DESIGN OF A NEURAL NETWORK BASED SVC CONTROLLER

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Abstract: A controller to control the output of a Static Var Compensator (SVC) to damp power system oscillations is developed in this paper. The proposed SVC controller is based on the discrete time filtered direct control theory by which a multilayer neural network with the hyperbolic tangent activation function is derived. Advanced weight tuning algorithm based on a modified delta rule and projection algorithm are used to update the weights of the proposed neural network (NN) and improve the learning rate. Simulation studies with the proposed controller on a single machine-infinite bus system show that the power system stability is improved and the proposed algorithm has a better performance than the traditional controllers.

Keywords: Electric power systems, Power system stabilizers, Damping, Neural networks, Nonlinear control, Direct digital control

1. INTRODUCTION

After many years of research and development of controllers to damp system oscillations, many methodologies and control algorithms have been developed. Power System Stabilizers (PSS) on generators have been employed in power systems for many years and provide very effective damping of generator oscillations, but power system oscillations are still a problem in power system operation. How to fully take advantage of the resource and ability in the system to further improve overall power system stability is an active topic in recent years. Damping in the transmission paths by taking full advantage of the resources available is a viable alternative.

With the rapid development in the power electronic technologies in recent years, the flexible AC transmission system (FACTS) has started to be widely used in the modern power systems. Since FACTS elements in power systems are controlled by power electronic components such as Gate Turn-off thyristors (GTOs) and Diodes, which are dynamically adjustable, FACTS equipment can also be used for system oscillation damping. Among various FACTS devices, SVCs are being used in power systems to compensate for reactive power and provide voltage support. They have the potential to be used for damping the oscillations, and work together with generator PSSs to improve the overall power system stability.

Considerable effort (Lerch,1991) (Ghandhari, 2002) (Wang, 1997,2000)(Canizares and Faur, 1999) (Armansyah, and Yorino, 2002) (Rahim, 2001) (Hiyama, 1999) has been devoted to the design of controls for SVCs to damp power system oscillations in recent years. Traditional PSS design methodology can also be used in the SVC PSS design, but it meets the same problem as in the generator PSS design. Uncertain system parameters determine that conventional PSS design method cannot keep the desired damping function for all operating conditions. As NNs have ability to globally approach any uncertain nonlinear system, the proposed SVC controller will be based on an NN to approach the nonlinear power system. The discrete time direct control theory described in (Jagannathan, 1996,1999) is selected to design the controller. The proposed controller needs only one neural network in comparison to the indirect control design methods that needs two: one for system parameter identification and another for control.

Overview of the proposed SVC controller is given in Section II. Selection of an NN for the controller and mathematical derivation of the discrete time direct control algorithm is demonstrated in Section III. Simulation results of the proposed controller are described in Section IV to show the effectiveness of the damping function of the proposed controller. Conclusions and future work are given in the last section.

2. OVERVIEW OF SVC CONTROLLER

Structure of an SVC controller is similar to that of a generator excitation controller. Automatic voltage regulator (AVR) is the primary control to adjust the voltage to the desired value at the system bus where the SVC is connected to support electrical power transmission. SVCs with only voltage control mode do not improve damping and in some conditions may even have negative impact on damping system oscillations (Hiyama, 1999). Therefore, a supplementary control should be added to the voltage controller to allow bus voltage to vary. This additional control signal can be provided through the voltage control loop.

Configuration of an entire SVC controller with a supplementary damping control is shown in Fig. 1. K_a and T_a are the gain and the time constant of the SVC AVR (SAVR). V_{amax} and V_{amin} are the upper and lower limits of the SAVR output, and V_{stmax} and V_{stmin} are the upper and lower limits of the output of the supplementary controller. V_{ref} is the reference voltage and V_m is the actual measured voltage of the bus. Many signals can be selected or combined as the input signal of the supplementary controller. In this paper, deviation of the generator angular speed is selected for the control design. Since it cannot be measured locally, deviation of the frequency can be used instead. The two signals have only a second order difference.

