Robust and Adaptive Load Frequency Control of Multi-area Power Systems with system parametric uncertainties via TDMLP

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Abstract- In this paper a robust and adaptive Temporal Difference learning based MLP (TDMLP) neural network for power system Load Frequency Control (LFC) is presented. Power systems, such as other industrial processes, are nonlinear and have parametric uncertainties that for controller design had to take the uncertainties into account. For this reason, in the design of LFC controller the idea of TDMLP neural network is being used. Some simulations with two interconnections are given to illustrate proposed method. Results on interconnected power system show that the proposed method not only is robust to increasing of load perturbations and operating point variations, but also it gives good dynamic response compared with traditional controllers. It guarantees the stability of the overall system even in the presence of generation rate constraint (GRC). To evaluate the usefulness of proposed method we compare the response of this method with RBF neural network and PID controller. Simulation results show the TDMLP has the better control performance than RBF neural network and PID controller.

Introduction

In power systems, one of the most important issues is the load frequency control (LFC), which deals with the problem of how to deliver the demanded power of the desired frequency with minimum transient oscillations [1, 2]. Whenever any suddenly small load perturbations resulted from the demands of customers occur in any areas of the power system, the changes of tie-line power exchanges and the frequency deviations will occur. 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 developed for the load frequency control. Among them, PID controllers [3], optimal [4], nonlinear [5] and robust [6-8] control strategies, and neural and/or fuzzy [9-11] approaches are to be mentioned. 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 papers have been published in the concept of variable structure systems [12], various adaptive control techniques [13] to the design of load frequency control. In this paper, because of the inherent nonlinearity of power system a new artificial neural network based intelligent controller, which has the advance adaptive control configuration, is designed. The proposed controller uses the capability of the MLP neural network based on Temporal Difference (TD) learning for the design of LFC controller. In this work, for the design of MLP neural network the idea of TD learning and applying it to nonlinear power system is being used. The motivation of using the TD learning for training of the MLP neural network is to take the large parametric uncertainties into account so that both stability of the overall system and good performance have been achieved for all admissible uncertainties. Moreover, the proposed controller also makes use of a piece of information which is not used in conventional controllers (an estimate of the electric load perturbation, i.e. an estimate of the change in electric load when such a change occurs on the bus). The load perturbation estimate could be obtained either by a linear estimator, or by a nonlinear neural network estimator in certain situations. It could also be measured directly from the bus. We will show by simulation that when a load estimator is available, the neural network controller can achieve extremely dynamic response. In this study, the TDMLP neural network is considered for control interconnected power system with two areas with power tie-lines to supply different consumers. The simulation results obtained are shown that the proposed controller not only has good performance in the presence of the generation rate constraint (GRC), but also gives good dynamic response compare to RBF neural network and PID controller. This paper is organized as follows: Section 2 describes the power system and its mathematical model. In section 3, the whole structure of the proposed TDMLP neural network is shown. Section 4 describes the application of TDMLP in LFC. Section 5 shows the simulation results that have been compared with RBF neural network and PID controller. Some conclusion and remarks is discussed in section 6.

Mathematical Model of Power System Plant

The power systems are usually large-scale systems with complex nonlinear dynamics. However, for the 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 i-th area power system. Each area including steam turbines contains governor and reheater stage of the steam turbine. According to Fig.1, time-constants of the T_{ri} , T_{ti} and T_{gi} are considered for the reheater, turbine and governor of the thermal unit, respectively. Wherever the actual model consists of the generation rate constraints (GRC) and it would influence the performance of power systems significantly, the GRC is taken into account by adding a limiter to the turbine and also to the integral control part all of areas to prevent excessive control action. The GRC of the thermal unit is considered to be 0.3 p.u. per minute ($\delta = 0.005$). All areas have governors with dead-band effects which are important for speed control under small disturbances. 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:

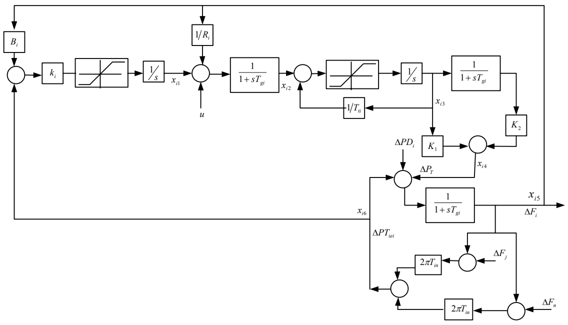

Figure 1. Block-Diagram of the ith area power system

$$\begin{aligned} \dot{\mathbf{x}}(\mathbf{t}) &= \mathbf{A}\mathbf{x}(\mathbf{t}) + \mathbf{B}\mathbf{u}(\mathbf{t}) \\ \mathbf{y} &= \mathbf{c}\mathbf{x}(\mathbf{t}) \end{aligned} \quad (1)$$

