PERFORMANCE OF THE RBF NEURAL CONTROLLER FOR TRANSIENT STABILITY ENHANCEMENT OF THE POWER SYSTEM

T. Atanasova, J. Zaprianov, ICSR - BAS
Sofia, Bulgaria

Abstract

To enhance the first swing stability a RBF neural network fastvalving controller is proposed. The solution approach is based on a recent fuzzy fastvalving control scheme. Disturbances in the PS are used for training the NN controller. The performance of the RBF neural controller is simulated in a single machine to an infinite bus power system.

1 INTRODUCTION

Parameters in the electrical power system (PS) change with time, slowly due to environmental effects or rapidly due to faults. Thus it is necessary to update the control law with system changes.

The design of adaptive controllers to improve the performance of the power system has been a topic of research for a long time. Neural networks (NN) are a suitable choice for the control of complex nonlinear plants since the conventional control methods show limitations in performance. Due to some desirable features such as local adjustment of the weights and mathematical tractability, radial basis function networks (RBF) have recently attracted considerable attention. When the basis functions are fixed, the outputs of the networks are linear in the coefficients (the network weights). Then the results of the theory of linear systems can be applied to the weight's adaptation and RBF net integration in control design.

One of the promising applications of NN in PS is in the area of power stabilization. Neural network based power system stabilizers (PSS) [1] have been shown to be very effective in damping out the PS lower frequency oscillations and experimentally have been shown to have much better performance over a conventional PSS. Another important application of NN controller is for transient stability enhancement. This is a subject of this paper.

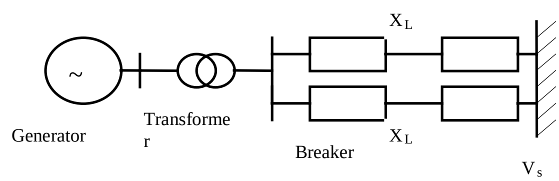
To enhance the first swing stability, a RBF neural network fastvalving controller is proposed. The solution approach is based on a recent fuzzy fastvalving control scheme [2]. But the fuzzy logic control suffers from the disadvantage of having to obtain fuzzy rules by trial and error and the requirement of good knowledge of the system behavior. The learning capabilities of a NN are used to overcome these problems. The RBF neural structure is selected as it is closely related to the fuzzy logic approach.

The objective of the fastvalving is to modulate the mechanical power input by suitable changing of the valve position. Thus the output of the RBF NN controller is the change in valve position. The inputs are the speed error and the variation in the electric power.

The performance of the RBF neural controller is simulated in a single machine to be an infinite bus power system.

2 DESCRIPTION OF THE MATHEMATICAL POWER SYSTEM MODEL

A simplified dynamic model of the power system is used, namely a single generator connected through two parallel transmission lines to a very large network approximated by an infinite bus. The model is shown below.



Single machine-infinite bus model.

The plant model considered can be written as follows [3]:
Mechanical equations:

$$\frac{d\,\delta(t)}{dt} = \omega(t)$$
$$\frac{d\,\omega(t)}{dt} = -\frac{D}{H}\,\omega(t) + \frac{\omega_0}{H}\,(P_m - P_e(t)), \tag{1}$$

Generator electrical dynamics:

$$\frac{d\,E'_q(t)}{dt} = (E_f(t) - E_q(t))\,\frac{1}{T_{d0}} \tag{2}$$

Electrical equations:

$$\begin{aligned}
E_q(t) &= \frac{x_{ds}}{x'_{ds}}\,E'_q(t) - \frac{x_d - x'_d}{x'_{ds}}\,V_s \cos\delta(t)\\
E_f(t) &= k_c u_f(t)\\
P_e(t) &= \frac{V_s E_q(t)}{x_{ds}} \sin\delta(t)\\
I_q(t) &= \frac{V_s}{x_{ds}} \sin\delta(t) = \frac{P_e}{x_{ad} I_f}\\
Q(t) &= \frac{V_s}{x_{ds}}\,E_q(t)\cos\delta(t) - \frac{V_s^2}{x_{ds}}\\
E_q(t) &= x_{ad} I_f(t),
\end{aligned} \tag{3}$$

$$V_t(t) = \frac{1}{x_{ds}}\{x_s^2 E_q^2(t) + V_s^2 x_s^2 + 2 x_s x_d x_{ds} P_e(t)\, ctg\,\delta(t)\}^{1/2} \tag{4}$$

For details of the other symbols used in the above equations, the reader can refer to the Ref. [4]. The parameters of the synchronous generator and the line parameters are given in the Appendix.

The measurable physical variables are Pe (t), Q (t), If (t) and ω (t).

