COORDINATION BETWEEN TRANSIENT AND DAMPING CONTROLLER FOR SERIES FACTS DEVICES USING ANFIS TECHNOLOGY

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Abstract: This paper deals with the control of the series FACTS (Flexible AC Transmission Systems) devices for the coordination between their transient stability controller and POD (Power Oscillation Damping) controller in multi-machine power systems. The design aspects and their implementation in form of fuzzy-logic coordination controller are presented. Furthermore, ANFIS (Adaptive Neuro-Fuzzy Inference System) is employed for the training of the proposed fuzzy-logic controller. The local signals of the FACTS devices are applied to achieve the coordination objectives. Digital simulations of multi-machine power system subjected to a wide variety of disturbances validate the efficiency of this approach. The proposed control scheme is not only robust, but also simple and easy to be realized in power systems.

Keywords: ANFIS, Coordinated control, Damping control, FACTS, Fuzzy logic, POD controller, Training, Transient controller

1. INTRODUCTION

Nowadays, FACTS devices are used to control power flow and to enhance system stability. Particularly, in recent years, with the deregulation of the electricity market, the traditional concepts and practices of power systems have changed. Better utilization of the existing power system to increase capacities by installing FACTS devices becomes imperative. FACTS devices are playing an increasing and major role in the operation and control of power systems.

Series FACTS devices are the key elements in the FACTS family . They are recognized as an effective and economical means to solve the following problems: steady state power flow control, transient stability control and power system oscillation damping control (Lei, *et al*., 2000). In this paper, the coordinated control of series FACTS devices is considered.

Usually, the coordination between FACTS transient controller and POD controller is achieved using a pre-set fixed time switch (Lei, *et al*., 2000). However, the optimal switching time is varied with different disturbances and different operating conditions. In the conventional approach, the switching time cannot be adjusted under different situations. This work focuses on the development of a fuzzy coordination controller between FACTS transient stability controller and POD controller. The switching time is then controlled by means of the fuzzy-logic approach. Furthermore, the parameters of the proposed controller are optimized using the ANFIS algorithm (Shing, and Jang, 1993).

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This paper is organized as follows: Following the introduction, power system model and FACTS location are considered in section 2. Then in section 3, the conventional FACTS control schemes are introduced. In section 4 and section 5, the structure and the ANFIS training of the fuzzy coordination controller are discussed in detail. The simulation results are given in section 6. Finally, brief conclusions are deduced.

2. POWER SYSTEM MODEL AND FACTS LOCATION

A modified 16-machine 68-bus system (Rogers, 1999) with series FACTS devices, as shown in Fig. 1, is simulated in this paper. Each generator is simulated using 6th order model and the FACTS devices are considered using the power injection model (Cai, and Erlich, 2002).

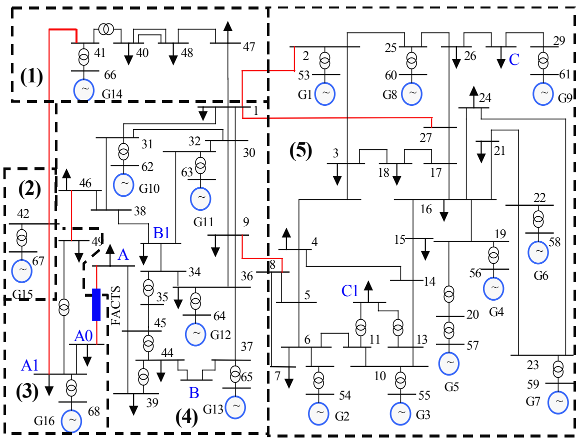


Fig. 1. One line diagram of 16-machine five-area power system

By means of the modal analysis, this system is divided into 5 areas (Rogers, 1999). Because there are three tie lines between area 4 and area 5, the main inter-area oscillation is between area 3 and area 4. The series FACTS devices are located between bus A and bus A0 (on the tie line between area 3 and area 4). The location of FACTS device is determined using the residue algorithm for damping of inter-area oscillations (Wang, 1999).

