A Study of Fuzzy Logic Based Damping Controller for The UPFC

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ABSTRACTS

The supplementary control of the UPFC can significantly enhance the damping of interconnect power systems. However, the conventional controller designed based on a linearized model cannot provide adequate damping signal over a wide range of operation points. In this paper, a fuzzy controller is designed as the substitute of the conventional controller. The parameters of the fuzzy controller are optimized through gradient descent training. Transient stability simulation and small signal analysis are conducted to test the performance of the controller. Computer results show that the fuzzy controller is very effective in damping the oscillation and has a better robustness.

1. INTRODUCTION

The unified power flow controller (UPFC) is regarded as one of the most versatile FACTS devices [1-3]. It can operate as a shunt or/and series compensator, a power flow controller, a voltage regulator or a phase shifter depending on its main control strategy.

A power frequency model for the UPFC is derived in [4] with its dc link capacitor dynamics included to study the effects of the UPFC on power system stability. A novel UPFC-network interface is also suggested in order to participate the UPFC model into the conventional transient stability analysis program with good convergence and accuracy in time simulation. Investigations on the UPFC main control effects show that the UPFC can improve system transient stability and enhance system transfer limit. The application of the UPFC to the modern power system can therefore lead to more flexible, secure and economic operation.

Modern power systems tend to be interconnected to yield the most economic benefits. However low frequency oscillation will occur on heavily loaded tie lines especially after a large or small disturbance. Sometimes the Power System Stabilizer (PSS) installed on a specific generator cannot provide effective damping for that kind of oscillation. In [4] it is shown that the addition of PSS-like supplementary controller to the UPFC main control can provide effective damping to the low frequency oscillation on heavily loaded tie lines of interconnected system. However, the conventional controller designed based on a linearized model cannot provide satisfactory performance over a wide range of operation points and under large disturbances.

2. THE UPFC MATHEMATICAL MODEL

A. UPFC Power Frequency Model

The power frequency model for the UPFC suggested in [4] is used in this study and is outlined as follow. Fig. 1 shows the schematic diagram for the UPFC, where \( n_s \), \( X_{sf} \) and \( n_s \), \( X_{sf} \) are the voltage ratio and the reactance of the shunt and series transformers respectively. All the variables used in the UPFC model are denoted in Fig. 1 with bold fonts representing phasors. The ac system uses per unit system with its variables calculated based on the system-side \( S_p \) and \( V_{ph} \), while the dc variables are expressed in SI units.

The UPFC dc link capacitor dynamics can be expressed as follows with harmonics and UPFC losses neglected:

\[
CV_s \frac{dV_s}{dt} = (P_s - P_c)S_p
\]

where

\( CV_s \frac{dV_s}{dt} \) is the capacitor charge rate, \( P_s \) is the ac system active power injection, \( P_c \) is the UPFC active power consumption, and \( S_p \) is the ac system per unit admittance.

Researchers [5, 6]. The fuzzy controller has a number of distinct advantages over the conventional one. It is not so sensitive to the variation of system structure, parameters and operation points and can be easily implemented in a large-scale nonlinear system. The most attractive feature is its capability of incorporating human knowledge to the controller with ease.

In this paper, a fuzzy logic based supplementary controller is designed to act as the substitute of the conventional one. The fuzzy damping controller (FDC) takes the power flow of the controlled line as the input signal. The output of the FDC is sent to the main control of the UPFC as the modulation signal for improving system damping. Scaling factors are inserted to the membership functions of both inputs and output for easy design of fuzzifier and defuzzifier. The gradient descent training method [5] is used to optimize the key parameters of the FDC. The related formulas and optimizing FDC parameters is presented. The performance of the designed FDC is evaluated through transient stability simulation and small signal analysis. A 4-machine interconnected power system with a UPFC installed in one of the tie lines is used as the test system. Computer test results show that the FDC is very effective in damping the inter-area power oscillation. In the meantime, it has a better robustness as compared with its conventional counterpart.
C. Mathematical model for other elements and the interface of the UPFC to ac network

The subtransient model is used for the generators with the third-order excitation control [7]. The mechanical power of each generator is approximately constant. Loads are expressed as constant impedance and the ac network is linear. The sequential solution method, which has been successfully used in ac/dc power system load flow and transient stability analysis for ac-dc interface, is extended for the UPFC interface to ac network. The detail can be found in [8].

