A PSO-Based Neuro-Sliding Mode Controller for the Stability Enhancement of Power Systems with UPFC

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Abstract: - This paper presents a particle swarm optimization (PSO)-based neuro-sliding mode controller for the transient stability enhancement of multimachine power systems with unified power flow controller (UPFC). The UPFC is modeled as controllable loads. These controllable parameters are obtained using the sliding mode control (SMC) strategy. A PSO-based single neuron controller is used to adapt the parameters of the SMC. The efficacy of this new approach in damping the local-mode and inter-area mode of oscillations over a wide range of operating conditions is confirmed by comparing the performance with that of a conventional proportional-plus-integral (PI) controller and that of a single neuron controller.

Key-Words: - UPFC, sliding mode control, neuron controller, particle swarm optimization.

1 Introduction

With the increasing electric power demand, power systems become stressed, resulting in undesirable voltage and frequency conditions. Different types of FACTS devices have been studied to show their effectiveness in enhancing stability and also in reducing electromechanical oscillations in interconnected power systems [1]. Amongst the several FACTS devices studied for system stabilization, UPFC provides the most versatile performance in damping out low frequency multimodal oscillations [2]. For many years, power system stabilizers (PSSs) have been one of the most common controls used to damp out oscillations and to offset the negative damping of automatic voltage regulators. However, during some operating conditions, this device fails to produce enough damping especially to inter-area modes [3] and, hence, there is an increasing interest in using FACTS devices to aid in damping of these oscillations.

The UPFC is a solid-state multi-functional FACTS controller with the primary objective of power flow control plus possible secondary functions of voltage support, transient stability improvement, oscillations damping, etc. The basic circuit arrangement of an UPFC is shown in Fig.1.

Several control strategies have been reported recently for the UPFC [2,3]. The PI regulator used for the control of FACTS devices is inadequate in providing suitable control and transient stability enhancement over a wide range of power system operating conditions [4]. A radial-basis-function neural network control scheme has also been suggested for the UPFC to damp out electromechanical oscillations [5]. Linearized power system models with UPFC have been developed in [6] and [7] to damp out inter-area oscillations. Since these controllers are derived from small-signal models at a given operating point, they are not globally optimal. Besides, the nonlinear nature of power systems necessitates the development of a non-linear controller. On the other hand, the fuzzy-logic approach provides a model-free control for the UPFC and is effective over the entire range of system operation. This fuzzy-logic-based approach uses linguistic rules for both the antecedent and consequent parts and, hence, not able to provide a wide variation of the control gains as may be required for many of the UPFC operations. Instead, a Takagi-Sugeno type fuzzy controller provides a wide variation of the control gains and could use either a linear consequent rule base or a nonlinear one. A recent version of this type of controller [8] is found to be very efficient for a wide variety of nonlinear control problems.

![Fig.1: Basic circuit arrangement of an UPFC.](image-url)
dynamics, a sliding mode strategy is adopted. The undesired chattering phenomenon of this approach has been eliminated in [9] by adopting a supervisory control. This paper aims at controlling the controllable parameters of the UPFC through a PSO-based neuro-sliding mode controller[3,9-11]. It is an approach of cooperative control that is based on the concept of combining neural networks, PSO, and the methodology of SMC.

2 System Model

2.1 UPFC Modeling

The basic circuit arrangement of an UPFC is shown in Fig.1. It is composed of a shunt transformer (AT), a series transformer (ST), a dc link capacitor, and two three-phase voltage source inverters. Fig.2 shows the simplified model of UPFC where, \( \rho_{se} |V_s| \) and \( \rho_{se} |V_a| \) are the voltages induced across ST and AT, respectively. The UPFC can also be represented as two current sources as shown in Fig.3.

Fig.2 UPFC equivalent circuit with controlled voltage sources

\[
\begin{align*}
\rho_{se} |V_s| & \text{ and } \rho_{se} |V_a| \text{ are the voltages induced across ST and AT, respectively.} \\
\rho_{sh} |V_s| & \text{ and } \rho_{sh} |V_a| \text{ are the voltages induced across SH and AT, respectively.}
\end{align*}
\]

Fig.3 UPFC equivalent circuit with controlled current sources

where, \( x_{sh}, x_{sh}, B_{se}, B_{sh} \) = series & shunt reactances and susceptances of UPFC inverter transformers, respectively.