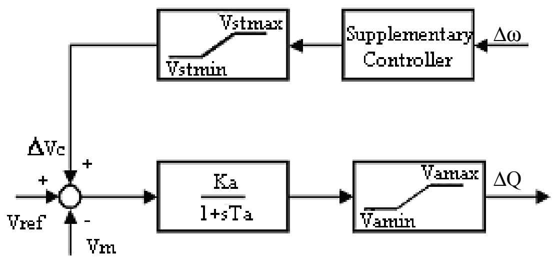

Fig. 1 SVC Controller Configuration

3. NN BASED SUPPLEMENTARY CONTROLLER

3.1 Neural network

Comparing structures of different NNs and learning algorithms, the multilayer preceptron structure with hyperbolic tangent function as the activation function is selected for the proposed NN and a modified Delta rule is used to update the weights.

Architecture of the proposed NN is shown in Fig. 2. The inputs of the NN are selected as the deviation of the generator angular speed and its two delays. There are 10 neurons in each of the first and second layers. Hyperbolic tangent function is used as the activation function of both the first and the second layers. In the third layer, the output layer, the activation function is selected as a linear function. $\mathbf{W_1}$, $\mathbf{W_2}$ and $\mathbf{W_3}$ are weight matrices and vector corresponding to the hidden layers and the output layer, respectively. $\mathbf{W_1}$ is a 3 by 10 matrix, $\mathbf{W_2}$ is a 10 by 10 matrix and $\mathbf{W_3}$ is a 10 by 1 vector.

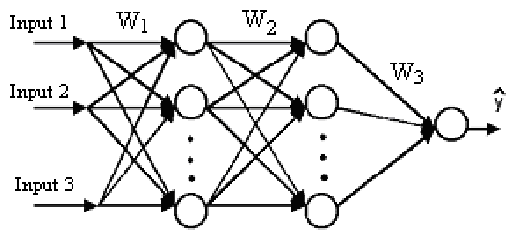

Fig. 2 Architecture of the Proposed Neural Network

For a given *input∈R*, the output of the proposed three-layer NN is given by the mathematical relationship:

$$\hat{y} = w_3^{\ T}\Phi(w_2^T\Phi(w_1^{\ T} Input)) \tag{1}$$

where Φ (•) is the hyperbolic tangent function.

A modification of the Delta learning algorithm described in (Jagannathan, 1996) is employed to update the weights of the proposed NN. In the case of a multilayer NN, this algorithm overcomes the need for persistent excitation. The extension of the Lyapunov theory for dynamic systems given in (Jagannathan, 1996) can guarantee the convergence of the weights.

The modified weight updating equations (2)-(4) are shown below.

$$\begin{aligned} W_1(k+1) &= W_1(k) - \alpha_1\Phi_1(k)[W_1(k)^T\Phi_1(k) + B_1k_v r(k)]^T \\ &\quad - \Gamma_1 \| I - \alpha_1\Phi_1(k)\Phi^T{}_1(k) \| W_1(k) && (2) \\ W_2(k+1) &= W_2(k) - \alpha_2\Phi_2(k)[W_2(k)^T\Phi_2(k) + B_2k_v r(k)]^T \\ &\quad - \Gamma_2 \| I - \alpha_2\Phi_2(k)\Phi^T{}_2(k) \| W_2(k) && (3) \\ W_3(k+1) &= W_3(k) + \alpha_3\Phi_3(k)r(k+1) \\ &\quad - \Gamma_3 \| I - \alpha_3\Phi_3(k)\Phi^T{}_3(k) \| W_3(k) && (4) \end{aligned}$$

where Γ_i is a positive design parameter with a value close to zero and β_i is another design parameter with a value smaller than kv_i. The last term of equations (2)-(4) is designed to improve the numerical stability of the network. The learning rate α_i can be fixed or varied. Fixed learning rate makes the convergence of the weights of a multilayer NN slow. So, projection algorithm (Jagannathan, 1996) shown in Eq. (5) is used to improve the learning rate in this paper.

$$\alpha_i = \frac{\xi_i}{\varsigma_i + \|\Phi_i(k)\|^2} \quad , \qquad i = 1,2,3 \tag{5}$$

where ς_i is a positive small number to reduce the numerical difficulty when the norm of $\Phi_i(k)$ is close to zero and ξ_i is the new adaptation gain of each layer. If adaptation gains of hidden layers are chosen as $0<\xi_i<2$ for i=1,2 and the adaptation gain of output layer is chosen as $0<\xi_3<1$, it is easy to prove that convergence conditions of Delta rule, which are $0<\alpha_i<2$ for i=1,2 and $0<\alpha_3<1$, are satisfied.

