Genetic-based neuro-fuzzy Design of FACTS Controller in Power System

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Abstract: This paper introduces a critical assessment for the effectiveness of thyristor controlled reactor (TCR) and voltage source inverter (VSI) based FACTS devices on multi-machine power system oscillation damping. The oscillation problem is analyzed from the point of view of damping and synchronizing torque components. An eigenanalysis is adopted to study different controllers, their location, and use of various control signals for the effective damping of these oscillations. To improve system damping over a wide range of operating conditions, it is desirable to adapt the parameters of each damping controller in the system. In order to do this, on-line measurements of local system signals at converter are chosen as input signals to an adaptive neuro-fuzzy inference system (ANFIS). The outputs of each neuro-fuzzy controller are the desired parameters of system damping controllers.

Keywords: Power Electronics, static exciters, TCSC, UPFC, Power system, Genetic, neuro-fuzzy.

I. INTRODUCTION

A problem of current interest in power system industry is the mitigation of low frequency oscillations. These oscillations are related to the dynamics of interarea power transfer and often exhibit poor damping. Although power system stabilizers (PSSs) provide supplementary feedback stabilizing signals, they play no roles in power flow control or voltage support. FACTS devices can be used to control the power flow and enhance system stability. A well-designed FACTS controller can not only increase the transmission capability but also improve the power system stability. A series of approaches have been made in developing damping control strategy for FACTS devices. In [1] a conventional lead-lag controller for UPFC to improve the oscillation damping of a single-machine infinite bus system is proposed. On the basis of the linearized model, the damping function of the UPFC is investigated.

A robust fixed-structured power system damping controllers using genetic algorithm is presented in [2]. The GA searches for an optimum solution over the controllers’ parameter space over wide spectrum of operating conditions. But this approach does not insure good damping at each individual operating point. The approach is used to design SVC and TCSC damping controllers.

A linear optimal controller is proposed [3] to enhance the system dynamics and to coordinate three SVCs depending on two control levels, the local control to insure optimum performer's at the local level and the global control to make the coordination by decoupling the state equation for each area. Also a state observer is suggested to obtain the unmeasured states.

The problem of coordination is also handled in [4], a coordinated controller is designed to control a TCSC and a TCPAR. The controller is designed according to the linear quadratic problem, the gain matrix is modified to allow the controller to depend on output feedback. Also, the system states are reduced since the controller is concerned with the range of frequencies of the inter-area modes. But, conversion from optimal into output feedback controller deviates the controller performance and results in a sub-optimal approach.

In [5], a coordinated design of PSS and SVC for single machine-infinite bus system is proposed. The coordinated design problem of robust excitation and SVC based controllers over a wide range of loading conditions and system configurations are formulated as an optimization problem with an eigenvalue-based objective function. The real-coded genetic algorithm is employed to search for optimal controller parameters. However, FACTS devices are always installed in multi-machine systems.

In this paper, the design problem is transformed into an optimization problem, where the continuous-parameter genetic algorithm is employed to search for the optimal settings of all system damping controllers for each individual operating point. Then, the controllers’ parameters in the system are tuned according to each operating point by an individual hybrid neuro-fuzzy controller. The procedure is implemented in a multi-machine power system with two thyristor controlled series capacitors (TCSCs).

II. NETWORK EQUATIONS

In order to establish the relationship between the internal quantities of different machines in the power system, a common reference frame (D, Q) which rotates at synchronous frequency of the steady state network currents is considered. This selection is based on those derived in [6]. This selection has many advantages, the important one is that the angle δ between the d-q frame of each machine and the selected D-Q frame is itself the rotor angle that is between the system slack bus and the q-axis of the generators. Each individual machine can be referred to the general reference frame as:

\[
\begin{bmatrix}
    v_{di} \\
    v_{qi}
\end{bmatrix} =
\begin{bmatrix}
    \cos\delta_i & \sin\delta_i \\
    -\sin\delta_i & \cos\delta_i
\end{bmatrix}
\begin{bmatrix}
    v_{di} \\
    v_{qi}
\end{bmatrix}
\]  

(1)
Where \( V_{Di} \) and \( V_{Qi} \) are the voltages w.r.t. common frame while \( V_{di} \) and \( V_{qi} \) are the voltages w.r.t. the internal machine axis. The nodal admittance matrix can describe the network:

\[
I_N = Y_{bus} V_n
\]