\( \rho_{se}, \alpha_{se} = \text{series voltage magnitude ratio (V}_{ST}/|V_s|) \) and angle of V\text{ST} with respect to V\text{s}, respectively.

\( \rho_{sh}, \alpha_{sh} = \text{shunt voltage magnitude ratio (V}_{AT}/|V_s|) \) and angle of V\text{AT} with respect to V\text{s}, respectively.

These current injections can be converted to appropriate real and reactive power injections at the respective buses. The real and reactive powers injected at the buses s and r are:

\[
P_s = \rho_{se} |V_s|^2 B_s \sin \alpha_s + \rho_{sh} |V_s|^2 B_s \sin \alpha_s
\]

\[
Q_s = \rho_{se} |V_s|^2 B_s \cos \alpha_s - B_s |V_s|^2 + \rho_{sh} |V_s|^2 B_s \cos \alpha_s
\]

\[
P_r = -\rho_{se} B_s |V_s|^2 \sin (\alpha_r + \alpha_s)
\]

\[
Q_r = -\rho_{sh} B_s |V_s|^2 \cos (\alpha_r + \alpha_s)
\]

Since \( \alpha_s = 0 \) for shunt inverter operation, (1) becomes

\[
P_s = \rho_{se} |V_s|^2 |B_s| \sin \alpha_s
\]

\[
Q_s = \rho_{se} |V_s|^2 |B_s| \cos \alpha_s
\]

For constancy of dc link voltage, the following relation should be satisfied.

\[
P_{sh} + P_{se} = 0
\]

where, \( P_{sh} \) and \( P_{se} \) are real powers exchanged with the power system by the shunt and the series inverters, respectively. As the shunt and series inverters are controlled independently, the exact power balance between the two is never achieved. To take care of this mismatch in real power, an additional term, \( |V_{si}||I_s| \), is used in (2).

\[
P_i = \rho_{se} |V_s|^2 B_s \sin \alpha_s + |V_s| |I_s|
\]

\[I_s = \text{real component of shunt converter current. The controllable loads are obtained from (1) as}
\]

\[
Y_s = (p_s - jq_s)/|V_s|^2, Y_c = (p_i - jq_i)/|V_i|^2
\]

Further, in equation (1), the parameters \( \rho_{se} \) and \( \alpha_{se} \) of the series voltage control circuit are controllable within limits

\[
0 \leq \rho_{se} \leq \rho_{se, max} \quad \text{and} \quad 0 \leq \alpha_{se} \leq 2\pi
\]

2.2 UPFC Control

To take care of the mismatch in achieving an exact real power balance between the series and shunt converters, the control scheme assumes that both the converters generate controllable voltage sources and the dc bus voltage remains substantially constant. Power flow control of the series converter is achieved by splitting the series voltage \( V_s \) into two components \( V_{sp} \) and \( V_{sq} \), with \( V_{sp} \) in phase with the transmission line current \( i_s \) and \( V_{sq} \) in quadrature with it. The transmission line current \( i_s \) is obtained from

\[
i_s = \sqrt{i_{sq}^2 + i_{sp}^2}
\]

and

\[
\begin{bmatrix}
V_{sp} \\
V_{sq}
\end{bmatrix} = \begin{bmatrix}
\sin \theta & \cos \theta \\
-\cos \theta & \sin \theta
\end{bmatrix} \begin{bmatrix}
V_{al} \\
V_{am}
\end{bmatrix}
\]

where

\[
\begin{align*}
V_{al} & = \rho_s \sin \alpha_s V_{al} - \rho_s \sin \alpha_s V_{al} \\
V_{am} & = \rho_s \sin \alpha_s \sin \alpha_s + \rho_s \cos \alpha_s V_{al}
\end{align*}
\]

\[
\theta = \tan^{-1}\left(\frac{i_{sp}/i_{sq}}{V_{sp}/V_{sq}}\right), \quad V_c = \sqrt{V_{sp}^2 + V_{sq}^2}
\]