In Eqs. (2) through (4), *r(k)* is the filtered error of the entire closed loop system and is introduced in the next section.

3.2Control design

In a discrete time model, the derivation of the generator angular speed at time *k+1* can be directly described as a function of its delays:

$$\begin{aligned}\Delta\omega(k+1) &= f(\Delta\omega(k),\Delta\omega(k-1),\cdots,\Delta\omega(k-n+1)) \\ &+ g(\Delta\omega(k),\Delta\omega(k-1),\cdots,\Delta\omega(k-n+1))u(k)+dis(k)\end{aligned} \quad (6)$$

where $f(\bullet)$and $g(\bullet)$ are uncertain nonlinear functions and $\Delta\omega(k)$ is the deviation of the generator angular speed at time *k*. *g* is bounded by $g_{min}<|g|<g_{max}$ in which g_{min} and g_{max} are positive limits . *u(k)* is the output of the supplementary controller and *dis(k)* is the disturbance generated from the system.

According to (Jagannathan, 1996), the damping problem can be transferred to a tracking problem by introducing a filtered error. For the desired trajectory x_{des}, which is zero for the damping problem, the tracking error at time *k* is:

$$e(k) = \Delta\omega(k) - x_{ndes}(k) \quad (7)$$

The filtered tracking error *r(k)* with n-1 delays is given as

$$r(k) = e(k) + \lambda_1 e(k-1) + \cdots + \lambda_{n-1} e(k-n+1) \quad (8)$$

where $e(k-1),\cdots,e(k-n+1)$ are delayed values of the error *e(k),* and $\lambda_{n-1},\cdots,\lambda_1$ are constant matrices selected so as $|z^{n-1}+\lambda_1 z^{n-2}+\cdots+\lambda_{n-1}|$ is stable. Using the same way of Eq (8), the filtered tracking error at time *k+1* can be written as:

$$\begin{aligned}r(k+1) &= e(k+1) + \lambda_1 e(k) + \cdots + \lambda_{n-1} e(k-n+2) \\ &= \Delta\omega(k+1) + \lambda_1 e(k) + \cdots + \lambda_{n-1} e(k-n+2)\end{aligned} \quad (9)$$

The above tracking problem, Eq(9), can be further modified to the following form, Eq(10), by dividing by *g(•)* on the both sides and lumping all the mismatched parts with the system disturbance term, *dis(k)*. $\underline{\Delta\omega}$(k) is a vector of the deviation of the generator angular speed and its delays.

$$\begin{aligned}g^{-1}(\underline{\Delta\omega}(k))r(k+1) &= g^{-1}(\underline{\Delta\omega}(k)))f(\underline{\Delta\omega}(k)) \\ &+ \lambda_1 e(k) + \cdots + \lambda_{n-1} e(k-n+2) + u(k) + dis(k)\end{aligned} \quad (10)$$

The ideal control *u(k)* for the given tracking system can be derived by cancelling all the terms except the disturbance part on the right hand side of Eq(10):

$$\begin{aligned}u(k) &= -g^{-1}(\underline{\Delta\omega}(k))f(\underline{\Delta\omega}(k)) + k_v r(k) \\ &- \lambda_1 e(k) - \lambda_2 e(k-1) - \cdots - \lambda_{n-1} e(k-n+2)\end{aligned} \quad (11)$$

where k_v is the diagonal gain vector. The term $k_v r(k)$ is employed to compensate the system disturbance and make the entire closed loop system stable.