Equation 2 can be written as:

\[
\begin{bmatrix}
I_{D1} \\
I_{Q1} \\
I_{Dn} \\
I_{Qn}
\end{bmatrix} = 
\begin{bmatrix}
G_{1i} & B_{1i} & \cdots & G_{ni} & B_{ni} \\
- B_{1i} & G_{1i} & \cdots & - B_{ni} & G_{ni} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
- B_{ni} & G_{ni} & \cdots & - B_{mn} & G_{mn}
\end{bmatrix}
\begin{bmatrix}
V_{D1} \\
V_{Q1} \\
V_{Dn} \\
V_{Qn}
\end{bmatrix}
\]

Where \( G_{ai} \) and \( B_{ai} \) are the real and imaginary parts of \( Y_{ii} \) respectively. Perturbing equation (3) gives:

\[
\Delta I_{D,Q} = G_{o} \Delta V_{D,Q} + V_{D,Q} \Delta G
\]  

Equation (4) indicates the way the FACTS devices models can be connected to the system.

To obtain the initial conditions of the system, load flow study should carried out to the system. Load flow of a power system with TCSC using Newton Raphson method is discussed in [7-9]. Let the TCSC be connected in the network between bus m and bus k as shown in Figure 1. The equivalent admittance matrix is:

\[
\begin{bmatrix}
\text{k} & \text{JX}_{TCSC} & \text{m}
\end{bmatrix}
\]

Fig. 1. The equivalent bus circuit.

\[
\Delta Y_{bus} = 
\begin{bmatrix}
-JB_{TCSC} & JB_{TCSC} \\
JB_{TCSC} & -JB_{TCSC}
\end{bmatrix}
\]

The primary function of the TCSC considered here is to control the active power flow through the line m-k. Varying the impedance of the TCSC through the appropriate firing angle controls this power. In this case the dimension of the Jacobian matrix of the system will be increased by one to calculate \( \Delta \alpha \) of the TCSC from the equation of \( \Delta P_{mk} \).

The way by which the TCSC model is connected to the power system power is through the matrix \( \Delta G \) so that:

\[
\begin{bmatrix}
\Delta I_{Dm} \\
\Delta I_{Qm} \\
\Delta I_{Dk} \\
\Delta I_{Qk}
\end{bmatrix} = G_{o} \Delta V_{D,Q} + 
\begin{bmatrix}
V_{Qm} - V_{Qk} \\
V_{Dm} - V_{Dk} \\
V_{Qk} - V_{Qm} \\
V_{Dk} - V_{Dm}
\end{bmatrix}
\]

where

\[
\Delta B_{TCSC} = B_{TCSC} \frac{\partial Y_{TCSC}}{\partial \alpha} \Delta \alpha
\]  

\( \Delta B_{TCSC} \) is considered as the control input to the system. The relation between the TCSC fundamental reactance and the thyristors firing angle is given in [7].

III. FACTS DEVICES DAMPING CONTROLLERS

A. Linearized Power System Model

In steady state stability studies, since it’s difficult to linearize and write the multi-machine power system equations directly in the form

\[
\dot{x} = Ax + Bu
\]

\[
y = Cx + Du
\]

The equations can be written in the following form:

\[
P \begin{bmatrix}
\dot{x} \\
y
\end{bmatrix} = Q[x] + R[u]
\]

Where \( P, Q, \) and \( R \) are real constant matrices with appropriate dimensions. The entries of these matrices are function of all the system parameters and depend on the operating conditions. The matrices \( P \) and \( Q \) can be partitioned as

\[
P = \begin{bmatrix}
I & A_1 \\
0 & A_2
\end{bmatrix} \quad Q = \begin{bmatrix}
O_1 \\
O_2
\end{bmatrix}
\]

The \( P \) matrix is of dimension \((n \times n)\) where \( n \) is the total number of state and algebraic variables. \( I \) is a unit matrix, \([0] \) is a null matrix.

B. Partial Pole-Placement Damping Controller

Pole-placement technique is used to locate the critical mechanical modes of the power system in a satisfactory location in the complex plain by using PSS [10]. The feedback control signal considered to the PSS is the generator speed which is one of the system states. Here, the same method will be used but it will be extended to feedback local algebraic variables (available at the FACTS devices location) to the FACTS devices damping controllers.