A. Operation Principle of the FDC

The input signal after passing through a washout block (or reset filter) forms the first signal $x_1$ which is corresponding to the line power increment $\Delta P_L$. The signal $x_2^*$ is the integration of $\Delta P_L$ with dc component filtered out. For a sinusoidal power oscillation of a certain frequency, we all know the signals $x_1^*$ and $x_2$ can span into a phasor plane. After proper scaling of the two
signals a phasor can be worked out with desired phase angle on the phasor plane. In real application we take $x_2 = -x_1^*$ as the second input signal of fuzzy damping control and consider that it is approximately in phase to the time derivative of $\Delta P_f$ from the phasor point of view based on the conventional frequency domain controller design widely used in PSS design. This signal has the advantages of having less noise and being smoother as compared with the time derivative of $\Delta P_f$. Two gains (or scaling factors) $K_1$ and $K_2$ are inserted to make $x_1' = K_1 x_1$ and $x_2' = K_2 x_2$ usually at a proper range of $[-1, 1]$ for easy design of the fuzzifier. The gain $K_3$ at the output path plays a similar role for easy design of the defuzzifier. It is clear that $K_1$, $K_2$ and $K_3$ should be optimized in order to get satisfied FDC performance.

The differentiable Gaussian membership function is used to fuzzifying the two input signals which is required by the GDT method. The triangular function is used to defuzzify the output fuzzy sets for its easy calculation. Seven fuzzy sets are defined for each of the input and output signals. They are NB, NM, NS, ZR, PS, PM and PB which stand for negative big, negative medium, negative small, zero, positive small, positive medium and positive big respectively. In the implementation, PB and NB are extended to reach $\pm 2$ respectively so as to fit the input signals of excessive range. Based on the human experience, the fuzzy rule base is formed. Table 1 shows the fuzzy rules which take the form:

**IF** $K_1 x_1$ is $A_i$ and $K_2 x_2$ is $B_j$ **THEN** output $y/K_3$ is $C_i$ where $A_i$ and $B_j$ are the input fuzzy sets with Gaussian membership functions, while $C_i$ is the output fuzzy set with triangular membership function.

In the FDC, singleton fuzzifier, centre average defuzzifier, and product inference engine are used for fuzzifying, defuzzifying and inference process respectively. If the rules in Table 1 are numbered from 1 to 49 row by row, the fuzzy rule implementation can then be expressed as the following nonlinear relation where the extended parts of the fuzzy sets PB and NB are ignored:

$$y = f(x) = \frac{\sum_{i=1}^{M} \sum_{j=1}^{p} \left( \frac{\sum_{i=1}^{M} \prod_{i=1}^{n} \left( \frac{K_1 x_1 - \bar{x}_1^r}{\sigma_1^r} \right)^2 + \sum_{i=1}^{M} \prod_{i=1}^{n} \left( \frac{K_2 x_2 - \bar{x}_2^r}{\sigma_2^r} \right)^2}{M} \right)}{M}$$

where $\bar{x}_i^r$ and $\sigma_i^r$ are centre and standard deviation of the Gaussian membership functions corresponding to the $r$th rule input fuzzy set of variable $x_i$; $\bar{x}_2^r$ is centre of the Gaussian membership function corresponding to the $r$th rule output fuzzy set of variable $y$; $M$: total number of the rules, $M=49$; $n$: total number of the input signals, $n=2$; $x = [x_1, x_2]$ and $y = K_3 x$.

### Table 1 Fuzzy rule base

<table>
<thead>
<tr>
<th>$K_1 x_1$</th>
<th>$K_2 x_2$</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>ZR</th>
<th>PS</th>
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<th>PB</th>
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**B. Gradient Descent Training (GDT) for FDC Coefficient Optimization**

The GDT method [5] is used as a deterministic approach to optimize $K_i$. This method is to make the designed FDC performance close to a desired characteristic. We assume that the desired input-output characteristic of the FDC is available and defined by a collection of input-output data, say from a well-designed conventional controller.