3. CONVENTIONAL FACTS CONTROLLER

Normally, series FACTS controller focuses on the following three control objectives (Lei, *et al*., 2000):

1 Steady state power flow control;
2 Transient stability control for improving the first swing stability;
3 Damping control to damp the power system oscillations.

3.1 Steady state power flow controller

In general, the constant line power strategy is used in power flow control (Lei, *et al*., 2000). The corresponding control loop is shown in Fig. 2, where P_{ref} and C_{ref} are reference values of the active power and the initial compensation value of the FACTS devices respectively. The output C_{FACTS} is the control variable of the series FACTS devices. For instance, for the control of TCSC (Thyristor Controlled Series Capacitor) it is the value of the series capacitance and for UPFC (Unified Power Flow Controller) it is the series injected voltage (Cai, and Erlich, 2002).

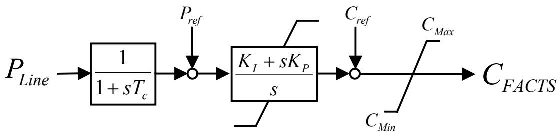


Fig. 2. Steady state power flow controller

3.2 FACTS transient stability controller

Following a large disturbance, the transient controller acts initially to give a maximum compensation level for a pre-set time T_0 (Lei, *et al*., 2000). The structure of the FACTS transient controller is shown in Fig. 3.

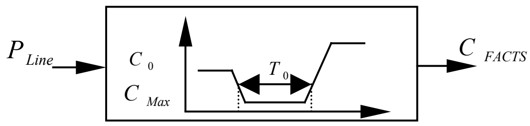


Fig. 3. Transient controller

3.3 FACTS POD controller

In general, the structure of series FACTS POD controller is similar to the PSS controller (Lei, *et al*., 2000). In Fig. 4, the FACTS POD controller is illustrated. It involves a transfer function consisting of an amplification block, a wash out block and two lead-lag blocks (Lei, *et al*., 2000; Rogers, 1999).

Commonly, local signals of FACTS devices are always applied for the damping control. In this simulation, the active power through the FACTS devices P_{line} is employed. As stated above, the output is C_{FACTS} which represents the control variable of the series FACTS devices.

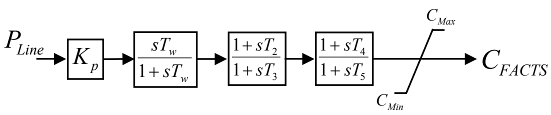


Fig. 4. POD controller

3.4 Conventional coordination method between FACTS transient controller and POD controller

The FACTS transient controller and POD controller achieve different control objectives in different operation states. Conventionally, in order to enhance transient stability and damp the subsequent oscillations, a switching control strategy is always used to coordinate between the two different controllers (Lei, *et al*., 2000). The switching control scheme is shown as follows:

1 Following a large disturbance, the transient controller acts first to maintain the transient stability of power systems;

2 After the pre-set switching time period T_0, the control is transferred to the POD controller to damp the post-fault oscillations.

The conventional coordination control scheme is shown in Fig. 5. (Lei, *et al.*, 2000)

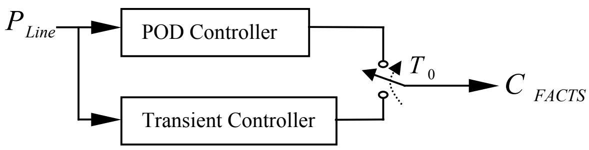


Fig. 5. Conventional coordination between FACTS transient and POD controller

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 the 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 the pre-set switching time T_0 may not be suitable for all above situations.

