In the forward pass, functional signals go forward till layer 4 and the consequent parameters *S2* are identified by the least squares estimate (LSE). In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent.

ANFIS training

The objective of ANFIS training is to train the fuzzy-logic controller so as to switch the FACTS transient controller adaptively in presence of uncertainties. The training procedure, i.e. the tuning of the fuzzy-logic controller, is achieved based on the batch learning technique using input–output training data set. Considering the computational complexity and the resulting performance, parameters are trained using the above-mentioned gradient descent and the LSE methods (hybrid learning rule) [2].

Fine-tuning of the membership functions

The human-determined membership functions are subject to the differences from person to person and from time to time, and therefore they are rarely optimal in terms of reproducing desired outputs [4]. In this simulation, due to the size of the input-output data set, the fine-tuning of membership functions is employed in the learning mechanisms.

Training of the fuzzy inference system

Using Equation 8 and the premise parameters, the overall system output can be expressed as a linear combination of the consequent parameters [2]:

$$\bar{y} = \sum_{i=1}^{9} \bar{\beta_i}.(p_{ci}x + q_{ci}y + r_{ci}) = F_c z_c \tag{8}$$

where

z_c is the vector which contains consequent parameters

F_c is the matrix of coefficients

As mentioned in the previous sections, in the forward training pass, using the initial values of S1, functional signals are transferred to layer 4 and then the vector $z_c$will be identified by means of the LSE. In the backward pass, the error rates propagate backward and the premise parameters *S1* are updated by the gradient descent [4].

Training data

The training data must cover a wide range of operation and disturbance conditions. Furthermore, they must also contain as much information as possible about the examined power systems. Therefore, power system with different fault sequences is simulated to obtain the training data.

Input data for the training

The two input data for the training ΔP_{Line} and ${\Delta Pe}/{\Delta t}$ can be obtained by means of the non-linear simulation.

The output data for training

Since the series FACTS device is installed to damp the power oscillations between area 3 and area 4, the output data for training can be determined by the difference of power angle between the these two areas. In this simulation, the corresponding center of power angles (COA) of each area (area 3: δ_{Area3}; area 4: δ_{Area4}) are employed for the investigation [5]:

$$\delta_{Area3}(t) = \frac{\sum_{kc\ Area\ 3} S_k H_k \delta_k(t)}{\sum_{kc\ Area\ 3} S_k H_k},\ \delta_{Area\ 4}(t) = \frac{\sum_{kc\ Area\ 4} S_k H_k \delta_k(t)}{\sum_{kc\ Area\ 4} S_k H_k} \tag{9}$$

where

H_k is the inertia constant of the k^{th} generator

S_k is the base power of the k^{th} generator

The first swing characteristic can be determined using δ_{Area3} and $\delta_{Area\ 4}$:

$$\delta(t) = \delta_{Area3}(t) - \delta_{Area\ 4}(t) \tag{10}$$

The ideal switching time from transient controller to POD controller is determined at the time when the derivative of Equation 10 vanished, i.e. $\frac{d\delta(t)}{dt} = 0$. However, this signal is employed only for the training procedure.

The complete training data set

The complete data for the training procedure are obtained from the following four events: three-phase short circuits at bus A (Local bus), B (Middle bus), C (Remote bus) and the load shedding at bus D (Load).

Each disturbance is simulated for one second. Therefore, there are discontinuities between the four parts. Figure 5 depicts the complete training data events.

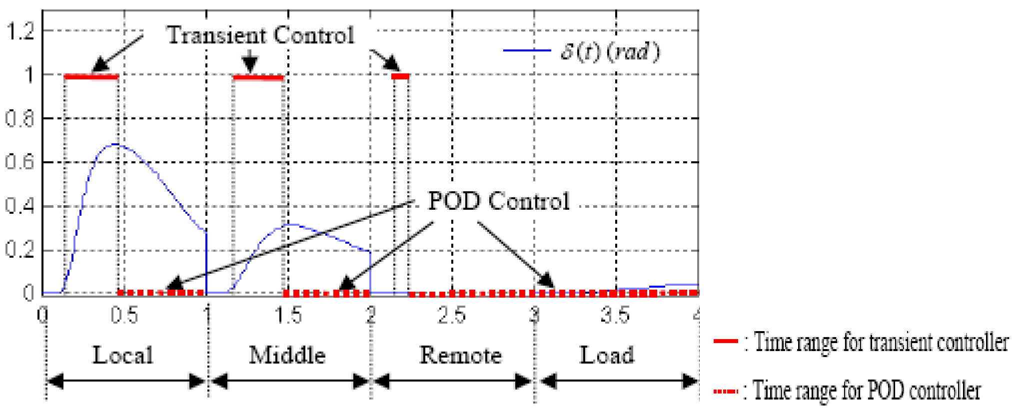


Figure 5: Training data.

