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A Generalized Neuron Based Adaptive Power System Stabilizer for Multimachine Environment

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Experimental studies of a generalized neuron based adaptive power system stabilizer

Abstract Artificial neural networks trained as intelligent controllers can easily accommodate the non-linearities and time dependencies of non-linear, dynamic systems. However, they require large training time and large number of neurons to deal with complex problems. Taking benefit of the characteristics of a generalized neuron (GN), that requires much smaller training data and shorter training time, a generalized neuron based adaptive power system stabilizer (GNAPSS) is proposed. It consists of a GN as an predictor, that predicts the plant dynamics, and a GN as a controller to damp low frequency oscillations. Results show that the proposed GNAPSS can provide a consistently good dynamic performance of the system over a wide range of operating conditions.

Keywords Adaptive PSS · Generalized neuron controller · Neural network · On-line training

1 Introduction

Power system stabilizers (PSSs) aid in maintaining power system stability and in improving dynamic performance by providing a supplementary signal to the excitation system (DeMello and Laskowski 1979). This is an easy, economical and flexible way to improve power system stability.

The commonly used PSS (CPSS) is a fixed parameter device designed using the classical linear control theory and a linear model of the power system at a specific operating point. It uses a lead/lag compensation network to compensate for the phase shift caused by the low frequency oscillation of the system during perturbation. By appropriately tuning the parameters of the lead/lag network, it is possible to make a system have the desired damping ability. Although this type of PSS has made great contribution in enhancing the operating quality of the power systems (DeMello and Laskowski 1979; Larsen and Swann 1981), it suffers from some problems (Grondin et al. 1993).

Power systems are highly non-linear systems. They operate over a wide range of operating conditions and are subject to multi-modal oscillations (Grondin et al. 1993). The linearized system models used to design fixed parameter CPSS can provide optimal performance only at the operating point used to linearize the system. Therefore, the following problems are presented in the design of the CPSS:

1. Selection of a proper transfer function that covers the frequency range of interest.
2. Automatic tracking of the system operating conditions.
3. Maintaining properly tuned parameters as system changes.

Application of the adaptive control theory can take into consideration the non-linear and stochastic characteristics of the power system (Pierre 1987; Shi-jie et al. 1986a). Parameters of an adaptive stabilizer are adjusted on-line according to the operating conditions. Many years of intensive studies have shown that the adaptive stabilizer can provide good damping over a wide operating range (Pierre 1987; Shi-jie et al. 1986a,b; Chen et al. 1993; Segal et al. 2000; Hosseinizadeh and Kalam 1999; Zhang et al. 1993) and can also work in coordination with CPSSs (Chaturvedi et al. 2004a; Swidenbank et al. 1999).

More recently, artificial neural networks (ANNs) and fuzzy set theoretic approach have been proposed for power system stabilization problems (Segal et al. 2000; Hosseinizadeh and Kalam 1999; Zhang et al. 1993; Shi-jie et al. 1986b; Abido and Abdel-Magid 1999; Hiyama and Lim 1989; Changaaron et al. 2000; Chaturvedi et al. 1999). Both techniques have their own advantages and disadvantage. The integration of these approaches can give improved results.
The commonly used neuron model has been modified to obtain a generalized neuron (GN) model using fuzzy compensatory operators as aggregation operators to overcome the problems such as large number of neurons and layers required for complex function approximation, that not only affect the training time but also the fault tolerant capabilities of the ANN (Hornik et al. 1989). Application of this GN as an adaptive PSS (GNAPSS) is described in this paper.

This paper describes an adaptive PSS (GNAPSS) based on a generalized neuron (GN) model using fuzzy compensatory operators as aggregation operators to overcome the problems such as large number of neurons and layers required for complex function approximation, that not only affect the training time but also the fault tolerant capabilities of the ANN (Hornik et al. 1989). Application of this GN as an adaptive PSS (GNAPSS) is described in this paper.