In order to coordinate the transient stability controller and the POD controller under different operating situations and different fault sequences, the fuzzy-logic coordination controller is proposed. The design procedure is as follows:

1 Determination of the structure of fuzzy-logic coordination controller;
2 ANFIS training of the fuzzy-logic controller;
3 Non-linear simulation for verifying the robustness of the proposed controller.

4. FUZZY COORDINATION CONTROLLER

As stated above, the objective is to achieve a good transient behavior and damping performance for the considered system. Therefore the controller must have the following function: By means of the FACTS local signals, design a time-variant switch for the coordination between the FACTS transient controller and POD controller. Moreover, the controller must also react robustly under different situations without knowing fault sequences occurring in the system.

In order to handle the uncertainties of fault sequences and different operating conditions, fuzzy-logic controller is employed. Practically, fuzzy-logic is one of the most successful approaches for utilizing the qualitative knowledge of a system to design a controller. Furthermore, fuzzy-logic controllers do not require the mathematical model of a system. They can cover a wider range of operating conditions and they are robust (Chedid, *et al.*, 2000). In this work, there are two control loops in the fuzzy coordination controller, as shown in Fig. 6, fuzzy-logic loop and protection loop.

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

$$\begin{aligned} \Delta P_{Line} &= P_{Line}^{(n+1)} - P_{Line}^{(0)} \\ \frac{\Delta P_e}{\Delta t} &= \frac{P_{Line}^{(n+1)} - P_{Line}^{(n)}}{\Delta t} \end{aligned} \tag{1}$$

where

ΔP_{Line}: Active power difference through FACTS device;
$P_{Line}^{(0)}$: The initial active power transferred through the FACTS device;
$P_{Line}^{(n)}, P_{Line}^{(n+1)}$: The active power transferred through the FACTS device at the sample time *n* and *n+1*;
Δt: The time step between two sample points.

The controller output $\bar{y}$ is the switching signal for the coordination between FACTS transient and POD controllers:

$\bar{y}$ =1: Transient controller should be employed;
$\bar{y}$ =0: POD controller should be employed.

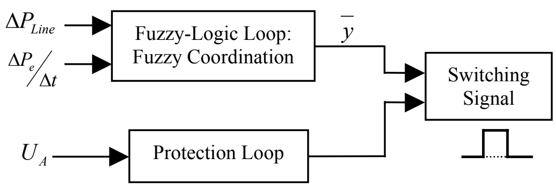


Fig. 6. Fuzzy coordination controller

4.1 Fuzzy-logic loop

The fuzzy-logic loop involves fuzzification, inference and defuzzification.

4.1.1 Fuzzification

Fuzzification is a process whereby the input variables are mapped onto fuzzy variables (linguistic variables). Each fuzzified variable has a certain membership function. In this work, the inputs are fuzzified using three fuzzy sets: B (big), M (medium) and S (small), as shown in Fig. 7.

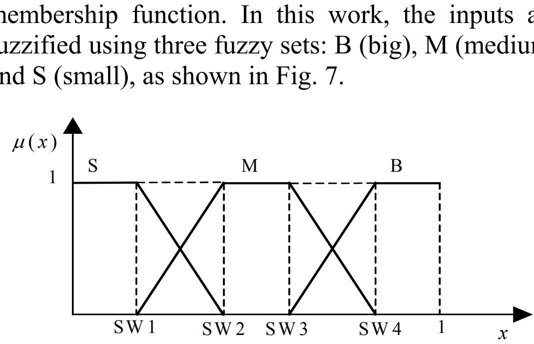


Fig. 7. Membership function

4.1.2 Inference

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

In this presentation, the Sugeno FIS (Shing, and Jang, 1993) is employed, because it is able to combine transparency of the rules and the accuracy of the predictions concomitantly. The outputs of the inference system are linear membership functions and the first-order Sugeno fuzzy model has the following form:

if x is A_1 and y is A_2 then $f_i = p_i x + q_i y + r_i$

where in this work, x is the ΔP_{Line} and y is the $\Delta P_e / \Delta t$ defined as (1). A_1 and A_2 are fuzzy sets in the antecedent, while p_i, q_i and r_i are the consequent parameters (Shing, and Jang, 1993). The fuzzy rules can be obtained from the system operation and the knowledge of the operator. In this paper, the rules are trained using the ANFIS technology.