Using the training data, the membership functions and the inference system can be optimized.

Training results

In this simulation, ANFIS is trained using 100 epochs and an initial step size of 10^4.

Membership functions

The initial membership functions are equally spaced with enough overlap within the input range as shown in Figure 3. These are typical membership functions to start with the ANFIS learning.

In order to fit the output of the training data, as given in Appendix 1, the initial membership functions of ${}^{\Delta Pe}/_{\Delta t}$ and ΔP_{Line} are changed completely. Figure 6 shows the optimized membership functions of ΔP_{Line}.

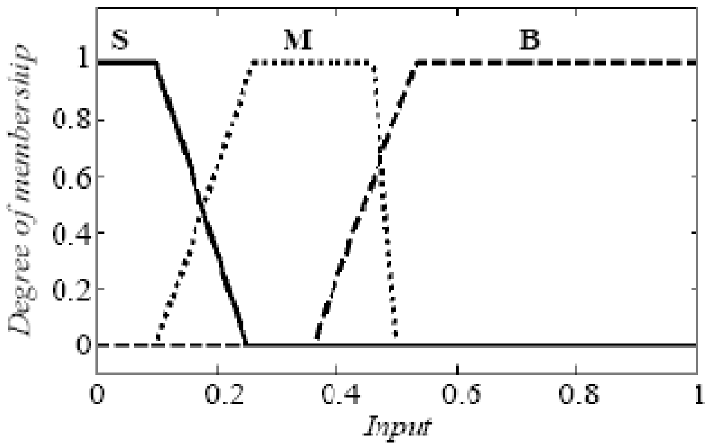


Figure 6: Optimized membership functions of ΔP_{Line}

Fuzzy inference system

Using the training data, the Sugeno fuzzy inference system is optimized by comparing its output with the objective output data.

Figure 7 shows the behavior of the trained fuzzy adaptive switching controller under the most critical training condition: a short circuit of 100 ms duration on the line between bus A0 and a supplementary bus. The near end (supplementary bus) and the remote end (bus A0) of the line are cleared at *t=0.2s* and *t=0.3* s respectively.

The difference between the output of the fuzzy adaptive switching controller and the objective between *t=0.2 s* and *t=0.3* s is due to the remote end clearance time, where there is an impulse in active power flow through FACTS devices. Other training results (middle bus, remote bus and loss of load) match pretty well the objective. The detail membership functions and the first-order Sugeno fuzzy model are given in Appendix 2.

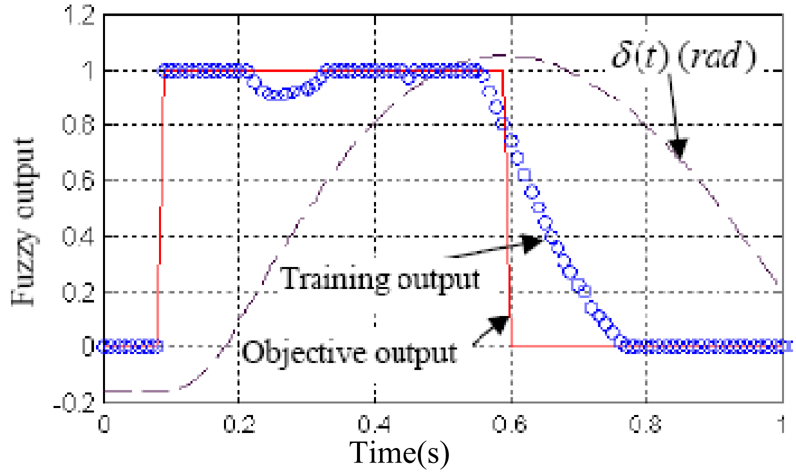
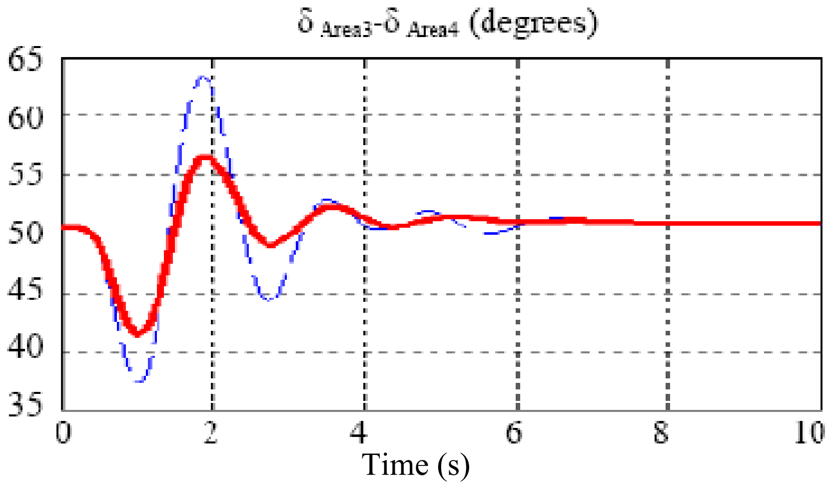