Fig. 2. Block diagram of a power system with damping controller.
For comparison study, a conventional P-I damping controller is considered for both the TCSC and the UPFC. The parameters of the controller are calculated by examining Figure 2. The transfer function of the controller is equal to the inverse transfer function of the system.

\[ H_{\text{damp}}(\lambda) = [C(\lambda I - A)^{-1}B + D]^{-1} \]

\[ = \frac{\tau_2\lambda}{1 + \tau_1\lambda} (k_p + \frac{k_i}{\lambda}) \]  

(11)

The gains \( k_p \) and \( k_i \) of the damping controller can be determined by substituting a pair of the pre-scribed mechanical mode eigenvalues \( \lambda_{1,2} \) into equation 10, so we have a pair of algebraic equations with two unknown \( k_p, k_i \).

C. Location and Input Signal to The Controller

There are many criterion in the literature used to determine the location and the feedback signal for the damping controllers. The residue index is used by [11] for the same purpose. The residue index together with the participation matrix [12] are used to determine the best location and feedback signal to the damping controller.

IV. SOFT COMPUTING

It is now realized that complex real-world problems require intelligent systems that combine knowledge, techniques and methodologies from various sources. These intelligent systems are supposed to possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions. It is frequently advantageous to use several computing techniques synergistically rather than exclusively, resulting in construction of complementary hybrid intelligent systems. The quintessence of designing intelligent systems of this kind is neuro-fuzzy computing: neural networks that recognize patterns and adapt themselves to cope with changing environments; fuzzy inference systems that incorporate human knowledge and perform inference and decision making. The integration of these two complementary approaches, together with certain derivative-free optimization techniques, results in a novel discipline called neuro-fuzzy and soft computing [13]. Jang and Sun [14] introduced the adaptive Neuro-Fuzzy inference system. This system makes use of a hybrid learning rule to optimize the fuzzy system parameters of a first order Sugeno system.

A. ANFIS Hybrid Training Rule

The ANFIS architecture consists of two training parameter set

1-The antecedent membership function parameters
2-The polynomial parameters [p, q, r]

In [14], The ANFIS training paradigm uses gradient descent algorithm to optimize the antecedent parameters and a least square algorithm to solve for the consequent parameters. Because it uses two very different algorithms to reduce the error, the training rule is called hybrid.

V. CONTINUOUS CODE D GENETIC ALGORITHM

Heuristically informed search techniques are employed in many artificial intelligence (AI) applications. When a search space is too large for an exhaustive search and it is difficult to identify knowledge that can be applied to reduce the search space, we have no choice but to use other, more efficient search techniques to find optimum solutions. The genetic algorithm (GA) is a candidate technique for this purpose.

Genetic algorithms are derivative-free stochastic optimization method based on the concepts of natural selection and evolutionary processes. There were first and investigated by John Holland in 1975[14].When the space parameters are continuous, it is more logically to represent them by floating-point numbers, in this case continuous parameter genetic algorithm has the advantage of requiring less storage than the binary genetic algorithm.

GAs usually keep a set of points as a population, which is then evolved repeatedly toward a better overall fitness value. In each generation, the GA constructs a new population using genetic operators such as crossover and mutation.

VI. SYSTE UNDER STUDY

The studied system is the IEEE 9-bus, 3-machine system, shown in Figure 3. The system consists of three generating stations; one of them is hydro while the others are steam stations. To address the problem of dynamic stability, each unit is equipped with static exciters, system data are found in [6].

![Fig.3. System under Study.](image)

Participation matrix [14] is used to classify system modes. Table I shows the mechanical and the interaction modes of the system after classification.

<table>
<thead>
<tr>
<th>TABLE I. SYSTEM MODES AFTER CLASSIFICATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanica l Modes</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Interaction Modes</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
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<tr>
<td></td>
</tr>
</tbody>
</table>
Table II shows the elements of the participation matrix corresponding to the mechanical modes. The three generators are equipped with static exciters, the effect of these exciters is to add negative damping torque component on generators shafts. This is the main cause of the unstable mode in the system.