4.1.3 Defuzzification

The defuzzification process transforms the fuzzy results of the inference into a crisp output. In this work, the weighted average method is employed (Shing, and Jang, 1993).

4.2 Protection loop

The protection loop is to protect the FACTS devices under large disturbances. Its input is the FACTS terminal voltage magnitude at bus A. For instance, under large disturbances, if U_A has a large difference (more than 15%) with the nominal voltage, the FACTS devices will be blocked to protect the power electronic devices.

5. ANFIS TRAINING

In this work, both membership functions and the inference system are optimized using ANFIS technology.

5.1 ANFIS structure

Commonly, the ANFIS has five layers. In layer 1, each node generates membership grades of a linguistic label (Chedid, *et al*., 2000). In this paper, as shown in Fig. 7, the trapezoid functions are selected. Parameters in this layer are referred to as premise parameters S_1 and they can be trained using the ANFIS learning algorithm (Shing, and Jang, 1993).

Every node in layer 2 is a fixed node and calculates the firing strength of teach rule via multiplication of the incoming signals (Shing, and Jang, 1993):

$$\omega_i = \mu_{Ai}(x) + \mu_{Bi}(y) \tag{2}$$

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 (Shing, and Jang, 1993):

$$\overline{\omega}_i = \omega_i \cdot \left(\sum_{i=1}^{n} \omega_i \right)^{-1} \tag{3}$$

In layer 4 there are only adaptive nodes and the i^{th} has the following output (Shing, and Jang, 1993):

$$f_i = \overline{\omega}_i (p_i x + q_i y + r_i) \tag{4}$$

where $\overline{\omega}_i$ is the output of layer 3. $\{p_i, q_i, r_i\}$ are referred to as the consequent parameter set S_2. They can also be trained using ANFIS learning algorithms.

The single node in layer 5 sums up all the incoming signals:

$$\overline{y} = \sum_{i=1}^{9} \overline{\omega}_i (p_i x + q_i y + r_i) \tag{5}$$

The ANFIS structure is shown in Fig. 8.

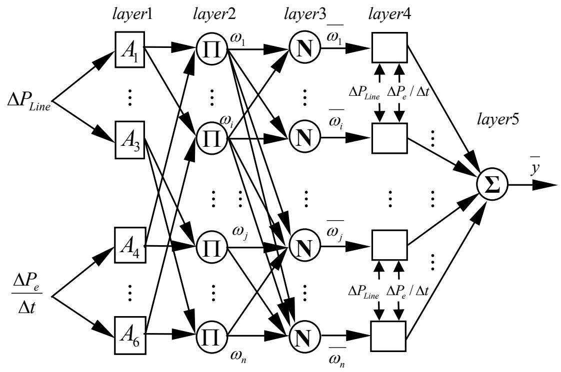


Fig. 8. ANFIS structure

5.2 ANFIS training

The objective of ANFIS training is to learn a good coordination between transient controller and damping controller in presence of uncertainties. The training procedure is achieved based on the batch learning technique, where the tuning of the fuzzy-logic controller is achieved with a back-propagation algorithm using input–output training data set. Considering the computation complexity and the resulting performance, parameters are trained using the gradient descent and the least square estimation (LSE) method (Chedid, *et al*., 2000).

5.2.1. Fine-tuning of Membership Function

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 (Shing, and Jang, 1993). In this simulation, since the size of available input-output data set is especially large, the fine-tuning of the membership functions is necessary. Therefore, the learning mechanisms are also employed for the determination of membership functions.

