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Adaptive Power System Stabilizer Using ANFIS and Genetic Algorithms

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Abstract— **This paper presents an adaptive Power System Stabilizer (PSS) using an Adaptive Network Based Fuzzy Inference System (ANFIS) and Genetic Algorithms (GAs). Firstly, genetic algorithms are used to tune a conventional PSS on a wide range of operating conditions and then, the relationship between these operating points and the PSS parameters is learned by the ANFIS. The ANFIS optimally selectes the classical PSS parameters based on machine loading conditions. The proposed stabilizer has been tested by performing nonlinear simulations using a synchronous machine-infinite bus model. The results show the robustness and the capability of the stabilizer to enhance system damping over a wide range of operating conditions and system parameter variations.**

I. INTRODUCTION

POWER system control requires a continuous balance between electrical generation and a varying load demand, while maintaining system frequency and voltage levels. The use of high performance excitation systems is essential for maintaining steady state and transient stability of modern synchronous generators and provides fast control of the terminal voltage. However, these fast acting exciters with high gains can contribute to oscillatory instability in the power system. This type of instability is characterized by low frequency oscillations which can persist or even grow in magnitude [1-2]. Several real examples have been recorded and studied [3-4].

In order to avoid this effect, supplementary stabilizing signals have been proposed in the excitation systems through lead/lag power system stabilizers [5] or PI - PID power system stabilizers [6]. The computation of the fixed parameters of these stabilizers is based on the linearized model of the power system around a nominal operating point.

The operating condition does change as a result of load variation and major disturbances, making the dynamic behavior of the power system to become different, at different operating points. Thus, if the parameters of the stabilizer are kept fixed, PSS performance is degraded whenever the operating point changes.

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Therefore, a good PSS design must consider a trade-off between adaptability to the changes of the dynamics of the plant and easy design.

From the seventies, developments in digital technology have made possible to implement new controllers using adaptive control techniques [7-10]. These stabilizers provide better dynamic performance over a wide range of operating conditions, but they suffer from the major drawback of requiring parameter model identification, state observation and feedback gain calculations in real-time. If there is some error in parameter identification, it can lead to generate incorrect control signals, reducing the robustness.

In last decade, Fuzzy Logic Controllers (FLCs) and Artificial Neural Network Controllers (ANNCs) being used as power system stabilizers, have been developed and tested [11-18]. Unlike other classical control methods, FLCs and ANNCs are model-free controllers; i.e they do not required an exact mathematical model of the controlled system. Moreover, speed and robustness are the most significant properties in comparison to the other classical schemes. But these controllers present some disadvantages. There are not practical systematic procedures for the Fuzzy PSS (FPSS) design, so the rules and the membership functions of the controller are tuned subjectively, making the design laborious and a time-consuming task. With respect to ANNCs, they have the capability of learning and adaptation, but they work like a 'black-box' and it is difficult to understand the behaviour of the network.

In order to make the design simpler, Genetic Algorithms (GAs) have been successfully applied to PSS design [19-22]. GAs define a global optimization technique based on the mechanics of natural selection and survival-of-the-fittest.

In the research reported in this paper, a conventional PSS for a single machine infinite bus system is tuned by an Adaptive Network based Fuzzy Inference System (ANFIS) trained from the input-output data generated by a GA. The advantages of this design are:

- The Genetic Algorithm uses a simple objective function which does not depend on the mathematical model of the electric power system.
- The ANFIS combines the advantages of FLCs and ANNCs, avoiding their problems.

The PSS parameters are modified on-line, in order to get a better response in the entire range of operation.

II. GENETIC ALGORITHMS AND ANFIS

A. Genetic Algorithms

Genetic Algorithms copy the process of the natural evolution. The principles of GAs were firstly published by Holland [23]. In GAs, the features characterizing an individual are often binary coded in bits and concatenated as a string. The string package made from different combinations of bits is referred to as a point in the solution space. The fundamental operations of a GA are:

Initialization. The GA does not work with a single string but with a population of strings, which evolves iteratively by generating new individuals taking the place of their parents. To begin, the individuals of the initial population are generated randomly. In our application, each string does code a set of PSS parameters.

Objective Function. The performance of each structure is evaluated according to its 'fitness', which is defined as the non-negative figure of merit to be maximized.