Figure 7: Training result.

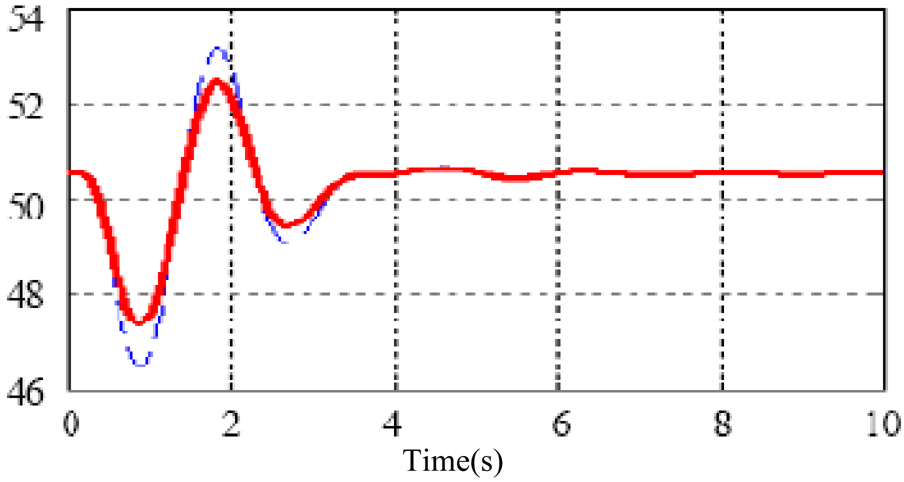
Simulation results

To verify the performance of the proposed controller, two disturbances are considered in the system, i.e. three-phase short circuits at the bus B_1 (area 4, local bus) and at the bus C_1 (area 5, remote bus) with duration of 100 ms and 150 ms respectively. Figure 8 demonstrates the rotor angle difference between area 3 and area 4 in case of using the conventional fix-time-switching controller and the fuzzy adaptive switching controller.



(a) Three-phase short circuit at bus B_1

δ_{Area3} - δ_{Area4} (degrees)



(b) Three phase short circuit at bus C1

– – : Conventional fix-time-switching controller
— : Fuzzy adaptive switching controller

Figure 8: Simulation results.

In comparison with the conventional fix-time-switching controller, the power system performs better with the proposed fuzzy adaptive switching controller and the dynamic performance is also improved. Particularly, as shown in Figure 8 (a), the proposed control scheme leads to significantly better transient behavior under the local bus disturbance.

Conclusion

This paper presents a new fuzzy adaptive FACTS transient controller design method using ANFIS technology. The approach adaptively actives transient stability controller for series FACTS devices during large disturbances.

Using the training data set, which is obtained by simulating over a wide range of operating situations and disturbance conditions, the parameters of the proposed controller are optimized using the ANFIS technology. The performance of the proposed controller can be verified for the large power system under different disturbances and

Simulation results validate the effectiveness of the proposed control strategy. Moreover, the approach is easy to realize and implement in real power systems.

Appendix 1: Membership function

	MFs	*SW1*	*SW2*	*SW3*	*SW4*
Input1 ΔP_{Line}	S	-0.5548	-0.06164	0.1244	0.2479
	M	0.1226	0.2477	0.4544	0.4875
	B	0.3538	0.5164	1.294	1.788
Input2 $\Delta P_e/\Delta t$	S	-6.75	-0.75	2.00	3.0
	M	2.006	3.00	9.0	10.
	B	8.9997	10	15.75	21.75

Appendix 2: Linear function of Sugeno model

i	p_i	q_i	r_i
1	-0.95	0.01	6.716
2	35.211	0.00989	6.010
3	22.1	0.59	0.0558
4	0.367	3.96	2.022
5	24.7	0.0295	3.648
6	-6.815	0.898	0.0815
7	3.12	0.039	6.108
8	0.445	1.97	0.464
9	0.073	0.8322	0.0751

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