The dynamics of the power control loop are given by

$$\begin{aligned} \dot{P}_m(t) &= -\frac{1}{T_T}P_m(t) + \frac{k_T}{T_T}X_E(t) \\ \dot{X}_E(t) &= -\frac{1}{T_G}X_E(t) + \frac{k_G}{T_G}\left(P_C(t) - \frac{1}{R\omega_0}\omega(t)\right) \end{aligned} \qquad (5)$$

where XE is the steam valve opening, Pc is the input power to the control system, Pm is the mechanical power input, kT and kG are gains of the turbine and the speed governor respectively and the corresponding time constants are given by TT and TG. The following constraint is placed on the speed valve opening $0 \leq XE \leq 1$.

3 THE RBF-NN BASED CONTROLLER

3.1 Radial Basis Function

Radial basis functions share many of the advantages of conventional feed forward (backpropagation) neural networks. Both types of networks with enough neurons and training data can approximate an arbitrary nonlinear function to a certain level of accuracy. RBF networks offer some other advantages in comparison with backpropagation networks [5]. When the basis functions are fixed, the outputs of networks are linear in the coefficients (the network weights). Then the results of the theory of linear systems can be applied to the weights adaptation and RBF networks integration in control design.

One of the commonly used radial basis function networks is the Gaussian radial basis function networks (GRBF), which is expressed by

$$f^{NN}(x) = \sum \alpha_k R_k(x),\ k = 1, 2, \ldots m, \qquad (6)$$

$$R_k(x) = \exp\left[-v_k^2 \left| x-c_k \right|^2\right], \qquad (7)$$

where Rk (x) -is the Gaussian activation function for the kth node, ck - center, vk -width, αê - amplitude.

The results of [6] indicate that the RBF NN are capable of on-line approximation of nonlinear function. The nonlinearities that are investigated are mild (cubic and sine function).

3.2 RBF - Controller

Generally the transient stability enhancement is accomplished by means of the following methods [2]:

1. reducing the fault severity
2. reducing the accelerating power.

Under large disturbances the dynamics of the power system differ widely form the pre-fault steady-state conditions and conventional PSSs may not be able to maintain the overall system stability. The feedback linearized controller may not perform satisfactory when there are limits placed on the actuators. The disadvantages of nonlinear excitation control based on feedback linearization are (i) requiring the machine angles in the case of a multimachine power system and (ii) it not being able to take care of the variations in the network parameters.

To enhance first swing stability an RBF neural network fastvalving controller is suggested.

In this approach an RBF NN is operated in parallel with a full load frequency adaptive control scheme. The detailed mathematical foundation of the adaptive control for the power system can be found in [2] and [7]. The neural network is able to monitor the system frequency. If there is a condition where the frequency values are corrupted, or the system is not sufficiently excited, then the RBF NN will be able to provide the power set points that may be directly communicated to those sets that provide system frequency control. The results of a number of power system simulations are presented.

The network was trained using a gradient descent procedure. The positions and the spreads of centers were not trained, because the simulations indicated satisfactory performance without such a computation-costly training. They were selected before training.

4 THE DIGITAL SIMULATION RESULTS

One possible strategy to design a controller for a given non-linear process is to use a model of the process to determine the proper control action.

The power system used for the simulation is described in section 2. The model has been implemented in an emulator by means of SIMULINK on MATLAB.

In the real power system there are always disturbances which can be used for training the neural network. In this chapter the following disturbances have been used in the simulation:

- three-phase short-circuit is applied at the generator terminal for 0.1 sec and the fault is switched off afterwards.
- three phase short circuit is applied at the generator terminal and cleared after 0.1 sec. The line is kept out of servise.
- 20% reduction in mechanical power input with measurement noise – white noise + 0.1sin(10t);

Fig. 1 represents the radial basis functions for the control signal that is shown on Fig. 2. Fig. 3 shows the response for the fault sequence 1 and Fig. 4 shows the response when the system is under more serious disturbance. The RBF approximation of ω=f(δ) with noise is shown in the Fig. 5 and the approximation error is in Fig. 6. For noisy data more neurons are needed in the RBFN structure to model the system dynamics. Fig. 7 shows the control for fault 3 and Fig. 8 shows the state variables.

5 CONCLUSION

To optimize the operation of the power system it is important to reinforce the development and implementation of more sophisticated control concepts – improved modelling of non-ideal electrical and mechanical parts; improved integrated simulation systems; appropriate control strategies. Radial basis function neural networks provide an attractive method for achieving these aims. They are faster to train than feed forward networks with sigmoidal activation nets. The RBF model structure is better suited for adaptive control, since if the basis functions are fixed, the model is linear in the coefficients. Another advantage of this technique is its robustness to NN modelling errors.

The RBF network abilities to provide control signal have been tested by digital simulations.