Suppose that we are given the following input-output pairs: $(x_1^{(j)}, x_2^{(j)}) = (x_1^{(j)}, x_2^{(j)}, y_j^{(j)}), j=1,2,\ldots,p$. $p$ is the total number of the input-output pairs available. The task is to design a fuzzy system with its input-output relation as (5) which can imitate the characteristic of the given input-output pairs, that is, to determine an optimal set of $\{K_i\}$, such that the matching error

$$e = \sum_{j=1}^{p} e_j = \sum_{j=1}^{p} \frac{1}{2} \left[ f(x_j^{(j)}) - y_j^{(j)} \right]^2$$

is minimized.

$$y = f(x) = \frac{\sum_{i=1}^{M} \sum_{j=1}^{p} \left( \frac{\sum_{i=1}^{M} \prod_{i=1}^{n} \left( \frac{K_1 x_1 - \bar{x}_1^r}{\sigma_1^r} \right)^2 + \sum_{i=1}^{M} \prod_{i=1}^{n} \left( \frac{K_2 x_2 - \bar{x}_2^r}{\sigma_2^r} \right)^2}{M} \right)}{M}$$

where $\bar{x}_i^r$ and $\sigma_i^r$ are centre and standard deviation of the Gaussian membership functions corresponding to the $r$th rule input fuzzy set of variable $x_i$; $\bar{x}_2^r$ is centre of the Gaussian membership function corresponding to the $r$th rule output fuzzy set of variable $y$; $M$: total number of the rules, $M=49$; $n$: total number of the input signals, $n=2$; $x = [x_1, x_2]$ and $y = K_3 x$.

**Fig. 5 Fuzzy damping controller for the UPFC**
The gradient descent algorithm is used to solve the problem through the following iteration:

$$K_{q+1} = K_q - \alpha \frac{\partial e}{\partial K}$$  \hspace{1cm} (7)

where $q$: the current iteration number; $- \frac{\partial e}{\partial K} = -\nabla K e$,
the optimal search direction; $\alpha$: the optimal step length;
$K=(K_i, K_z, K_{JT})$.

According to (6), we have ($l=1, 2, 3$)

$$\frac{\partial e}{\partial K_l} = \sum_{j=1}^{p} \left( f(x^{(j)}_l) - f(x^{(0)}_l) \frac{\partial f(x^{(0)}_l)}{\partial K_l} \right)$$  \hspace{1cm} (8)

Let

$$\alpha^* = \prod_{i=1}^{p} \exp \left( - \frac{K_i x_i - \bar{x}_i}{\sigma_i} \right)^2$$  \hspace{1cm} (9)

we have

$$f(x) = K_i \sum_{i=1}^{3} \frac{\partial f(x)}{\partial K_i}$$  \hspace{1cm} (10)

From (5) and (6) - (9), for $l=1, 2$, we can derive

$$\frac{\partial f(x)}{\partial K_l} = K_i \left( \frac{\sum_{i=1}^{3} \frac{\partial f(x)}{\partial K_i}}{\sum_{i=1}^{3} \frac{\partial f(x)}{\partial K_i}} \right)$$  \hspace{1cm} (12)

$$\frac{\partial f(x)}{\partial K_l} = -2\alpha^* \left( \frac{K_i x_i - \bar{x}_i}{\sigma_i} \right) \frac{x_i}{\sigma_i}$$  \hspace{1cm} (13)

If $l=3$, we have:

$$\frac{\partial f(x)}{\partial K_3} = \sum_{i=1}^{3} \frac{\partial f(x)}{\partial K_i}$$  \hspace{1cm} (14)

The GDT process can be conducted as follows based on an initial guess of $K_l (l=1, 2, 3)$:

1) Use equations (12) to (14) to calculate $\frac{\partial f(x)}{\partial K_l} (l=1, 2, 3)$.
2) Substitute these derivatives into equation (8) to calculate $-\nabla K e = \left[ \frac{\partial e}{\partial K_1} \frac{\partial e}{\partial K_2} \frac{\partial e}{\partial K_3} \right]^T$  \hspace{1cm} (15)
3) In the opposite direction of the gradient ($-\nabla K e$), search an optimal step length $\alpha$ (see (11)) to minimize the mismatch $e$. A new set of $\{K\}$ can be obtained.
4) Repeat steps 1 to 3 till $\frac{\partial e}{\partial K_l}$ is smaller than the given tolerance. The final set of $\{K\}$ is taken as the solution.