2 Adaptive GN based power system stabilizer

Most work done on adaptive PSS design uses self-tuning adaptive control approach as it is a very effective adaptive control scheme (Pierre 1987; Shi-jie et al. 1986a; Chen et al. 1993). The structure of a self-tuning adaptive controller has two parts: an on-line plant model predictor and a controller.

The plant model is updated by the on-line predictor each sampling period to track the dynamic behavior of the plant. Then a suitable control strategy is used to calculate the control signal based on the updated plant model. Any one out of a number of control strategies, such as minimum variance, generalized minimum variance, pole assignment, pole shift (PS) control (Chen et al. 1993), can be used in the self-tuning adaptive control.

Studies have shown that an adaptive PSS can adjust its parameters on-line according to the changes in environment, and maintain desired control ability over a wide operating range of the power system. Taking advantage of the neural networks to easily accommodate non-linearities and time dependencies of non-linear dynamic systems, a GN is used to develop an adaptive PSS. A brief description of the GN model (Hornik et al. 1989) is given in the Appendix.

2.1 GN predictor

Identification procedure includes setting up a suitably parameterized identification model and adjusting the parameters of the model to optimize a performance function based on the error between the plant and the identified model output.

A schematic diagram of the GN based plant predictor using forward modeling is shown in Fig. 1. A GN predictor is placed in parallel with the system and has the following inputs:

\[ X_i(t) = \{y_{vector}, u_{vector}\} \]  

where

\[ y_{vector} = \{y(t), y(t-T), y(t-2T), y(t-3T)\} \]

\[ u_{vector} = \{u(t-T), u(t-2T), u(t-3T)\} \]

The plant model is updated by the on-line predictor each sampling period to track the dynamic behavior of the plant. Then a suitable control strategy is used to calculate the control signal based on the updated plant model. Any one out of a number of control strategies, such as minimum variance, generalized minimum variance, pole assignment, pole shift (PS) control (Chen et al. 1993), can be used in the self-tuning adaptive control.

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2.2 Training of GN-predictor

Training of an ANN is a major exercise, because it depends on various factors (Laurence 1994; Widrow and Lehr 1990; Mizumoto 1989) such as the availability of sufficient and accurate training data, suitable training algorithm, number of neurons in the ANN, number of ANN layers and so on. The GN-Predictor with only one neuron is able to cope with the problem complexity, as the selection of the number of neurons and layers is not required. Training of the proposed GN Predictor has two steps, off-line training and on-line update.

Off-line training of the GN predictor for the PSS was performed with data acquired from simulation studies on a generating unit model, equipped with a governor and an AVR, and connected to a constant voltage bus through a double circuit transmission line. The seventh order model of the synchronous machine, the transfer functions of the AVR and governor and the parameters are given in the Appendix. In off-line training, the GN Predictor is trained for a wide range of operating conditions i.e. output power ranging from 0.1 to 1.0pu and the power factor ranging from 0.7 lag to 0.8 lead. Similarly, a variety of disturbances, such as change in reference voltage, input torque variation, one transmission line outage and three phase fault on one circuit of the double circuit transmission line, are also included in the training.

Error between the system output and the GN predictor output at a unit delay, called the performance index, \( J_i(t) \), of the GN predictor is used as the GN predictor training signal:

\[ J_i(t) = \frac{1}{2} [y_i(t) - y(t)] \]

where \( y_i(t) \) is the GN predictor output with unit delay.

The dynamics of the plant can be viewed as a non-linear mapping as below:

\[ y(t + T) = f_i(X_i(t)). \]

Therefore, the GN-predictor for the plant can be represented by a non-linear function \( F_i \).

\[ y_i(t + T) = F_i(X_i(t), W_i(t)), \]

where, \( W_i(t) \) is the matrix of GN predictor weights at time instant \( t \).
The weights of the GN predictor are updated as

$$W_i(t) = W_i(t - T) + \Delta W_i(t),$$

where $\Delta W_i(t)$, change in weight depending on the instantaneous gradient, is calculated by

$$\Delta W_i(t) = -\eta_i J_i(t + T) \frac{\partial J_i(t)}{\partial W_i(t)} + \alpha \Delta W_i(t - T),$$

where $\eta_i$ – learning rate and $\alpha$ – momentum factor for GN predictor.