Since f*(•)* and *g(•)* are unknown, a multilayer neural network described in section II is used to approach the nonlinearly uncertain part in Eq (11). Their relationship can be described as:

$$W\Phi(\underline{\Delta\omega}(k)) = g^{-1}(\underline{\Delta\omega}(k))f(\underline{\Delta\omega}(k)) + \varepsilon(k) \quad (12)$$

where $\varepsilon(k)$ is the error between the output of the neural network and the actual value of the original system. The actual control *u(k)* of the closed loop system after employing the neural network can be changed to:

$$\begin{aligned}u(k) &= -W\Phi(\underline{\Delta\omega}(k)) + k_v r(k) \\ &- \lambda_1 e(k) - \lambda_2 e(k-1) - \cdots - \lambda_{n-1} e(k-n+2)\end{aligned} \quad (13)$$

Substituting Eq (13) in the tracking system, Eq (10), the closed-loop tracking error system can be expressed as

$$g^{-1}(\underline{\Delta\omega}(k))r(k+1) = k_v r(k) + \varepsilon(k) + dis(k) \quad (14)$$

According to theorem 2.2 in (Jagannathan, 1996), the closed-loop tracking error, Eq (14), is a state strict passive system if the following condition is satisfied.

$$k_v^T k_v < I / g^2_{\max} \quad (15)$$

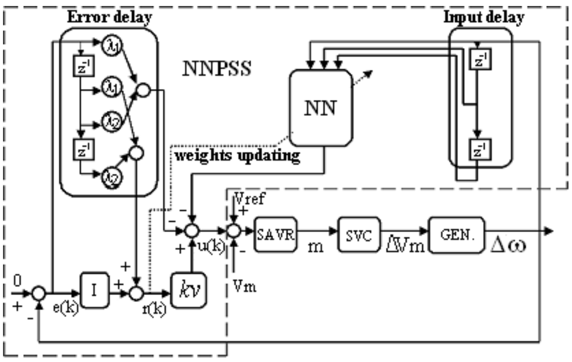

Fig. 3 Structure of the Closed Loop System

3.3 Structure of the closed loop system

The entire closed loop system is shown in Fig.3. The error filter order *n=3.* The output of the error delay block forms the portions of the filtered error *r(k)* and *r(k+1*), which are used to update the weights of the NN and calculate the output of control. The output of the PSS, *u(k),* adjusts the firing angles of GTOs of SVC to make the system bus voltage to vary. The variation of the voltage generates a damping torque on the rotor of the generator to realize the damping function.

4. SIMULATION STUDIES

A schematic representation of the single machine infinite bus power system model with an SVC at the middle bus is shown in Fig. 4. The SVC is composed of a cascade multi-level inverter and an energy storage device. In practice, dc capacitors are usually used for energy storage.

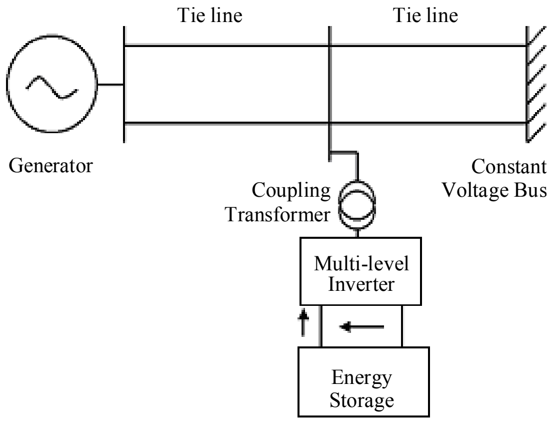

Fig. 4 Single Machine Infinite Bus System with an SVC

Park's seventh order model (Kundur, 1994) of a synchronous machine is used to represent the dynamics of the generating unit. A standard IEEE ST1A generator AVR is added to the generator to control the generator terminal voltage and another AVR, Fig 1, adjusts the output of the SVC to control the voltage of the middle bus. The supplementary controller is used to generate the damping signals. Mathematical model and the parameters are given in the Appendix.

