

# Application of Radial Basis Function Networks to Power System Load Frequency Control

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*Abstract: An application of Artificial Neural Networks (ANN) to Load Frequency Control (LFC) of nonlinear power systems is presented in this paper. Power systems, such as other industrial processes, have parametric uncertainties that for controller design had to take the uncertainties into account. For this reason, to LFC controller design is being used of robust control theories and to improve stability of nonlinear system, in the various operating point and under different disturbances this controller has been reconstructed with the use of neural network capability based on Radial Basis Function (RBF). The motivation of using the robust control for training of the RBF neural networks controller is taking the large parametric uncertainties into account so that both stability of the overall system and good performance have been achieved for all admissible uncertainties. The variation bounds of power system parameters are obtained by changing parameters by 20% to 30% simultaneously from their typical values. Our simulation results on a single machine power system show that the proposed nonlinear neural controller can achieve good performance and stability of the overall system even in the presence of generation rate constraint (GRC).*

**Keywords:** robust control, load frequency control, power systems, artificial neural networks,

## 1. Introduction

Load frequency control (LFC), is a very important issue in power system operation and control for supplying sufficient and reliable electric power with good quality [1]. A load frequency control is essential for maintaining frequency system in its nominal value. Since the operating point and the loading conditions in power systems are changing constantly. Thus, to improve the stability and performance of the power system, generator frequency should be setup under different loading conditions. For this reason many control approaches have been represented for load frequency control after 1970 decade [2].

An industrial plant, such as a power system, always contains parametric uncertainties. As the operating point of a power system and its parameter changes continuously, a fixed controller may no longer be suitable in all operating conditions. In order to take, the parametric uncertainties into account, several authors have applied the concept of variable structure systems

[3,4], various adaptive control techniques [5] to the design of load frequency control. In recently years, fuzzy logic [6], neural networks methods [7,8], robust control [9-11] and improved  $H_{\infty}$  control [12,1] has been applied to the design of LFC.

In this paper, a new nonlinear Artificial Neural Network (ANN) controller is designed which has an advance adaptive control configuration. The proposed controller uses the capability of ANN based on Radial Basis Function (RBF) for design of the LFC controller. In this work, for the design of nonlinear ANN controller is being used the idea of  $H_{\infty}$  robust controller and applying it to nonlinear power system. The motivation of using the robust control for training of the RBF neural networks controller is taking the large parametric uncertainties into account so that both stability of the overall system and good performance have been achieved for all admissible uncertainties. The required data for training and testing RBF network at variety operating points under load step disturbances with the design of  $H_{\infty}$  robust controllers had been obtained. Our simulation results on a single machine power system show that the proposed controller not only has good performance in the presence of the generation rate constraint (GRC), but also ensure the stability with complex nonlinear dynamics.

## 2. Plant Model

The power systems are large-scale systems with complex nonlinear dynamics. However, for design of LFC, the linearized model around operating point is sufficient to represent the power system dynamics [1]. Fig.1 shows the block diagram of one area power system. Wherever the actual model is with generation rate constraints (GRC) and it would influence the performance of power systems significantly. Thus, the GRC is taken into account by adding a limiter to the turbine and also to the integral control part to prevent excessive control action. The GRC of the thermal unit 0.3 p.u. per minute ( $\delta = 0.005$ ) is considered. The governor dead-band is also assumed to be 0.06%. Based on the suitable state variable chosen in Fig. 1, the following state-space model will be obtained:

$$\begin{aligned} \dot{x} &= Ax + B_1 u + Fd \\ y &= C_1 x \end{aligned} \quad (1)$$



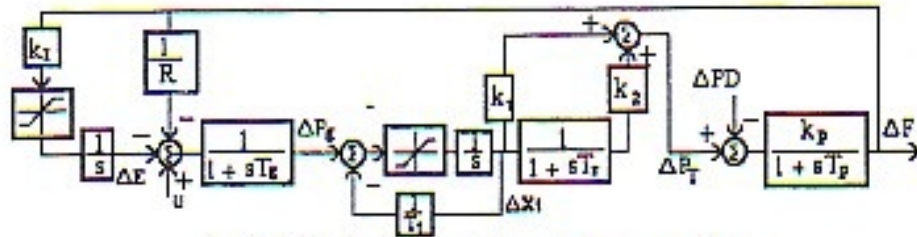


Fig.1 - Block-diagram of a single machine power system

where

$$x = [\Delta F \quad \Delta P_D \quad \Delta X_1 \quad \Delta P_f \quad \Delta F]^T$$