4. COMPUTER SIMULATION RESULTS

A two-area 4-machine interconnected power system [7] shown in Fig. 6 is used as the test system with a UPFC installed in one of the tie line 101-13. At steady state, about 700 MW power is generated from each of the generators. The loads on buses 3 and 13 are 967 MW and 1767 MW respectively. About 400 MW power is transferred from area 1 to area 2 through the parallel tie lines. The parameters of the UPFC system and its main control can be found in the appendix.

In order to get a set of training sample data for the FDC and compare the controller performance, a PSS-like conventional supplementary controller (CSC) is well designed based on the linear control theory with its dynamic response to a certain disturbance served as the FDC training sample data. The disturbance considered is a stub three-phase fault on tie line 3-101 close to the terminal bus 3, which is cleared in 0.05sec. without line tripping. Because of the high non-linearity of the system transients right after the fault, the training data exceeds the FDC output limit $[-0.2, 0.2]$ will have negative impacts on training results. Therefore, 250 samples in the time period of 4sec. - 9sec. are collected for FDC training.

The selection of initial value is very important for gradient descent training. The preferred $K_l$ is roughly selected through trail and error as $K = (0.5, 1.5, 0.5)$. Applying the gradient descent algorithm formulated previously, $K$ converges very fast to the value: $K_{GDT} = (0.43, 1.82, 0.75)$.

B. Time simulation results

The performance of the FDC is tested using time simulation. The disturbance used is still the three-phase fault on tie line 3-101 close to the terminal bus 3. Two cases are studied:

Case 1: Fault occurs at $t = 0.5$ sec. and cleared in 0.1 sec. without line tripping.
Case 2: Fault occurs at $t = 0.5$ sec. and cleared in 0.075 sec. by tripping line 3-101.

From Fig. 7 & 8, we can see that when there is no supplementary controller installed to the UPFC, the damping of the system is very poor even though the system is stable. The addition of either the CSC or the FDC can increase the system damping significantly and reduce the first swing peak angle slightly. The computer results show that the FDC is more effective in damping the rotor-angle oscillation. Also, as the system topology and operation point has changed, the FDC still performs very well. This indicates that the FDC has a better robustness as compared with its conventional counterpart.
The eigenvalue analysis is carried out in order to have a clearer insight of the FDC performance. Perturbation method is used in forming the system matrix in FDC case.

Table 2 System Eigenvalue (interarea mode)

<table>
<thead>
<tr>
<th>Eigenvalue</th>
<th>No SC</th>
<th>CSC</th>
<th>FDC</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.081 + j2.89</td>
<td>-0.431 + j2.48</td>
<td>0.490 + j2.92</td>
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</table>

We can see from Table 2 that the interarea mode of oscillation is improved by the addition of the supplementary controller. In addition, the FSC can result in a larger negative shift of the eigenvalues which means the system is more stable under small disturbances.

5. CONCLUSIONS

The application of fuzzy logic theory to the design of the supplementary controller for the UPFC is investigated. Gradient descent training is applied to optimise the parameters of the FDC. Transient stability simulation and small signal analysis are conducted to examine the performance of the FDC as compare with the conventional counterpart. The computer results show that the designed FDC has a superior performance over the CSC in improving damping of the system and has better robustness.

6. ACKNOWLEDGEMENT

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7. REFERENCE


8. APPENDIX

Parameters of the UPFC and its control system

The UPFC model:

- \( V_p = 220 \text{ kV}, S_p = 100 \text{ MVA} \)
- \( n_l = 0.05, n_2 = 0.25, X_l = 0.00025 \)
- \( X_p = 0.05 \) (all in p. u.)

UPFC main control:

- \( K_1 = 0.05, T_1 = 0.01, K_2 = 1.0, T_2 = 0.05, K_3 = 5.0, T_3 = 0.1, K_d = 5.0, T_d = 0.1 \)
- \( V_{dref} = 44 \text{ kV} \)

The parameters of the CSC:

- \( K_c = 0.83, T_w = 3.0s, T_i = T_d = 0.02s, T_2 = T_3 = 0.33s, \text{ lim_max} = 0.2, \text{ lim_min} = -0.2 \)