5.2.2. Training of the Fuzzy Inference System

Using (5) and the premise parameters, the overall system output can be expressed as a linear combination of the consequent parameters:

$$\overline{y} = \sum_{i=1}^{9} \overline{\omega}_i (p_i x + q_i y + r_i) = \mathbf{Cz} \tag{6}$$

where **z** is the vector of consequent parameter and **C** is the matrix of coefficients (Chedid, *et al*., 2000).

The learning algorithm is composed of a forward pass and a backward pass. In the forward pass, using the available values of S_l, functional signals go forward till layer 4 and the consequent parameter vector **z** are identified by means of the LSE. In the backward pass, the error rates propagate backward and the premise parameters S_l are updated by the gradient descent (Shing, and Jang, 1993).

5.3 Training data

The training data must cover a wide range of operation and disturbance conditions. Furthermore, they must 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.

The two inputs for the training data: ΔP_{Line} and $\Delta P_e / \Delta t$ can be obtained with the non-linear simulation. The output data for training can be determined by the difference of power angle between the two areas. In this paper, the corresponding center of power angles (COA) (Pavella, *et al*., 2000) of each area (δ_{Area3}, δ_{Area4}) are employed for the investigation:

$$\delta_{Area3}(t) = \frac{\sum_{k \in Area3} S_k H_k \delta_k(t)}{\sum_{k \in Area3} S_k H_k}$$
$$\delta_{Area4}(t) = \frac{\sum_{k \in Area4} S_k H_k \delta_k(t)}{\sum_{k \in Area4} S_k H_k} \tag{7}$$

where
H_k — The inertia constant of the k[th] generator;
S_k — The base power of the k[th] generator.

The first swing characteristic can be determined using δ_{Area3} and δ_{Area4}.

$$\delta(t) = \delta_{Area3}(t) - \delta_{Area4}(t) \tag{8}$$

The switching time from transient controller to POD controller is determined at the time for which $d\delta(t)/dt = 0$. This signal is employed only for the training procedure.

The whole training data is composed of four parts: Three-phase short circuits at bus A (Local bus), B (Middle bus) and C (Remote bus) are simulated. Furthermore, the load shedding at bus D (Load) is also simulated to train the fuzzy inference system. Therefore, there are discontinuities between the four parts. The training data is shown in Fig. 9.

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

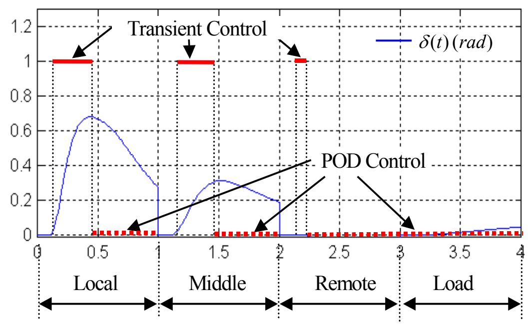


Fig. 9. Training data
: Time range for transient controller
: Time range for POD controller

5.4 Training results

In this work, ANFIS is trained using 100 epochs and an initial step size of 10^{-4}.

5.4.1. Membership functions

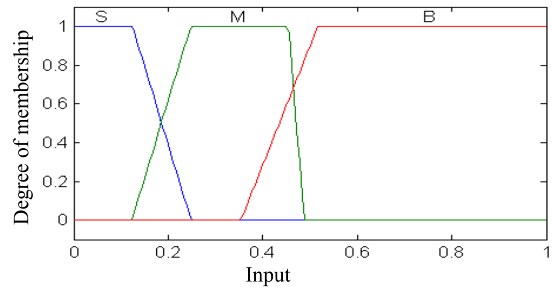


Fig. 10. Membership functions of ΔP_{Line}

The initial membership functions are equally spaced with enough overlap within the input range as shown in Fig. 7. These are typical membership functions to start with for the ANFIS learning.

The final membership functions of ΔP_{Line} are shown in Fig. 10. In order to fit the output of the training data, the initial membership functions are greatly changed. Similarly, the final membership functions of $\Delta Pe / \Delta t$ are also obtained, as shown in Appendix.