$$y = \Delta F, d = \Delta PD, a(4,3) = (k_1 + k_2)/T_f, -k_1/T_f$$

$$A = \begin{bmatrix} 0 & 0 & 0 & 0 & k_1 \\ -\frac{1}{T_g} & -\frac{1}{T_g} & 0 & 0 & -\frac{1}{RT_g} \\ 0 & \frac{1}{T_f} & -\frac{1}{T_f} & 0 & 0 \\ 0 & \frac{k_1}{T_f} & a(4,3) & -\frac{1}{T_f} & 0 \\ 0 & 0 & 0 & \frac{k_2}{T_f} & -\frac{1}{T_f} \end{bmatrix}$$

$$B^T = \begin{bmatrix} 0 & \frac{1}{T_g} & 0 & 0 & 0 \end{bmatrix}$$

$$F^T = \begin{bmatrix} 0 & 0 & 0 & 0 & -\frac{k_1 + k_2}{T_f} \end{bmatrix}, C = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

As the important characteristics of power system such as are changing of the generation, Loading conditions and system configuration. Therefore, parameters of the linear model described previously depend on the operating points. In this paper the range of the parameter variations are obtained by change of simultaneously  $T_g$  by 50% and all other parameters by 20% of their typical values which are given below:

$$T_g = 20, k_1 = 120, T_f = 0.3, T_p = 10, T_r = 0.1,$$

$$k_2 = k_3 = 0.5, R = 2.4, kI = 0.05,$$

Denoting the  $i$ th parameter by  $\alpha_i$ , the parameter uncertainty is formulated as:

$$\alpha_i = \alpha_{ie} + \delta_i \Delta \alpha_i, |\delta_i| \leq 1, i = 1, 2, \dots \quad (2)$$

$$\alpha_{ie} = \frac{(\bar{\alpha}_i + \underline{\alpha}_i)}{2}, \Delta \alpha_i = \bar{\alpha}_i - \underline{\alpha}_i$$

where  $\bar{\alpha}_i$  and  $\underline{\alpha}_i$  stand for the maximum and minimum value, respectively. Table 1 shows the system uncertainties with their nominal, maximum and minimum values.

Table 1 - System uncertainties

Uncer.	$\underline{\alpha}_i$	$\alpha_{ie}$	$\bar{\alpha}_i$	$\Delta \alpha_i$
$\frac{1}{T_g}$	8.33	10.42	12.5	2.07
$\frac{1}{T_g R}$	2.983	4.7	6.51	1.81
$\frac{1}{T_f}$	2.78	3.4735	4.167	0.6935
$\frac{1}{T_r}$	0.0833	0.1042	0.125	0.0208
$\frac{k_2}{T_f}$	4	8	12	4
$\frac{1}{T_p}$	0.033	0.0665	0.1	0.0335

Using these above definitions, the state-space model along with uncertainties system will be separated as[1]:

$$\begin{cases} \dot{x} = A_x x + B_x u + B_w w + Fd \\ z = C_x x + C_u u + C_w w \\ y = C_x x \\ w = \Delta x \end{cases} \quad (3)$$

And the structured uncertainty block is:

$$\Delta = \text{diag}(\delta_1, \dots, \delta_n); \delta_i \in \mathbb{R}, |\Delta|_{\infty} \leq 1$$

### 3. Design of $H_\infty$ - Robust Controller

The objective of controller design in single machine power system is damping of frequency oscillations, stability of the overall system for all admissible uncertainties and load disturbances. Thus, frequency deviation ( $\Delta F$ ) is considered as controller input. Fig. 2 shows the design problem in  $H_\infty$  general structure, in which  $P_0$  contains nominal plant and all parametric uncertainties. In order to take modeling error into account, the  $W_z$  is considered and  $W_p$  also indicating of system performance. The weights have been selected to be as:

$$W_p(s) = \frac{0.33s + 5}{5s + 0.03}, W_z(s) = \frac{0.1s + 1}{s + 1}$$

These weights have been selected by trial and error after analyzing many different simulation results.  $P$  in Fig. 2 is the generalized plant that should be obtained as  $H_\infty$  standard equation [13]. After obtaining the generalized plant of a single machine power system, the algorithm described in [14] was used to design the robust LFC controller.