\( V_{sd}, V_{sd}, V_{sq}, V_{sq}, V_{sd}, \text{ and } V_{sq} \) are the direct- and quadrature- axis components of current and voltages, respectively. The phase and quadrature components of \( V_c \) are obtained from PI regulators as explained in next section. Further, controllable parameters \( \rho_{se} \) and \( \alpha_{se} \) of the series circuit are related to \( V_{sp} \) and \( V_{sq} \) as

\[
\rho_{se} = \sqrt{V_{sp}^2 + V_{sq}^2} / |V_s|
\]

\[
\alpha_{se} = \tan^{-1}(V_{sp}/V_{sq}) + \tan^{-1}(i_{sd}/i_{sq}) - \tan^{-1}(i_{sd}/i_{sq})
\]
The dynamic equations of the UPFC are centered around the dc link capacitor. The dynamics of dc link voltage neglecting the losses is represented as:

\[
\dot{V}_{dc} = \frac{1}{C_{Vdc}} \left[ I_{dc} - B_{d} P_{m} \right] \left[ V_{dc} \right] \left[ \sin(\theta_{d} + \alpha_{d}) \right] + k_{p} \left( V_{dc} - V_{dc}^{*} \right) dt
\]

where, \( I_{dc} \) is obtained using a simple PI controller as:

\[
I_{dc} = K_{pdc} \left( V_{dc}^{ref} - V_{dc} \right) + K_{idc} \int \left( V_{dc}^{ref} - V_{dc} \right) dt
\]

The values of the gains are given in the Appendix.

### 2.3. Synchronous Machine Model

Each synchronous generator is modeled as a third order model equipped with a simple automatic voltage regulator and a PSS and its dynamics are:

\[
p\delta = \omega - \omega_{0}\,; \quad p\omega = \frac{m}{H} (P_{m} - P_{e})
\]

\[
pE_{f} = (E_{f0} + \Delta E_{f} - E_{f}') - (x_{d}' - x_{d}') j_{d}'\,/\tau_{d}'
\]

\[
p\Delta E_{f} = K_{e} \left( V_{m} - V_{r} + u \right) - \Delta E_{f} / \tau_{e}
\]

where, \(-6.0 \leq E_{f} \leq 6.0\,; \quad P_{m} = E_{f}' j_{q} + (x_{d}' - x_{d}') j_{d}'

The control \( u \) in (14) is obtained from the PSS control loop as follows:

\[
u = K_{p} (s_{e} / 1 + s_{t}) \left( (1 + s_{t}) / (1 + s_{t}) \right) \Delta \omega
\]

where the values of all gains and constants are given in the Appendix.

### 2.4. Conventional PI controller

The phase and quadrature components of \( V_{a} \) are obtained from PI regulators as follows:

\[
V_{a} = e_{a} \left( K_{p} + \frac{K_{i}}{s} \right)
\]

\[
V_{q} = e_{q} \left( K_{p} + \frac{K_{i}}{s} \right)
\]

\[
e_{a} = Q_{ref} - Q_{out} \left( \frac{K_{i}}{1 + s T_{e}} \right) + (\theta_{m} - \theta_{m})
\]

\[
e_{q} = P_{ref} - P_{out} \left( \frac{1}{1 + s T_{e}} \right) + (\theta_{m} - \theta_{m}) \times \left( \frac{K_{i} \theta_{m}}{1 + s T_{e}} \right)
\]

\[
P_{line} \quad Q_{line}
\]

\[
P_{line} = \text{real and reactive powers flowing in the line 7-8 towards bus 8, respectively.}
\]

The control block diagram of PI controller is given in Fig.4. The gains of the PI controller are optimized using ITSE criterion. The values of all gains and constants are given in the Appendix.

### 3. Sliding Mode Controller

The sliding surfaces \( \sigma_{p} \) (for \( v_{up} \) control) and \( \sigma_{q} \) (for \( v_{up} \) control) are defined as:

\[
\sigma_{p} = \lambda_{p} e_{p} + \lambda_{q} e_{q} + \frac{v_{up}(k) - v_{up}(k-1)}{h}
\]

\[
\sigma_{q} = \lambda_{p} e_{p} + \lambda_{q} e_{q} + \frac{v_{up}(k) - v_{up}(k-1)}{h}
\]

where, \( e_{p} \) and \( e_{q} \) are given in (19) and (18), respectively. The parameters \( \lambda_{p} \) to \( \lambda_{q} \) are tuned using PSO based neuron adaptive controller as explained in next section. \( \sigma_{p} \) and \( \sigma_{q} \) can be rewritten as:

\[
\sigma_{p} = \lambda_{p} e_{p} + \lambda_{q} e_{q} + \frac{v_{up}(k) - v_{up}(k-1)}{h}
\]