5.4.1. Fuzzy inference system

Using the training data, the Sugeno fuzzy inference system is optimized by comparing its output with the objective output data. Fig. 11 shows the most critical training result. A short circuit of 100 ms duration is simulated on the line between bus A0 and a supplementary bus. The near end (supplementary bus) and the remote end (bus A) of the line are cleared at t=0.2 s and t=0.3 s respectively. The difference between the training output and the objective output 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. The other training results (middle bus, remote bus and loss of load) match pretty well the objective output. The detail membership functions and the first-order Sugeno fuzzy model are shown in Appendix.

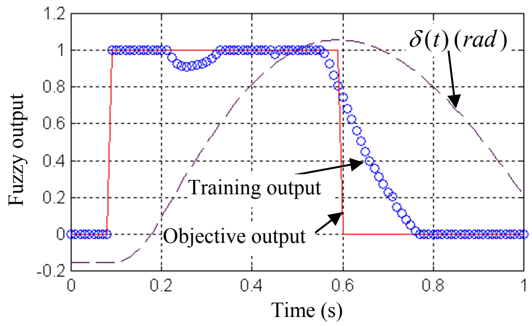
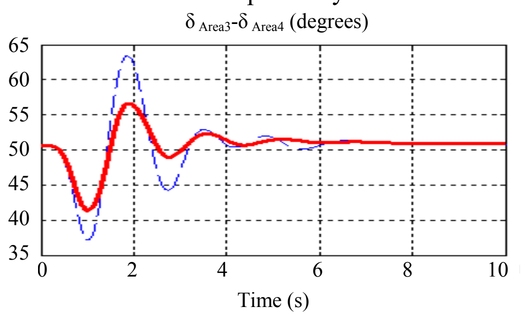


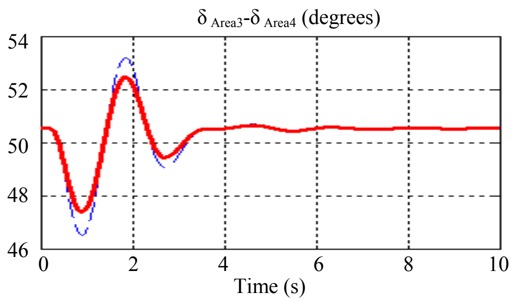
Fig. 11. Training result

6. SIMULATION RESULTS

To verify the performance of the proposed controller, different disturbances are simulated: Three phase short circuits are applied on bus B1 (area 4, middle bus) and bus C1 (area 5, remote bus). The duration of the short circuits are 100 ms and 150 ms respectively. Fig. 12 demonstrates the rotor angle difference between Area 3 and Area 4 in case of using the conventional controller and the fuzzy coordination controller respectively.



(a) Three phase short circuit on bus B1



(b) Three phase short circuit on bus C1

Fig. 12. Simulation results
- – Conventional fix-time-switching coordinated control
— Fuzzy coordinated control

In comparison with the conventional fix-time-switching controller, the examined power system performs better with the proposed fuzzy coordination controller and the dynamic performance is quite improved. Particularly, as shown in Fig. 12 (a), the proposed control scheme leads to significantly better transient behavior under the middle bus disturbances.

7. CONCLUSION

This paper presents a new fuzzy coordination controller for the series FACTS devices to coordinate their transient stability controller and POD controller in multi-machine power systems. Using the training data set, which is obtained by simulating over a wide range of operation and disturbance conditions, the parameters of the proposed controller are optimized using the ANFIS technology. The performance of the proposed controller is verified under different disturbances. Simulation results validate the robustness of the proposed control scheme. Moreover, this approach is also simple and easy to be realized in power systems.

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APPENDIX

Table 1 Membership functions

	MFs	α_1	α_2	α_3	α_4
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

Table 2 Linear functions 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