Genetic Operations. With the evaluation of the fitness function of all individuals, the GA generates a new and improved population from the old one. Most commonly used operations are the following: *Reproduction.* It is an operation whereby an old string is copied into a 'mating pool' according to its fitness. More highly fitted strings receive a higher number of copies in the next generation. *Crossover.* Crossover exchanges genetic material from two parent chromosomes, allowing their beneficial genes to be combined in their offspring. *Mutation.* It is an operation which is able to create new genetic material in the population, changing some chromosomes according to a probabilistic law.

B. ANFIS

ANFIS was proposed by [24]. In this neural fuzzy control system, the consequents of the Takagi-Sugeno (TS) fuzzy rules are linear combinations of their preconditions. The TS fuzzy rules are in the following forms:

Rule j: IF x_1 is A_1^j AND x_2 is A_2^j … AND x_n is A_n^j

THEN $y = f_j = a_0^j + a_1^j x_1 + a_2^j x_2 + ... + a_n^j x_n$ (1)

ANFIS is composed of six functional layers, as shown in Fig. 1:

In layer 1, every node is an input node that just passes external signals to the following layer.

In layer 2, every node is an adaptive one with a node function defined by:

$$\mu_{A_i^j}(x_i) \tag{2}$$

where x_i is the input to the ith-node and A_i^j is the linguistic label (*large, small,* etc.) associated with this node. The output of this node specifies the degree to which the given x_i satisfies the quantifier A_i^j. In this study, the function $\mu_{A_i^j}(x_i)$ is the bell-shaped function with a maximum value equal to 1 and a minimum value equal to 0, with the following parameters $\{a_i^j, b_i^j, c_i^j\}$:

$$\mu_{A_i^j}(x_i) = \left(1 + \left(\frac{x_i - c_i^j}{a_i^j}\right)^{2b_i^j}\right)^{-1} \tag{3}$$

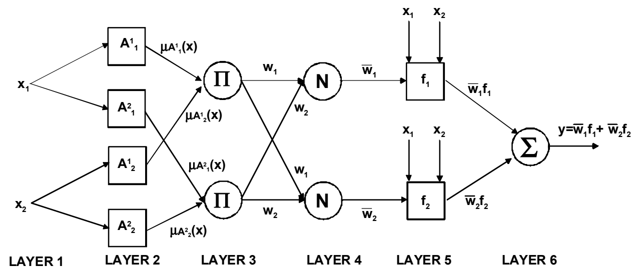

Fig. 1. Architecture of ANFIS system.

Parameters in this layer are referred to as *premise* or *precondition parameters* S_1 and can be trained using the ANFIS hybrid learning algorithm.

Every node in layer 3 is a fixed node which multiplies the incoming signals. Each node output represents the firing strength of a rule, hence, the nodes perform the fuzzy AND operation.

$$\omega_j = \mu_{A_1^j}(x_1)\mu_{A_2^j}(x_2), \quad j = 1,2 \tag{4}$$

Nodes in layer 4 are fixed nodes and calculate the ratio of the firing strength of the j-th rule to the sum of all firing strengths of the rules:

$$\overline{\omega}_j = \frac{\omega_j}{\sum_{j=1}^{2} \omega_j} \tag{5}$$

In layer 5, every node j in this layer is an adaptive node and has the following output:

$$\overline{\omega}_j(p_j x_1 + q_j x_2 + r_j) \tag{6}$$

where $\{p_j, q_j, r_j\}$ is referred to as the *consequent parameter set* S_2. They can also be trained using ANFIS learning algorithms.

The single node in the layer 6 is a fixed node that computes the overall output as the summation of all incoming signals, i.e.,

$$y = \sum_j \overline{\omega}_j f_j \tag{7}$$

The ANFIS hybrid learning algorithm is composed of a forward pass and a backward pass. In the forward pass, keeping constant the available values of the premise parameters set S_1, functional signals go forward until layer four and the consequent parameter vector $\{p_j, q_j, r_j\}$ is identified by means of the least squares estimate (LSE), solving the over constrained simultaneous linear equations shown in (8).