**TABLE II.**

APART OF THE PARTICIPATION MATRIX CORRESPONDING TO THE MECHANICAL MODES

<table>
<thead>
<tr>
<th>Mech. States</th>
<th>$\lambda_{1,2} = -0.71 \pm 10.6i$</th>
<th>$\lambda_{3,4} = -0.59 \pm 7.9i$</th>
<th>$\lambda_{5,6} = 0.12 \pm 1.06i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \omega_1 \Delta \delta_1$</td>
<td>0.0056</td>
<td>0.1394</td>
<td>0.3240</td>
</tr>
<tr>
<td>$\Delta \omega_2 \Delta \delta_2$</td>
<td>0.0841</td>
<td>0.3349</td>
<td>0.0895</td>
</tr>
<tr>
<td>$\Delta \omega_3 \Delta \delta_3$</td>
<td>0.4180</td>
<td>0.0502</td>
<td>0.0548</td>
</tr>
</tbody>
</table>

VII. THE POWER SYSTEM WITH TCSCS

The effective location of TCSCs will be examined by checking the following locations:
1-In series with line 4-5 that connects generators #1 and #2.
2-In series with line 8-6 that connects generators #1 and #3
3-In series with line 6-7 that connects generators #2 and #3.

The three lines are the longest lines in the system and each line is compensated to the same level. Table III shows the residue index for the selected locations and with the line current and the line power as the feedback signal. The residue index coincides with the participation matrix elements in that, regarding system damping, lines 4-5 and 8-6 are the favorable lines to be installed with the TCSCs. The residue index of the line power is greater than that of the line current.

**TABLE III.**

THE RESIDUE INDEX FOR THE LINE CURRENT AND POWER FEEDBACK SIGNALS FOR TCSC IN DIFFERENT LOCATIONS

<table>
<thead>
<tr>
<th>Location</th>
<th>Line current</th>
<th>Line power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line 4-5</td>
<td>0.0594</td>
<td>0.7248</td>
</tr>
<tr>
<td>Line 8-6</td>
<td>0.0248</td>
<td>0.6091</td>
</tr>
<tr>
<td>Line 6-7</td>
<td>0.0003</td>
<td>0.0007</td>
</tr>
</tbody>
</table>

A TCSC with $X_c = 0.05$ pu and $X_l = 0.01$ pu is installed between bus’s 4 and 5 (these values insure about 30% line compensation when the thyristors are off). Line 8-6 will be compensated by 65% using another TCSC. System modes without damping controller are given in Table IV. The series capacitors slightly enhance the damping ratio of the critical mode and has no effect on the oscillation frequency or on the field-excitation modes.

The first TCSC in line 4-5 will now be installed with damping controller to locate this unstable mode to a stable location. System modes with the first damping controller are given in Table V. The calculated gains for the controller are $k_{p1} = -0.0759$ and $k_{i1} = -0.1163$.

**TABLE IV.**

SYSTEM MODES WITHOUT THE DAMPING CONTROLLERS

<table>
<thead>
<tr>
<th>Mechanical Modes</th>
<th>$\Delta \omega_1 \Delta \delta_1$</th>
<th>$\Delta \omega_2 \Delta \delta_2$</th>
<th>$\Delta \omega_3 \Delta \delta_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.08 ± 0.93i</td>
<td>-0.59 ± 7.9i</td>
<td>-0.73 ± 10.57i</td>
</tr>
<tr>
<td>Interaction Modes</td>
<td>-1.18 ± 0.80i</td>
<td>-3.83</td>
<td>-0.73 ± 0.85i</td>
</tr>
<tr>
<td>TCSC Modes</td>
<td>-12.11, -0.06</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The second TCSC (with line 8-6) damping controller will be designed to enhance the damping in the second mechanical mode. This mode will be shifted from $-0.54 \pm 8.18i$ to $-0.73 \pm 8.5i$. The required controller gains are $k_{p2} = 0.6604$ and $k_{i2} = -0.6349$. System modes with the second TCSC damping controller are given in Table VI.

GA will be used to search in the parameter space of the two controllers to maximize the damping ratio of system modes.