The off-line training is performed with 0.1 learning rate and 0.4 momentum factor. After off-line training is finished, i.e. the average error between the plant and the GN-predictor outputs converges to a small value, the GN-predictor represents the plant characteristics reasonably well, i.e.

$$y(t + T) = f_i(X_i(t)) \approx y_i(t + T) = F_i(X_i(t), W_i(t)).$$

it is connected to the power system for on-line update of weights. The learning rate and momentum factor are very crucial factors in on-line updating and greatly affect the performance of the GN predictor. If the value of learning rate is high then the response of the GN may go unstable, and if it is too low then time required to modify its behavior is large. The momentum factor is used to overcome the problem of local minima of GN. Hence, for on-line training, the values of these factors were chosen carefully based on the previous experience.

On-line performance of the GN predictor on a physical model of the generating unit connected to a constant voltage bus for a transient three-phase to ground fault of 100 ms duration is shown in Fig. 2. Performance in response to the removal of one line from the double circuit transmission line and re-energized after 5 s is shown in Fig. 3. The error, difference between the speed predicted by the GN predictor and the system speed, can be seen to be very small.

### 2.3 GN controller

A schematic diagram of the GN controller is shown in Fig. 4. The plant consists of the single machine connected to the constant voltage bus as described above. The last four sampled values of the output are used as input to the GN controller. Besides the output, the past three control actions are also given to the GN controller as inputs. These inputs are normalized in the range 0.1–0.9. The output of the GN-controller is the control signal $u(t)$.

$$u(t) = F_C(X_i(t), W_c(t)),$$

where, $W_c(t)$ is the matrix of neural controller weights at time instant $t$. The $u(t)$ is de-normalized to get the actual control action and then sent to the plant and the GN-predictor simultaneously.
2.4 Training of GN controller

Training of the proposed GN controller is also done in two steps—off-line training and on-line update. In off-line training, the GN controller is trained for a wide range of operating conditions and a variety of disturbances similar to those used in training the predictor. Off-line training data for the GN controller has been acquired from the system controlled by the CPSS described in the Appendix. For this purpose, the CPSS was tuned for each operating condition.

The performance index of the neural controller is

\[ J_c(t) = \frac{1}{2} [y_d(t + T) - y_d(t + T)]^2, \tag{7} \]

where \( y_d(t + T) \) is the desired plant output at time instant \( (t + T) \). In this study it is set to be zero.

The weights of the GN controller are updated as

\[ W_c(t) = W_c(t - T) + \Delta W_c(t), \tag{8} \]

\[ \Delta W_c(t) \text{, change in weight depending on the instantaneous gradient, is calculated by} \]

\[ \Delta W_c(t) = -\eta_c \omega_c (t + T) \frac{\partial J_c(t)}{\partial u(t)} \frac{\partial u(t)}{\partial W_c(t)} + \alpha_c \Delta W_c(t - T) \tag{9} \]

where \( \eta_c \) = Learning rate for GN controller

\( \alpha_c \) = Momentum factor for GN controller.

Off-line training is started with small random weights (±0.01) and then updated with relatively high learning rate and momentum factor (\( \eta_c = 0.1 \) and \( \alpha_c = 0.4 \)).

After off-line training is finished, the proposed controller is connected to the power system for on-line update with learning rate (\( \eta_c = 0.001 \)) and momentum factor (\( \alpha_c = 0.01 \)). In on-line updating of GN-controller weights, expected error is calculated from the one step ahead predicted output, \( y_1(t + T) \), of the GN-predictor. The expected error is then used to update the weights on-line. Parameters of the GN predictor and controller are adjusted every sampling period. This allows the controller to track the dynamic variations of the power system and provide the best control action.