$$\begin{bmatrix} \varpi_1^{(1)} & \varpi_1^{(1)} x_1^{(1)} & \dots & \varpi_2^{(1)} x_2^{(1)} \\ \varpi_1^{(2)} & \varpi_1^{(2)} x_1^{(2)} & \dots & \varpi_2^{(2)} x_2^{(2)} \\ \vdots & \vdots & \vdots & \vdots \\ \varpi_1^{(p)} & \varpi_1^{(p)} x_1^{(p)} & \dots & \varpi_2^{(p)} x_2^{(p)} \end{bmatrix} \cdot \begin{bmatrix} r_1 \\ p_1 \\ q_1 \\ r_2 \\ p_2 \\ q_2 \end{bmatrix} = \begin{bmatrix} d^{(1)} \\ d^{(2)} \\ \vdots \\ d^{(p)} \end{bmatrix} \tag{8}$$

where $\left[\left(x_1^{(k)}, x_2^{(k)}\right), d^{(k)}\right]$ are the k-th training pair, with $k=1, 2,..p$, and $\varpi_1^{(k)}$ and $\varpi_2^{(k)}$ are the third-layer outputs associated with the input $\left(x_1^{(k)}, x_2^{(k)}\right)$.

In the backwards pass, the error rates propagate backward and the premise parameters S_1, $\varpi_1^{(k)}$ and $\varpi_2^{(k)}$, are updated by the gradient descent [24].

III. PROPOSED ADAPTIVE PSS

The proposed PSS is shown in Fig. 2, where the ANFIS system adjusts the PSS parameters processing the operating points data defined by the active power output, P_t, reactive power output, Q_t, and the terminal voltage, V_t of the generator.

A widely used conventional lead-lag PSS is considered in this paper:

$$V_{PSS} = \frac{T_\omega}{1 + sT_a} K_{PSS} \frac{1 - sT_1}{1 + sT_2} \omega \tag{9}$$

where T_ω is set to be 2.0 s.

ANFIS outputs are the optimal PSS parameters generated by the genetic algorithm in this particular operating point defined by the inputs.

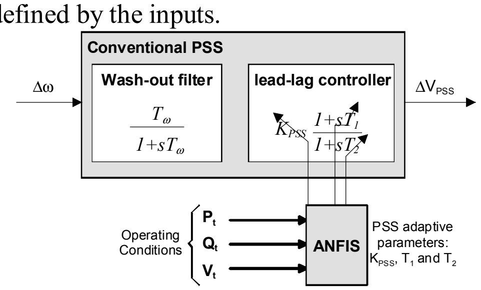

Fig. 2. Proposed Adaptive PSS.

The PSS design is divided in two different parts:

A. Tuning the conventional PSS using GA in different operating points, storing the PSS optimal parameters and the operating conditions.
B. Training the ANFIS system with the stored data.

A. Collecting the training data

Firstly, a GA is used to adjust the PSS parameters on a wide spectrum of operating conditions, i.e., the generator power output ranging from 0.1 *p.u.* to 1.1 *p.u.*, and the power factor ranging from 0.7 lead to 0.1 lag. Similarly, a wide range of possible disturbances is used for the training. These disturbances are: reference voltage in the range of –0.1 to 0.5 *p.u.*, input mechanical torque variation from –0.2 *p.u.* to 0.2 *p.u.*, one transmission line outage and three phase fault on one of the double circuit transmission lines connected to the generator.

Starting in a particular operating point, the GA searches the PSS parameters that optimize the fitness function:

$$f_k = \frac{1}{1 + \int_{t_1}^{t_2} t\left|\Delta\omega(t)\right| dt} \tag{10}$$

where t_1 and t_2 are the study time limits and $\Delta\omega(t)$ represents the speed deviation of the generator. The PSS parameters K_{PSS}, T_1 and T_2 are selected so as to maximize the objective function f_k.

The advantage of the selected fitness function as opposed to other functions proposed in [20], [21] and [25], is that minimal dynamic plant information is needed. It is only necessary to measure the speed deviation of the generator instead of identifying on-line the electric power system model parameters, needed to design the PSS by a pole-placement technique.

For a given operating point, the objective function is evaluated with an initial population randomly generated. Each individual in the initial population has an associated fitness function value. Using this information, GA operations are applied to produce the next generation. These two steps, evaluation of the objective function and generation of the new population, are repeated from generation to generation until the population does converge, producing the optimum PSS parameters for this particular operating point.