In order to show the effectiveness of the proposed NN PSS, a conventional PSS (CPSS) with a transfer function shown in Eq.(16) is also employed to compare the damping effect.

$$G_{PSS}(s) = K_{PSS}\frac{T_W s}{1+sT_W}\cdot\frac{(1+sT_2)(1+sT_4)}{(1+sT_1)(1+sT_3)} \tag{16}$$

where K_{PSS} is the gain of the PSS, T_w is the washout time constant. T_1 through T_4 are the time constants used to adjust the phase shift of the output. By appropriately tuning these design parameters, it can produce a desired damping function for the designed operating condition.

4.1 Network training

In the training period, initial weights are selected as small random numbers between [-0.1, +0.1] and the controller is applied to the system model. The training of the proposed controller can be conducted by applying one or a series of system disturbances on the system until the controller can get the desired damping effect. The training of the controller in this paper is conducted by applying a 0.05 p.u step increase in the mechanical torque of the generator at the initial condition of P= 0.7 p.u., p.f =0.85 lag. Then the input torque is returned to the initial value at 3 s. It can be seen from Fig. 5 that at the second disturbance, the controller can provide the desired damping and the final weights are chosen as the initial weights for the remaining simulations.

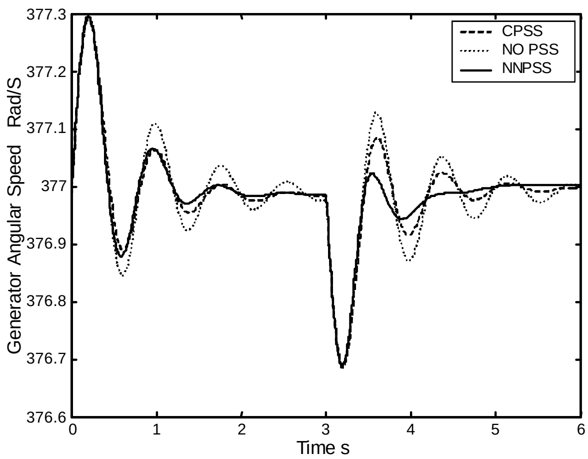

Fig. 5 Training of the Network. Initial Condition P=0.7p.u., p.f. = 0.85 lag

4.2 Normal operating condition

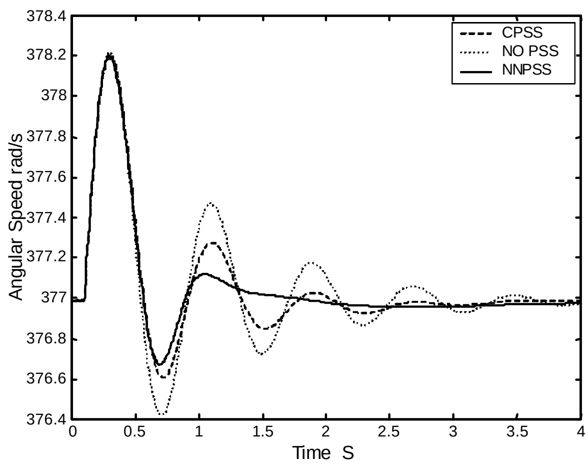

Fig. 6 Generator Angular Speed in Response to a 0.2 p.u. Step Increase in Torque. Initial Condition P=0.7p.u., p.f. = 0.85 lag

The normal operating condition of the single machine power system is set at P= 0.7 p.u., power factor 0.85 lag. A 0.2 pu step increase in the mechanical torque of the generator is applied at 0.1 s. A comparison of angular speeds of a system with the proposed SVC controller (NNPSS), with a SVC CPSS and without control (NO PSS) is shown in Fig. 6. It is easy to see that, in the first peak, there is no difference between CPSS and NNPSS, but from the second peak, NNPSS can damp the system oscillation much faster than CPSS.

4.3 Leading power factor condition

This test is conducted at the condition of P=0.7 p.u. and p.f. =0.9 lead. The disturbance is applied at 0.1 s with a 0.2 p.u. step increase in the mechanical torque. The results in Fig. 7 show that NNPSS has a better performance in damping the oscillations than CPSS.