3 Experimental studies

Behavior of the proposed GNAPSS has been investigated on a physical model in the Power System Research Laboratory at the University of Calgary, Alberta, Canada. The physical model consists of a three-phase 3-kV A micro-synchronous generator connected to a constant voltage bus through a double circuit transmission line. Each circuit is modeled by six series connected \( \Pi \) sections. Each section is equivalent of 50 km length. The transmission line parameters are the equivalent of 1,000 MVA, 300 km and 500 kV. A field time constant regulator has been employed to adjust the transient field time constant to the desired value.

The governor turbine characteristics are simulated using the micro-machine prime mover. It can be achieved by dc motor which is controlled as a linear voltage to torque converter. An overall schematic diagram of this physical model is shown in Fig. 5. The laboratory model consists of the turbine \( M \), the generator \( G \), the transmission line, the AVR, a digital signal processor (DSP) board and a Man-machine interface. In the experimental studies, deviation of the generator output power was taken as the plant output due to its ease of measurement.

The GNAPSS control algorithm was implemented on a single board computer, which uses a Texas Instruments TMS320C31 DSP to provide the necessary computational power. The DSP board is installed in a personal computer with the corresponding development software and debugging application program. The analog to digital input channel of the DSP board receives the input signal and control signal output is converted by the digital to analog converter. Studies at various sampling intervals showed that performance outside the 20–100 ms range deteriorated significantly. A sampling period of 30 ms was used for the studies described in this paper.

Performance of the GNAPSS was compared with an IEEE type PSS1A CPSS also implemented on the same DSP, with a 1 ms sampling period. The fixed parameter CPSS was designed for the operating condition of \( P = 0.9 \) pu, \( Q = 0.4 \) pu. First the GN-predictor was tested alone under various operating conditions and compared with the actual plant results as shown in Fig. 6. It can be seen that the predictor can track the plant very closely for a variety of changes in operating conditions.

The performance of the GNAPSS was tested for a number of operating conditions as described below.

3.1 Single-phase to ground fault test

In this experiment, with the generator operating at \( P = 0.8 \) pu, 0.9 pf lead, a transient 100 ms single-phase to ground fault was applied in the middle of one transmission line. The system performance is shown in Fig. 7. It can be observed that the GNAPSS is able to reduce the magnitude of system oscillations.

![Fig. 5 Experimental setup for Laboratory Power System model](image-url)
3.2 Two-phase to ground fault test

Results of a two-phase to ground fault test at $P = 0.8 \text{ pu}$, 0.9 pf lead at the middle of one transmission line are shown in Fig. 8.

3.3 Three-phase to ground fault test

A transient three-phase to ground fault was applied for 100 ms at different operating conditions at the middle of one transmission line at 0.5 s. An illustrative result at $P = 0.5 \text{ pu}$, 0.9 pf lag is given in Fig. 9.

Results in Figs. 7 through 9 show that the GNAPSS provides consistently good performance even though the disturbance changes significantly in severity.

3.4 Removal of one line

In this test, with the generator operating at $P = 0.8 \text{ pu}$, 0.9 pf lag, one circuit of the double circuit line was disconnected at 0.5 s and re-connected at 1.75 s. The results in Fig. 10 show that in this type of fault also the system performance with the GNAPSS is very good in terms of damping the oscillations.

4 Conclusions

A GN based adaptive PSS has been implemented and its performance has been tested on a physical model of a single machine – constant voltage bus power system. The GNAPSS is not designed for a specific operating point. It is first trained off-line for a wide range of generator operating conditions. Parameters (i.e. the weights of GN) of the controller are
Fig. 9 Experimental results for a 3-phase to ground fault at $P=0.5$ pu, 0.9 pf lag

Fig. 10 Removal of one line and reconnection

updated on-line. With the learning ability through on-line update of weights the GN based PSS can track the changes in operating conditions. In this control architecture, no reference model is needed since the GN predictor tracks the system output and predicts the output one-step ahead. The predicted output of the GN predictor helps in tuning the GN controller weights on-line.