Once the PSS parameters are tuned, these data are stored together with the loading condition and the algorithm starts again in a different operating point. All the data collected constitute the training set.

B. ANFIS Training

A total of 5000 input-output data pairs were obtained for the training of the ANFIS.

The ANFIS transforms a fuzzy inference engine into an adaptive network that learns the relationship between inputs, defined by the operating conditions, and outputs, defined by the PSS parameters. These relationships are learned independently for each PSS parameter, using 3 ANFIS, in order to improve the converge speed of the ANFIS hybrid learning algorithm.

Choosing the correct number of membership functions is a fundamental question often raised in these applications. Usually this number is determined experimentally in a similar way to choosing the number of neurons in the hidden layer of an artificial neural network. But there are other methods based on pruning or growing the network. Pruning algorithms start with a larger network and then prune it to desired size [27], [28]. On the opposite, growing algorithms start with a small network and gradually increase it to appropriate size [29]. In this paper, the number of membership functions for each input variable is determined by trial and error for simplicity.

In this study, five linguistic variables for each input variable were use to get the desired performance.

IV. SIMULATION STUDIES

To demonstrate the effectiveness of the proposed PSS whose parameters are adapted by the ANFIS, time domain simulations were performed for the generator under major disturbance conditions over a wide range of loading conditions. Test cases are similar to those proposed in [11-13] and [15-22], to verify the PSS behavior.

The considered system is a synchronous machine connected to an infinite bus through two parallel transmission lines as shown in Fig. 3.

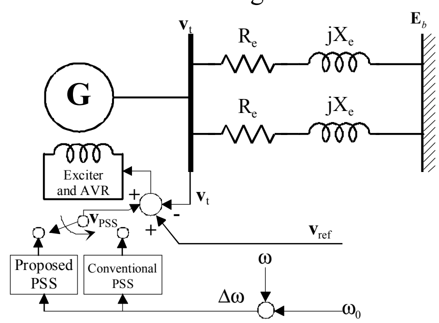

Fig. 3. Single machine infinite bus system with two transmission lines.

The nonlinear model equations used to simulate the generating unit, AVR and conventional PSS (CPSS) are given in the Appendix.

The CPSS is adjusted to give optimal performance for the operating point of 1 p.u. generated power, and 0.97 power factor lag.

A. *Input Torque Reference Step Change*

With the generator operating at an active power of 1 p.u. and power factor lag of 0.97, a 25% step decrease in the input torque reference was applied at *t=0.2* s.

The speed deviation of the generator for the proposed PSS and the conventional PSS are shown in Fig. 4. With the selected PSS parameters, the CPSS and the proposed PSS responses were very close to each other.

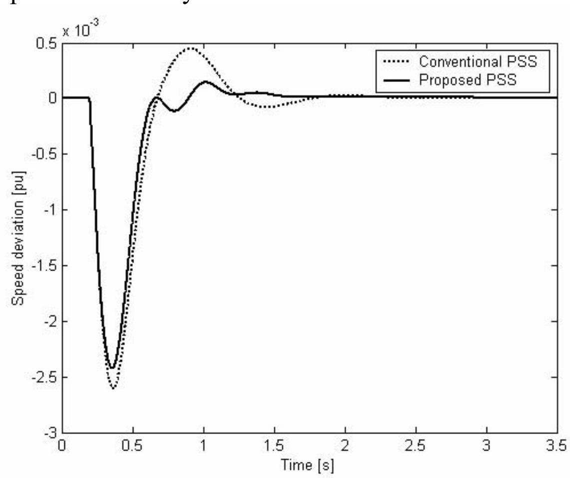

Fig. 4. Speed deviation for a –0.25 p.u. mechanical input torque reference step change, *P=1* p.u. and *pf=0.97* p.u.

Changing the operating point to 0.6 p.u. generated power and a power factor lead of 0.82, a 25 % step decrease in input torque reference was applied at *t=0.2* s. The speed deviation for the proposed PSS and the conventional PSS are shown in Fig. 5. The proposed PSS shows better damping.