\[
\sigma_{q} = \lambda_{p} e_{p} + \lambda_{q} e_{q} + \frac{v_{up}(k) - v_{up}(k-1)}{h}
\]

where, \( k \) is iteration number and \( h \) is step length (0.01). The reachability condition for the sliding mode control is used to obtain \( v_{up} \) and \( v_{up} \) as follows:

\[
\sigma = -\eta \, \text{sgn} \, \sigma, \quad \sigma \sigma < 0, \quad \text{and} \quad \eta > 0.
\]

\[
\eta \quad \text{is a positive constant} \quad (=0.012). \quad \text{Substituting} \quad (24) \quad \text{in} \quad (23) \quad \text{yields},
\]

\[
\dot{v}_{up}(k) = h \left( -\eta \, \text{sgn} \, \sigma - \lambda_{p} e_{p} - \lambda_{q} e_{q} + \frac{v_{up}(k-1)}{h} \right)
\]

Similarly, substituting (24) in (23) yields,

\[
\dot{v}_{up}(k) = h \left( -\eta \, \text{sgn} \, \sigma - \lambda_{p} e_{p} - \lambda_{q} e_{q} + \frac{v_{up}(k-1)}{h} \right)
\]

### 4. PSO-based Neuro SMC

A simple PSO-based neural controller in the form of an adaline is given in Fig.5. For the on-line learning, two sliding surfaces \( \sigma_{up} \) and \( \sigma_{q} \) are defined as:

\[
\sigma_{up} = \dot{e}_{up} + \lambda \, e_{up}
\]

\[
\sigma_{up} = \dot{e}_{up} + \lambda \, e_{up}
\]

where, \( \lambda \) is a positive constant \((=5)\).

\[
e_{up} = \left( y(k+1) - y(k) \right) / \beta + \left( u(k) - u(k-1) \right)
\]

\[
\beta = 0.01 \quad \text{(a small positive constant)}
\]

\[
\dot{u}(k) = \beta u(k) - u(k-1)
\]

where, \( y(k), y(k+1) = P_{line} \) at \( k^{th} \) and \( (k+1)^{th} \) steps, respectively.

\[
u(k), \quad u(k+1) = \text{control input signal,} \quad v_{up}, \quad \text{at} \quad k^{th}, \quad \text{and} \quad \text{(k+1)^{th}} \quad \text{steps, respectively.}
\]

The weight update model is given by:

\[
\lambda_{p} = \lambda_{p} + \eta \, \text{sgn} \, \sigma_{up} \, e_{up} \, \left( f_{u} \right) + \frac{\lambda_{p}}{\lambda_{u}}
\]

\[
\lambda_{p} = \lambda_{p} + \eta \, \text{sgn} \, \sigma_{up} \, e_{up} \, \left( f_{u} \right) + \frac{\lambda_{p}}{\lambda_{u}}
\]

Fig. 4: Block diagram of the conventional PI controller.
and \( \lambda_{b,i} = \lambda_{a,i} + \alpha \text{sign}(\sigma_{a,i}) | e_{a,i} | f_{a,i} - e_{a,i} \) \( \lambda_{a,i}^{(PSO)} \) (32)

where, \( X_{f,i} = \lambda_{a} \times \Delta P_{f,i} + \lambda_{b} \times \Delta P_{b,i} \) \( \lambda_{a} \) (33)

\( \Delta P_{f,i} = (P_{\text{ref}} - P_{\text{inv}}) \) \( \lambda_{b} \) (34)

\( X_{g,i} = \lambda_{a} \times \Delta Q_{f,i} + \lambda_{b} \times \Delta Q_{b,i} \) \( \lambda_{a} \) (35)

\( \Delta Q_{f,i} = (Q_{\text{ref}} - Q_{\text{inv}}) \) \( \lambda_{b} \) (36)

\( f_{H_{,}xp} = \frac{-1}{1 + e^{-x_{r}}} \) \( f_{H_{,}yp} = \frac{-1}{1 + e^{-y_{r}}} \) are log-sigmoid functions.

\( \alpha \) is a positive constant(0.01). Convergence of \( \lambda_{1} \) to \( \lambda_{4} \) is guaranteed by a proper choice of \( \alpha \). The PSO algorithm used for tuning the control parameters is explained in next section.