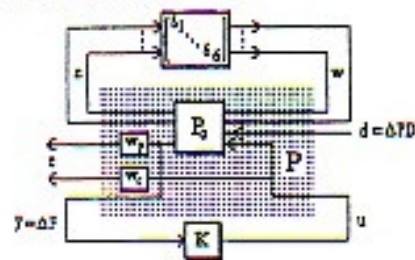


Fig. 2- The robust control configuration for the system

### 4. Nonlinear Controller Design Based on ANN

One way of minimizing the frequency oscillation in a single area power system is by using closed-open steam valve method, in which the governor improves the transient stability of the system. The nonlinear controller will produce control signal to the governor. Recently, computational intelligence systems and within them neural networks, which in fact are model free dynamics, has been used widely for approximation



functions and mappings. The main feature of neural networks is their ability to learn from samples and generalizing them, and also their ability to adapt themselves to the changes in the environment. In fact, neural networks are very suitable for problems in the real world. They can map from a set of patterns in the input space to a set of desired values in the output space. In other words, neural networks try to emulate the learning activities of the human brain, but in a very simplified fashion. These networks are composed of many simple computational units called neurons, which have fast responses to the inputs. These networks with participation in an especial kind of parallel processing provide possibility of modeling any kind of nonlinear relation. More accuracy, robustness, generalized capability, parallel processing, learning static and dynamic model of MIMO systems on collected data and its simple implementation are some of the important characteristics of neural networks that caused wide application of this technique in different branch of science and industries, especially in power system and design of the nonlinear control system [8,14].

#### 4.1. Radial Basis Function Neural Networks

In the simplest form, a radial basis function network consists of three layers; the input layer, which has source (input) nodes; the hidden layer, which has enough number of neurons; and the output layer, which defines the response of the network with regard to the applied inputs. The mapping from the input layer to the hidden layer is nonlinear, whereas the mapping from the hidden layer to the output layer is linear. The structure of the RBF network is shown in Fig 3.

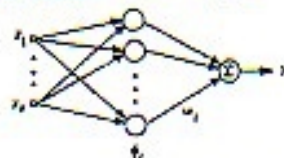


Fig.3- The architecture of radial basis function neural network

In this network, the radial basis functions are Green functions with the following form:

$$\varphi_i(x) = G(\|x - t_i\|) = \exp\left(-\|x - t_i\|^2\right), \quad i = 1, \dots, M \quad (4)$$

where  $M$  is the number of neurons in the hidden layer, which can be less or equal to the number of training samples. The output of this network is an approximation of the desired output and is obtained as follows:

$$f^*(x) = \delta + \sum_{i=1}^M w_i \varphi_i(x) \quad (5)$$

The weights in the output layer  $w_i$  and the center of the Green functions  $t_i$  will be obtained during the training of the network [14]. Radial basis function neural networks differ from multilayer perceptron in several respects. RBF networks have a single hidden layer, whereas MLP networks may have one or more hidden layer. In these networks activation function between input layer and hidden layer are nonlinear and

between hidden layer and output layer are linear, but in MLP networks activation function each hidden layer with its previous layer was nonlinear and output layer may be linear or nonlinear.

#### 4.2. Optimal Nonlinear ANN Controller Design

Fig.4 shows the block diagram of the closed-loop system, consisting of nonlinear neural network controller. The data required for RBF neural network training is obtained from the  $H_\infty$  robust controller design in different operating conditions and under various load disturbances. The objective of LFC controller design is damping the frequency deviation with minimizing transient oscillation under the different load conditions. Thus, frequency deviation is chosen as neural network input. The output of the neural network is the control signal, which is applied to the governor.

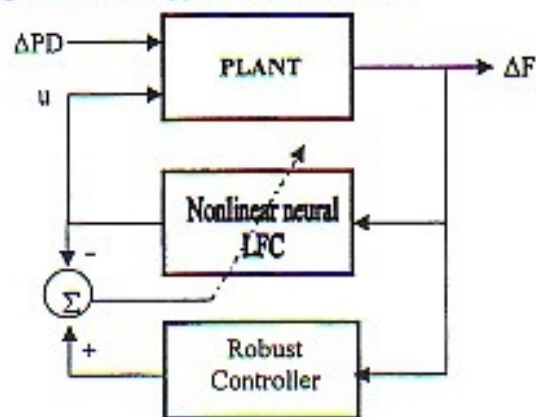


Fig.4 - Block diagram of the nonlinear neural network controller

#### 5. Simulation Results

For small sampling time, it can be shown that the discrete-time model is almost the same as the continuous-time model. Hence, the simulations have been carried out in MATLAB using continuous-time domain functions. In this study, the application of RBF neural controller for LFC in power system is investigated. The performance of ANN controller is compared with  $H_\infty$  controller and PI controller, which has been widely used in power systems.