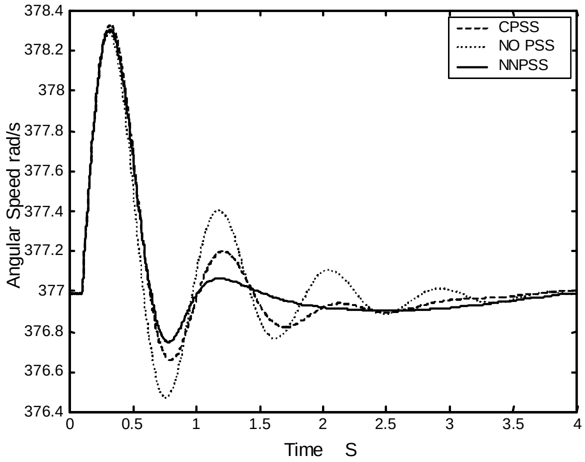

Fig. 7 Generator Angular Speed in Response to a 0.2p.u. Step Increase in Torque. Initial condition P=0.7p.u., p.f. = 0.9 lead

4.4 Light load condition

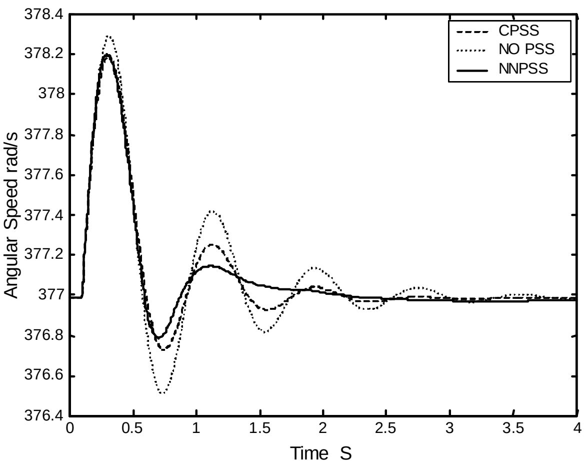

Fig. 8 Generator Angular Speed in Response to a 0.2 p.u. Step Increase in Torque. Initial Condition P=0.2 p.f.=0.85 lag

The generator operating condition is changed to P = 0.2 p.u. and p.f. = 0.85 lag, and a 0.2 pu step increase of the input mechanical torque is applied at 0.1 s. The response of the system is shown in Fig. 8. It is seen that at this operating condition both NNPSS and CPSS have better performance at the first peak than in the normal condition. After the first peak, the NNPSS can take full advantage of the SVC capacity to damp the system oscillations. Therefore, the NNPSS has better damping performance than the CPSS.

4.5 Three-phase short circuit condition

A 0.1s three-phase short circuit fault is applied on one transmission line very close to the generator bus. Performance of the controller is shown in Fig. 9. Starting from the second peak, both the NNPSS and CPSS provide an effective damping of the system.

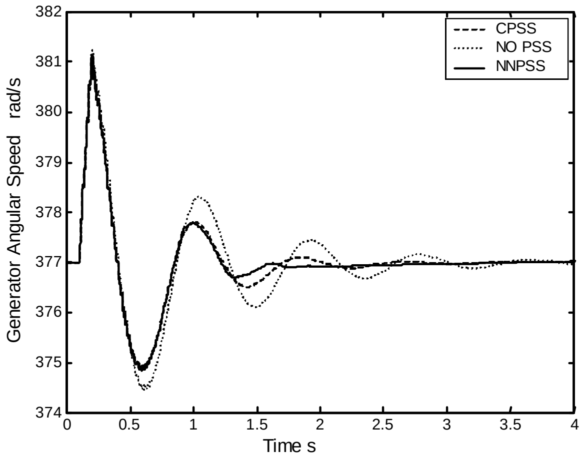

Fig. 9 Generator Angular Speed in Response to a Three Phase Short Circuit at a Tie Line Close to the Generator Bus. Initial Condition P=0.7p.u. p.f. = 0.85 lag

5. CONCLUSIONS

A discrete time multilayer NN based SVC controller is proposed. The discrete time filtered direct control algorithm is used to design the proposed supplementary controller that needs only one neural network to do both the system identification and control. The weights of the network are dynamically updated according to the filtered error of the entire closed-loop system. Studies show that the selected filter order is sufficient for the system control to correct the error of the entire closed loop system. Additional studies, not included due to lack of space, show that a combination of the NNPSS on the SVC and a PSS on the generator can work together and the combination is more effective than the system having only one of the PSSs.