Due to its adaptation capability, the GNAPSS can incorporate the non-linearities involved in the system. Studies described in the paper show that the performance of the GN based adaptive PSS can provide very good performance over a wide range of operating conditions.

Appendix A: Generalized neuron model

The sigmoidal thresholding function and ordinary summation or product as aggregation functions in the common neuron models fail to cope with the non-linearities involved in real life problems. To deal with these, the proposed model has both sigmoidal and Gaussian functions with weight sharing. The GN model has flexibility at both the aggregation and threshold function level to cope with the non-linearity involved in the type of applications dealt with as shown in Fig. 11 The neuron has both $\Sigma$ and $\pi$ aggregation functions. The $\Sigma_1$ aggregation function has been used with the sigmoidal characteristic function ($f_1$) while the $\pi$ aggregation function has been used with the Gaussian function ($f_2$) as a characteristic function.

Step 1 The output of the $\Sigma_1$ part with sigmoidal characteristic function of the generalized neuron is

$$O_\Sigma = f_1(s_{\text{net}}) = \frac{1}{1 + e^{-\lambda_s s_{\text{net}}}}$$

where $s_{\text{net}} = \sum W_{\Sigma_1}X_i + X_{o\Sigma}$

$\lambda_s$ – Gain scale factor for $\Sigma$ part.

Step 2 The output of the $\pi$ part with Gaussian characteristic function of the GN is

$$O_\pi = f_2(p_{\text{net}}) = e^{-\lambda_p p_{\text{net}}^2}$$

where $p_{\text{net}} = \Pi W_{\pi}X_i + X_{o\pi}$

$\lambda_p$ – Gain scale factor for $\Pi$ part.

Step 3 The final output of the neuron is a function of the two outputs $O_\Sigma$ and $O_\pi$ with the weights $W$ and $(1-W)$, respectively.

$$O_{pk} = O_\pi \ast (1-W) + O_\Sigma \ast W.$$  (12)

The neuron model described above is known as the summation type compensatory neuron model, since the outputs of the sigmoidal and Gaussian functions are summed. Similarly, the product type compensatory neuron models may also be developed. It is found that in most of the applications summation type compensatory neuron model works well (Chaturvedi et al. 2004) and is the one used for the development of the adaptive GN based PSS.

In this paper, summation and product are used at the aggregation level for simplification, but one can take other fuzzy aggregation operators such a max, min or compensatory operators too. Similarly, the thresholding functions are only sigmoidal and Gaussian function for the proposed GN,
but other functions like straight line, sine, cosine, etc. can also be used. The weighting factor may be associated with each aggregation function and thresholding function. During training, these weights change and decide the best functions for the GN. The learning algorithm of GN model is given in (Chaturvedi et al. 2001). The GN has been used for various applications like forecasting (Chaturvedi et al. 1999), modeling and simulation (Chaturvedi et al. 2004a) and control (Chaturvedi et al. 2001, 2002, 2004a).

Appendix B: System model and its parameters

1. The generating unit is modeled by seven first order nonlinear differential equations (Shi-jie et al. 1986b).
2. The AVR and exciter used in the system have the transfer functions respectively:
   \[ A(s) = \frac{k_a}{(1 + s T_a)} \quad E(s) = \frac{k_e}{(1 + s T_T)} \]
3. The governor used in the system has the transfer function
   \[ g = \left[ a + \frac{b}{1 + s T_g} \right] \]
4. The conventional PSS has the following transfer function
   \[ G(s) = -k_3 \left[ \frac{s T_q}{(1 + s T_q)} \right] \left[ \frac{(1 + s T_1)}{(1 + s T_2)} \right] \left[ \frac{(1 + s T_3)}{(1 + s T_4)} \right] \]

References

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