Figs. 5 to 7 depict the performance of RBF,  $H_\infty$  and PI controller when 2% load step disturbance is applied to the system. Fig. 5 shows the results for the parameters at their nominal values and  $\delta = 0.005$ . Fig. 6.a shows the performance of controller with the applying %1 load step disturbance to system when only one parameter ( $K_p$ ) is changed to 180 and the others parameters are at their nominal values and also GRC is decreased to  $\delta = 0.0017$ . In Fig. 6.b %2 load step disturbance applied to system whereas the parameters and GRC are decreased from their nominal values to the minimum values and GRC to  $\delta = 0.005$ , too. Fig. 7 shows the responses of controllers when the parameters are



increased from their nominal values to their maximum values and 2.5% load step disturbance is applied to system.

Remark 5.1: The simulation results show that the proposed RBF controller is very effective and not only has good performance, even in the presence of the GRC, but also ensures the stability of the overall system especially when the parameters and the operating conditions of the system are changed.

Remark 5.2: From the simulations results in Fig. 5b we can see that the responses of the overall system are more sensitive to the plant gain  $K_p$ , as compared to other parameters.

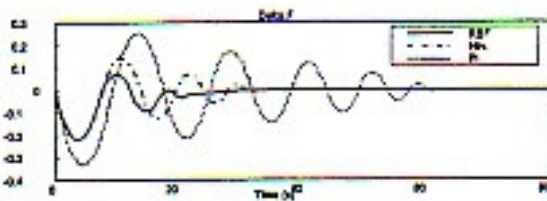


Fig. 5- The performance of controllers with nominal parameters and  $\Delta PD = 2\% \ \& \ \delta = 0.005$

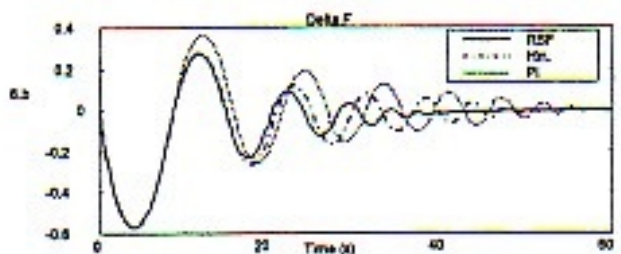
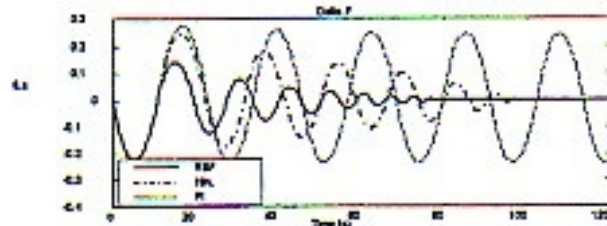


Fig. 6- The performance of controllers: (a) with  $K_p = 180$  and  $\Delta PD = 1\% \ \& \ \delta = 0.0017$  (b) with minimum parameters and  $\Delta PD = 2\% \ \& \ \delta = 0.005$

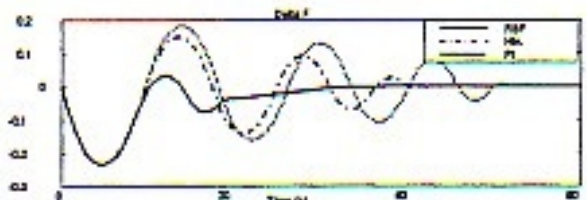


Fig. 7- The performance of controllers with maximum parameters and  $\Delta PD = 2.5\% \ \& \ \delta = 0.005$

## 6. Conclusion

In this paper, a new RBF network load-frequency controller has been proposed to improve power system performance. This control strategy was chosen because power systems involve many parametric uncertainties with varying operating conditions. The proposed controller is effective and can ensure that the overall system will be stable for all admissible uncertainties and load disturbances. The simulation results show that the proposed RBF neural network controller can achieve good performance even in the presence of GRC, especially when the system parameters are changing.

## 7. References

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