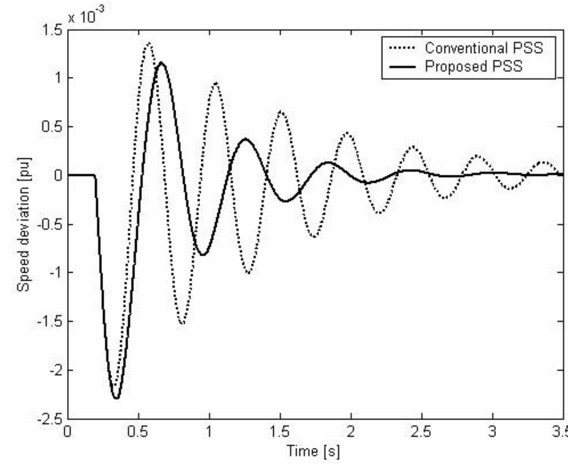

Fig. 5. Speed deviation for a –0.25 p.u. mechanical input torque reference step change, *P=0.6* p.u. and *pf=-0.82* p.u.

B. *Switching of one line*

At an operating point of 0.9 p.u., 0.98 power factor lag, one circuit of the double circuit transmission line was switched off at *t=9* s. Before the line disconnection, 0.2 p.u. step increase in the input torque reference was applied at *t=1* s and removed at *t=5* s. A second 0.2 p.u. step increase in the input torque reference was applied at *t=13* s. and removed at *t=17* s. during the transmission line fault. The response of the system with both conventional PSS and the proposed PSS is shown in Fig. 6. The response with the proposed PSS shows less oscillations than the conventional PSS and demonstrates better performance.

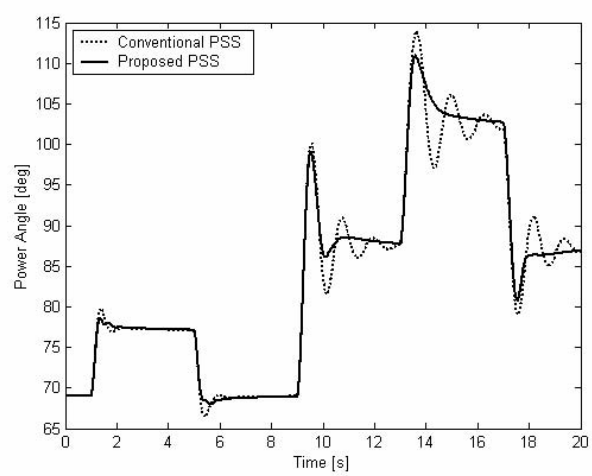

Fig. 6. Power angle for a ±0.2 p.u. input torque reference step change at *P=0.9* p.u. and *pf=0.98* p.u. during the switching of one of the transmission lines.

The parameters selected values of the proposed PSS during this simulation are shown in Fig. 7.

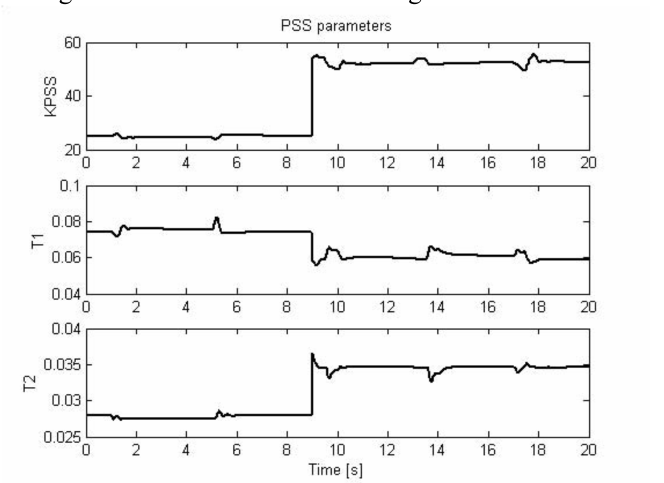

Fig. 7. Proposed PSS tuned parameters.

C. *Three phase to ground fault*

Three phase to ground fault locating at 50 % of the distance along line is applied at $t=0.5$ s. and the fault is cleared at $t=0.773$ s.

Responses without stabilizer and with conventional PSS and proposed PSS are shown in Fig. 8. Systems without stabilizer and with conventional PSS are both unstable. The system with proposed PSS is highly oscillatory, but it is stable.