**TABLE V.**

SYSTEM MODES WITH THE FIRST DAMPING CONTROLLER

<table>
<thead>
<tr>
<th>Mechanical Modes</th>
<th>$\Delta \omega_1 \Delta \delta_1$</th>
<th>$\Delta \omega_2 \Delta \delta_2$</th>
<th>$\Delta \omega_3 \Delta \delta_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.15 ± 0.90i</td>
<td>-0.54 ± 8.18i</td>
<td>-0.73 ± 10.57i</td>
</tr>
<tr>
<td>Interaction Modes</td>
<td>-1.11 ± 0.74i</td>
<td>-3.71</td>
<td>-0.74 ± 0.85i</td>
</tr>
<tr>
<td>TCSC Modes</td>
<td>-12.11, -0.06</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**TABLE VI.**

SYSTEM MODES WITH THE TWO DAMPING CONTROLLER

<table>
<thead>
<tr>
<th>Mechanical Modes</th>
<th>$\Delta \omega_1 \Delta \delta_1$</th>
<th>$\Delta \omega_2 \Delta \delta_2$</th>
<th>$\Delta \omega_3 \Delta \delta_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.21 ± 1.17i</td>
<td>-0.73 ± 8.50i</td>
<td>-0.99 ± 11.22i</td>
</tr>
<tr>
<td>Interaction Modes</td>
<td>-0.83 ± 0.82i</td>
<td>-2.71</td>
<td>-0.72 ± 0.41i</td>
</tr>
<tr>
<td>TCSCs Modes</td>
<td>-12.26, -0.03</td>
<td></td>
<td>-5.14 ± 3.46i</td>
</tr>
</tbody>
</table>

IX. APPLICATION OF ANFIS TO ADAPT TCSCS SUPPLEMENTARY DAMPING CONTROLLERS GAINS

The fixed-gain controllers as determined in previous section have been designed based on the nominal operating conditions of the system. In reality, the operating conditions change with time and, as a result, the dynamic performance of the system will change. Thus, to maintain good dynamic response at all possible operating conditions, the controllers’ gains need to be adapted based on system operating conditions. ANFIS will be used in this work to adapt the controllers’ gains of both the TCSCs damping controllers in real time. Before ANFIS can be used, it is necessary to determine a proper set of training patterns. Each training pattern comprises a set of input data and
corresponding output data. For each TCSC damping controller, an ANFIS will be designed to adapt its gains. The input for each ANFIS will be the line active power and line current. For a pair of $P_a$ and $I$ in each line, we can proceed to determine a set of PI controllers’ gains using GA, and the results are employed as the ANFIS outputs.

Table VII shows a part of the training patterns obtained by GA for each ANFIS. For each operating point, the obtained controllers’ parameters are quite different.

<table>
<thead>
<tr>
<th>Case #</th>
<th>$P_a$</th>
<th>$I_a$</th>
<th>$K_{P_a}$</th>
<th>$K_{I_a}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.8063</td>
<td>0.8692</td>
<td>-0.1238</td>
<td>0.4451</td>
</tr>
<tr>
<td>2</td>
<td>-0.8933</td>
<td>0.9492</td>
<td>0.4656</td>
<td>2.3275</td>
</tr>
<tr>
<td>3</td>
<td>-1.1077</td>
<td>1.1870</td>
<td>-0.0906</td>
<td>-0.0723</td>
</tr>
<tr>
<td>4</td>
<td>-1.3173</td>
<td>1.4339</td>
<td>-0.0625</td>
<td>1.6305</td>
</tr>
</tbody>
</table>

IX. SYSTEM PERFORMANCE WITH ANFIS DAMPING CONTROLLERS

The performance of the proposed ANFIS damping controllers has been investigated. The response of the system with fixed-gain genetic-based damping controllers designed at normal operating conditions and with the adaptive ANFIS damping controllers is compared.

A 0.05 p.u step increase in the mechanical power reference input of generator # 1 is applied at $t = 0.0$ and not removed. System response for this disturbance is shown in Figure 4.

![Figure 4](image_url)

**Fig. 4.** Actual and predicted $k_p$ from the first ANFIS

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X. CONCLUSION

1- This paper illustrates the superiority of the FACTS devices damping controllers based upon ANFIS and GA over the fixed parameter controllers. The proposed controllers stabilize the system for different operating conditions. A novel hybrid technique based on ANFIS is proposed to adapt system damping controllers’ gains to improve the damping characteristics of system over a wide range of operating conditions. The proposed ANFISs were trained based on real-time measurements of local signals available at pendulum's angle and position. Damping controllers’ gains can be determined by the ANFISs, which makes the proposed stabilizer relatively simple and suitable for practical on-line implementation.

REFERENCES