5. PSO ALGORITHM

PSO is a novel stochastic optimization technique that has its origin in the motion of a flock of birds searching for food, fish schooling and swarm theory. PSO is initialized with a specific number of random particles. The fitness value of each particle is evaluated based on the fitness function to be optimized and the particle with the best fitness value is chosen as the solution. By updating the velocities and directions of particles, a new generation is obtained. This process continues until an optima or a specified tolerance is obtained.

In each generation, particles are updated based on three ‘best’ values. The first one is the best solution of the \( i^{th} \) particle that has achieved so far, \( \text{pbest} \). The second one is the best solution obtained so far by any particle, \( \text{gbest} \). The third one is the local best (lbest). When a particle takes part of the population as its topological neighbors, the best solution among its neighborhood is a local best. This neighborhood topology tends to delay convergence and therefore allow more exploration. It has been stated that smaller, overlapping neighborhoods was often more effective [11]. In this paper, overlapping neighborhood is used to find lbest and each particle updates its velocity according to any one of the equations (37-39) and limits its velocity according to (40). Then each particle is updated according to (41).

\( \forall i \), \( \text{pbest}(t+1) = \begin{cases} \text{pbest}(t), \text{ if } f(x,(t+1)) \leq \text{pbest}(t) \\ f(x,(t+1)) \end{cases} \) \( \text{pbest}(t) \) (46)

The global and local best solutions are updated as:

\( \forall i \), \( \text{gbest}(t+1) = \begin{cases} \text{gbest}(t), \text{ if } \text{gbest}(t+1) \leq \text{gbest}(t) \\ \text{gbest}(t+1) \end{cases} \) \( \text{gbest}(t) \) (47)

\( \forall i \), \( \text{lbest}(t+1) = \begin{cases} \text{lbest}(t), \text{ if } \text{lbest}(t+1) \leq \text{lbest}(t) \\ \text{lbest}(t+1) \end{cases} \) \( \text{lbest}(t) \) (48)

where \( v_{x,i} \) and \( v_{y,i} \) are the particle velocity, \( i \) is the particle number which varies from 1 to population size, \( d \) varies from 1 to the dimension of problem space \( j \) (j=4), \( t \) is the generation step, \( \omega \) is the weight factor (\( \approx 1 \)), \( c_{1} \), \( c_{2} \) and \( c_{3} \) are learning factors (2.0 to 4.0), \( \text{rand} \) is a random number, \( x_{d,i} \) is the current particle, \( p_{b}, g_{b} \) and \( l_{b} \) represent the positions corresponding to \( \text{pbest}, \text{gbest} \) and \( \text{lbest} \), respectively, \( K_{1}, K_{2} \) and \( K_{3} \) are constriction factors, \( v_{\text{max}} \) represents the maximum change a particle can have during a generation, and \( x_{\text{max}} \) and \( x_{\text{min}} \) represent the maximum and the minimum limits of the particles. These operations increase the particle’s initial diversity and enable the swarm to overcome preconvergence problem. In this version, \( m \) dimensions are randomly chosen to learn from (37). Some of the remaining dimensions are randomly chosen to learn from (38) while the other remaining dimensions learn from (39). The fitness function used for evaluation is:

\( f(x) = \frac{1}{1 + e^{-x}} = \frac{1}{1 + \left( \sum_{i=1}^{n} (e_{c,i} + e_{a,i}) / n \right)} \)

where, \( n \) is the number of input-output pairs. The best fitness values are updated at each generation based on (46), where \( f \) denotes the fitness function.

\( \forall i \), \( \text{pbest}(t+1) = \begin{cases} \text{pbest}(t), \text{ if } f(x,(t+1)) \leq \text{pbest}(t) \\ f(x,(t+1)) \end{cases} \) \( \text{pbest}(t) \) (49)

\( \forall i \), \( \text{gbest}(t+1) = \begin{cases} \text{gbest}(t), \text{ if } \text{gbest}(t+1) \leq \text{gbest}(t) \\ \text{gbest}(t+1) \end{cases} \) \( \text{gbest}(t) \) (50)

\( \forall i \), \( \text{lbest}(t+1) = \begin{cases} \text{lbest}(t), \text{ if } \text{lbest}(t+1) \leq \text{lbest}(t) \\ \text{lbest}(t+1) \end{cases} \) \( \text{lbest}(t) \) (51)
6. Simulation Results