In order to get maximum benefits from the proposed neural network based SVC controller in practical systems, further studies need to be carried out. Performance of the proposed control algorithm in a multi-machine system will be investigated in future to verify the coordination between the proposed NN controller and generator PSSs.

APPENDIX

The generator model is based on the Park's seventh order model.

$$\dot{\lambda}_d = v_{gd} + r_s i_d + \omega_b(\omega+1)\lambda_q$$
$$\dot{\lambda}_q = v_{gq} + r_s i_q - \omega_b(\omega+1)\lambda_d$$
$$\dot{\lambda}_{kd} = -r_{kd} i_{kd}$$
$$\dot{\lambda}_{kq} = -r_{kq} i_{kq}$$
$$\dot{\lambda}_f = Ef - r_f i_f$$
$$\dot{\omega} = \frac{\omega_b}{2H}(Tm + gov + K_d\dot{\delta} - Te)$$
$$\dot{\delta} = \omega\omega_b$$

According to (Armansyah and Yorino, 2002), SVC can be modeled as a voltage source behind a step up transformer. The voltage along the *d* and *q* axes is a function of the magnitude and angle of the dc voltage. The value of *m* can be controlled to adjust the output of the SVC.

$$e_d = (1+m)Vdc\cos(\Psi)$$
$$e_q = (1+m)Vdc\sin(\Psi)$$

The transfer function of the governor is selected as:

$$gov = [a_g + \frac{b_g}{1+sTg}]$$

The generator AVR and the exciter model used in the system is from the IEEE standard P421.5, 1992, Type ST1A.

Generator and tie line parameters are:

$r_s = 0.007$ $r_f = 0.00089$ $r_{kq} = 0.023$ $x_{kd} = 1.1500$
$r_{kd} = 0.023$ $x_q = 0.743$ $x_d = 1.24$ $Kd = -0.027$
$x_{md} = 1.126$ $x_{mq} = 0.626$ $x_f = 1.33$ $H = 3.46$
$x_{kq} = 0.625$ $r_e = 0.0$ $x_e = 0.3$

SVC, SVC AVR, SVC CPSS and NNPSS parameters are:

$x_T = 1.0$ $K_a = 50$ $T_1 = 0.05$ $T_3 = 0.05$
$r_T = 0.0$ $T_a = 0.01$ $T_2 = 0.03$ $T_4 = 0.07$
$V_{a\max} = 999$ $V_{a\min} = 999$ $T_w = 1.65$ $K_{PSS} = 0.1$
$V_{st\min} = -0.1$ $V_{st\max} = 0.1$ $\lambda_1 = 0.1$ $\lambda_2 = 0.1$
$kv = 0.45$ $B_1 = 0.2$ $B_2 = 0.3$ $\varsigma = 0.05$
$\xi_1 = \xi_2 = 1.5$ $\xi_3 = 0.9$

Governor, and generator AVR parameters are:

$a_g = -0.001328$ $b_g = -0.17$ $T_g = 0.25$ $K_A = 200$
$T_F = 1.0$ $K_F = 0.05$ $T_A = 0.01$ $T_c = 0.05$
$V_{IMIN} = -999$ $V_{AMAX} = 999$ $V_{OEL} = 999$ $V_{AMIN} = -999$
$T_b = 0.03$ $V_{UEL} = -999$ $V_{UEL} = -999$ $V_{RMAX} = 999$
$V_{IMAX} = 999$ $V_{RMIN} = -999$

All resistances and reactances are in per unit and time constant in seconds.

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