From the simulation results the following conclusions can be obtained:

1). The RBF NN approach proposed in this paper is effective in designing of a non-linear controller.

2). More investigation is needed concerning on-line training of the RBF NN controller for the power system with unknown disturbances. The input signal u is constrained to upper and lower limits as is the rate. It is a current research area.

3). A possible direction of investigation is in the partitioning the RBF NN to deal with parts of the dynamics of the system. The RBF NW based controller can be considered as only a subnet of the more complex hierarchical neurocontrol architecture for the power system, and it is a subject of future work. *

APPENDIX

Example system parameters used in simulation studies are as follows:

$\omega 0$ =314.159; D=5.0; H=4.0s; Td0=6.9s; kc=1; xd=1.863; x'd=0.257; xT=0.127; xL=0.4853; kT = kG = 1; TT = 2; TG =0.2; R= 0.05 p.u.; f0=50 Hz.

xds=xT+0.5xL+xd; x'ds= xT+0.5xL+x'd; xs= xT+0.5xL;.

The physical limit of the excitation voltage is max |kcuf(t)|=1.8 p.u.

The operating point is $\delta 0$=72o, Pm0=0.9 p.u., Vt0=1.0 p.u.

6 REFERENCES

[1] S. Cheng, R. Zhou, L. Guan. "An On-line Self-learning Power System Stabilizer Using a Neural Network Method", IEEE Trans. on Power Systems, vol. 12, no. 2, May, pp. 926-930, 1996.

[2] P. S. Babu, A. Ghosh, Sachchidanand, "A Coordinated Fuzzy Fastvalving Controller for Transient Stability Enhancement of SMIB System", ECC'97, Brussels, July, 1997.

[3] A. R. Bergen, "Power System Analysis", Prentice-Hall, Englewood Cliffs, NJ, 1986.

[4] Y. Wang, D. Hill, R. Middleton, L. Gao, "Transient Stability enhancement and voltage regulation of power systems", IEEE Transactions on Power systems, 8(2): 620-627, 1993.

[5] R.M. Sanner, J.-J.E. Slotine. "Gaussian networks for direct adaptive control". IEEE Trans. Neural Networks, 3:837-863, 1992.

[6] M.A. Shah, P.H. Meckl, "On-line control of a nonlinear system using radial basis function neural networks". Proceedings of the American Control Conference, Seattle, Washington, pp. 4265-4269, 1995.

[7] Y. Wang, D. Hill, R. Middleton, L. Gao, "Transient Stabilization of Power Systems with an Adaptive Control Law", Automatica, 30(9):1409-1413, 1994.

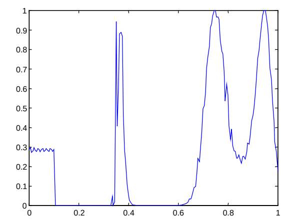


Fig. 1

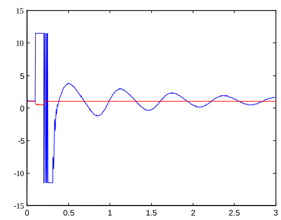


Fig. 2

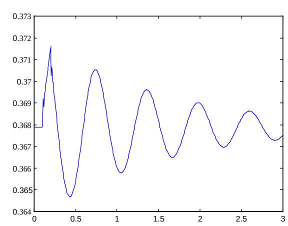


Fig. 3

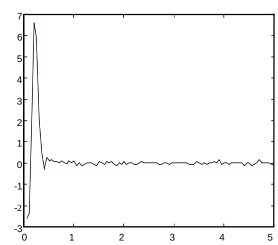


Fig. 4

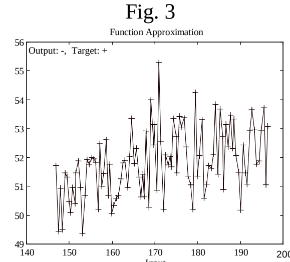


Fig. 5

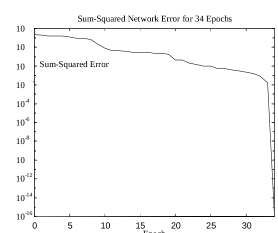


Fig. 6

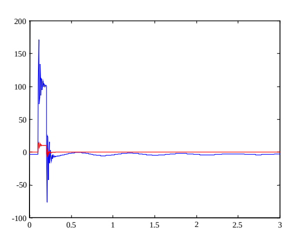


Fig. 7

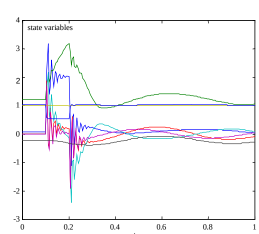


Fig. 8

* The financial support of the National Foundation of Scientific Researches is appreciated (TN 605/96).