For the simulation, a four-machine two-area power system of Fig. 6 is considered. The system data is given in [1]. A modulating signal is generated either from the power flow or phase angle difference between buses 8 and 9. This modulating signal is added to the constant power flow control of the series element. \( \theta_{89} \) can be obtained from:

\[
\Delta P_{89} = \frac{|V_8| |V_9| \sin(\theta_8 - \theta_9)}{X_{89}}
\]

(49)

If \( \theta_8 - \theta_9 \) is small, \( \sin(\theta_8 - \theta_9) \approx \theta_{89} \) and \( |V_8| |V_9| \approx |V_9|^2 \)

Hence

\[
\theta_{89} = \Delta P_{89} X_{89} / |V_9|^2
\]

(50)

Case 1:

Taking machine G3 as reference and the pre-disturbance operating condition in p.u. as \( P_1 = 0.556 \), \( Q_1 = 0.206 \), \( P_2 = 0.556 \), \( Q_2 = 0.261 \), \( P_3 = 1.374 \), \( Q_3 = 0.150 \), \( P_4 = 0.556 \), \( Q_4 = 0.224 \), a three-phase fault of 0.1s duration is simulated at the middle of the transmission line connecting buses 9 and 10. The local and inter-area modes of oscillations and the DC capacitor voltage variation are shown in Figs.7-9, respectively. It is clearly found that the system oscillations are damped very well by the proposed controller and the overshoots and settling time are well controlled.

Case 2:

To validate the effectiveness of the proposed controller, operating conditions of the power network are changed to \( P_1 = 0.5 \), \( Q_1 = 0.206 \), \( P_2 = 0.611 \), \( Q_2 = 0.261 \), \( P_3 = 1.478 \), \( Q_3 = 0.181 \), \( P_4 = 0.444 \), \( Q_4 = 0.224 \), and a three-phase fault of 100ms duration is created at the middle of the transmission line connecting bus-7 and bus-8. The local mode and inter-area mode of oscillations are presented in Figs.10 and 11, respectively. From the figures it is clearly found that the system oscillations are damped much faster using the proposed controllers.

Case 3:

In order to test the effectiveness of the proposed controller, the same fault of case-2 is simulated with a fault clearing time of 200ms. Figs.12 and 13 show the inter-area and local mode of oscillations,
respectively. From the responses, it can be seen that
the instability of PI controller is overcome by the
proposed controller.

Fig.13: Local-mode of oscillation

7. Conclusion
A new UPFC control design for improving the
transient stability of power systems is presented in
this paper using the concepts of SMC, neural
adaptation scheme and PSO technique. The control
gains of the SMC are adapted by using a PSO-based
adaline. The performance of the proposed controller
is evaluated vis-à-vis the conventional PI and neuro-
sliding mode controls to validate its superior
performance. This new controller is found to be
to very effective to fault location and provides
significant transient stability improvements over a
wide range of operating conditions. Using this new
controller, both inter-area and local modals of
oscillations are damped much faster and its fault
clearing time is improved considerably.

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Appendix
Parameters of the studied system (in per unit unless
indicated specially)

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<th>Ke</th>
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<th>H(s)</th>
<th>τ'_e(s)</th>
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Table 1: Generator data

UPFC data:
\[ x_\omega = 0.0006, V_{\omega_{\text{max}}} = 0.1, V_{\omega_{\text{min}}} = -0.1, V_{\text{op}_{\text{max}}} = 0.1, \]
\[ V_{\text{op}_{\text{min}}} = -0.1, V_{\text{d_{bus}}} = 31.113 \text{kV}, C = 5500 \text{ } \mu F \]

Time constants of PSS transfer function:
\[ K_{\text{p}} = 12, K_{\text{t}} = 0.35, K_{\tau} = 0.05 \]

<table>
<thead>
<tr>
<th>K_{\text{STAB}}</th>
<th>K</th>
<th>T_{\text{a}}(s)</th>
<th>T_{\text{a}}(s)</th>
<th>T_{\text{a}}(s)</th>
<th>T_{\text{a}}(s)</th>
<th>T_{\text{a}}(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>1.0</td>
<td>0.1</td>
<td>0.01</td>
<td>1.0</td>
<td>0.01</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 2: Damping controller data

Conventional PI controller
\[ K_{\text{p}} = -0.05, K_{\text{i}} = -0.013 \text{ (Q controller)} \]
\[ K_{\text{p}} = -0.05, K_{\text{i}} = -0.013 \text{ (P controller)} \]
\[ K_{\text{dc}} = 0.1, K_{\text{ilc}} = 0.1 \]