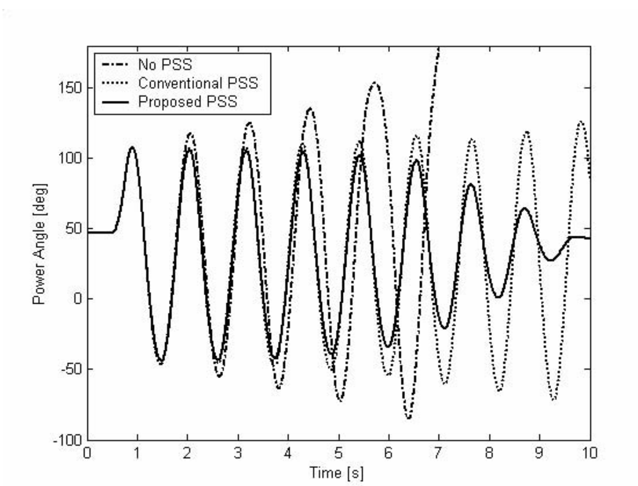

Fig. 8. Three phase to ground fault.

V. CONCLUSION

An adaptive power system stabilizer based on an Adaptive-Network-Based Fuzzy Inference System and Genetic Algorithms is presented in this paper. The effectiveness of this scheme has been investigated through nonlinear simulations. The following conclusions are derived from the results:

- Since PSS parameters are adjusted by a genetic algorithm, minimal knowledge about the system is required and there is no need for system model linearization.
- Due to the selected fitness function, opposite to other functions proposed in other papers, there is no need to identify the power system model parameters. So this PSS design, which is not based on a pole-placement technique, saves time and reduces the complexity of the design.
- The ANFIS combines the advantages of artificial neural networks and fuzzy logic controllers, that is, adaptation and robustness.
- Since the proposed design modifies the parameters of the installed classical PSS, there is no need to change the actual PSS in the generator.

Test results for various operating conditions and disturbations show that the proposed stabilizer is able to provide good damping over a wide operating range and improves the overall system performance.

APPENDIX

System Model:

$$\frac{d\delta}{dt} = \omega_0 \omega \ , \ \frac{d\omega}{dt} = \frac{1}{M}\left(T_{mech} - D_{\omega}\omega - T_{elec}\right) \qquad (A.1)$$

where, T_{mech} and T_{elec} are the input (mechanical) and output (electrical) torques of the generator, respectively; M is the inertia constant and D_{ω} is the damping coefficient, δ y ω are the rotor angle and speed, respectively.

The internal voltage equations are:

$$\frac{dE'_q}{dt} = \frac{1}{T'_{d0}}\left(E_{FD} - E'_q - \left(x_d - x'_d\right)i_d\right) \qquad (A.2)$$

$$\frac{dE'_d}{dt} = \frac{1}{T'_{q0}}\left(-E'_d - \left(x_q - x'_q\right)i_q\right) \qquad (A.3)$$

$$T_{elec} = E'_d i_d + E'_q i_q + \left(x_q - x'_d\right)i_q i_d \qquad (A.4)$$

$$Z_e^2 = r_e^2 + \left(x_e + x'_q\right)\left(x_e + x'_d\right) \qquad (A.5)$$

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \frac{1}{Z_e^2}\begin{bmatrix} r_e + r_s & x_e + x'_q \\ -\left(x_e + x'_d\right) & r_e + r_s \end{bmatrix}\begin{bmatrix} E'_d \\ E'_q \end{bmatrix} - \frac{E_b}{Z_e^2}\begin{bmatrix} r_e + r_s & x_e + x'_q \\ -\left(x_e + x'_d\right) & r_e + r_s \end{bmatrix}\begin{bmatrix} \sin\delta \\ \cos\delta \end{bmatrix} \qquad (A.6)$$

The IEEE Type-ST1 excitation system is considered in this study:

$$\frac{dE_{FD}}{dt} = \frac{K_A}{T_A}\left(V_{ref} - V_t + V_{PSS}\right) - \frac{E_{FD}}{T_A} \qquad (A.7)$$

where K_A and T_A are the gain and time constant of the excitation system, V_{ref} is the reference voltage and V_t is the terminal voltage.

For the conventional PSS, the following transfer function is considered:

$$V_{PSS} = \frac{T_{\omega}}{1 + sT_{\omega}} K_{PSS} \frac{1 + sT_1}{1 + sT_2}\omega \qquad (A.8)$$

where T_{ω} is the wash-out filter time constant.

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