Where x is a 12 by 1 state vector, $\underline{u} = [u_1 \quad u_2 \quad \Delta P_{D1} \quad \Delta P_{D2}]^T$, $A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$,

$$B = \begin{bmatrix} B_1 & 0 & F_1 & 0 \\ 0 & B_2 & 0 & F_2 \end{bmatrix} \qquad B_i = \begin{bmatrix} 0 & \dfrac{1}{T_{gi}} & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$a_{43} = \frac{k_1 + k_2}{T_{ti}} - \frac{k_2}{T_{ri}} \qquad a_{65} = -2\pi \sum_{j \neq i} T_{ij}$$

$$A_{ij} = [a_{zk}] \quad z = k = 1,2,\ldots,6 \quad , \quad a_{zk} = \begin{cases} -2\pi T_{zk} & z = 6, k = 5 \\ 0 & \text{otherwise} \end{cases}$$

$$A_{ii} = \begin{bmatrix} 0 & 0 & 0 & 0 & K_{1i}B_i & K_{1i} \\ -\dfrac{1}{T_{gi}} & 0 & 0 & -\dfrac{1}{T_{gi}R_i} & 0 & 0 \\ 0 & \dfrac{1}{T_{ti}} & -\dfrac{1}{T_{ti}} & 0 & 0 & 0 \\ 0 & \dfrac{K_1}{T_{ri}} & a_{43} & -\dfrac{1}{T_{ri}} & 0 & 0 \\ 0 & 0 & 0 & \dfrac{K_{pi}}{T_{pi}} & -\dfrac{1}{T_{pi}} & -\dfrac{K_{pi}}{T_{pi}} \\ 0 & 0 & 0 & 0 & a_{65} & 0 \end{bmatrix}$$

The submatrices A_{12} and A_{21} are similar. The outputs are defined to be the frequency deviations (ΔF_i) and the deviation of transmission power line (ΔP_{tie}). As the important characteristics of power systems such as: changing of the generation, loading conditions and system configuration are. 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_n, T_{12} by 50% and all other parameters by 20% of their typical values which are given below:

$T_{pi}=20$, $K_{pi}=120$, $T_{ti}=0.3$,
$T_{Hi}=T_{gi}=0.1$, $T_{ri}=10$, $R_i=2.4$,
$K_1=K_2=0.5$, $T_{12}=0.0707$

Denoting the ith parameter by a_i the parameter uncertainty is formulated as:

$$a_i=a_{i0}+\delta_i a_i,\ |\delta_i|\le 1,\ i=1,2,\dots,\ a_{i0}=\frac{\underline{a_i}+\overline{a_i}}{2},$$

$$\Delta a_i=\overline{a_i}-a_{i0} \tag{2}$$

Where $\overline{a_i}$ and $\underline{a_i}$ 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.	$\underline{a_i}$	a_{i0}	$\overline{a_i}$	Δa_i
$\frac{1}{T_{gi}}$	8.33	10.42	12.5	2.07
$\frac{1}{T_{gi}R}$	2.983	4.7	6.51	1.81
$\frac{1}{T_{ti}}$	2.78	3.473	4.167	0.6935
$\frac{1}{T_{ri}}$	0.0833	0.1042	0.125	0.0208
$\frac{K_p}{T_p}$	4	8	12	4
$\frac{1}{T_{pi}}$	0.033	0.0665	0.1	0.0335
T_{12}	0.049	0.0707	0.093	0.0223

Temporal Difference Based MLP neural Networks

Most of new learning algorithms like reinforcement learning, Q-learning and the method of temporal differences are characterized by their fast computation and in some cases lower error in comparison with the classical learning methods. Fast training is a notable consideration in some control applications. In reinforcement learning, there is no teacher available to give the correct output for each training example, which is called unsupervised Learning. The output produced by the learning agent is fed to the environment and a scalar reinforcement value (reward) is returned. The learning agent tries to adjust itself to maximize the reward [15-17]. Often the actions taken by the learning agent to produce an output will affect not only the immediate reward but also the subsequent ones. In this case, the immediate reward only reflects partial information about the action. This is called delayed-reward [18][19]. Temporal difference (TD) learning is a type of reinforcement learning for solving delayed-reward prediction problems. Unlike supervised learning, which measures error between each prediction and target, TD uses the difference of two successive predictions to learn that is Multi Step Prediction. The advantage of TD learning is that it can update weights incrementally and converge to a solution faster [20]. In a delay-reward prediction problem, the observation-outcome sequence has the form $x_1,x_2,x_3,\dots,x_m,z$ where each x_t is an observation vector available at time $t, 1\le t\le m$ and z is the outcome of the sequence. For each observation, the learning agent makes a prediction of z , forming a sequence: $P_1,P_2,P_3,\dots,P_m$.

Assuming the learning agent is an artificial neural network, update for a weight w of the network with the classical gradient descent update rule for supervised learning is:

$$\Delta w=-\alpha\nabla_w E \tag{3}$$

Where α is the learning rate, E is a cost function and $\nabla_w E$ is the gradient vector. A simple form of E can be

$$E=\frac{1}{2}\sum_{t=1}^{m}(P_t-z)^2 \tag{4}$$

where P_t and z have been described at above. From equations (3) and (4), Δw will be calculated as follows:

$$\Delta w=-\alpha\sum_{t=1}^{m}(P_t-z)\nabla_w P \tag{5}$$

in [21] Sutton derived the incremental updating rule for equation (5) as:

$$\Delta w_t=\alpha(P_{t+1}-P_t)\sum_{k=1}^{t}\nabla_w P_k\ ,\quad t=1,2,\dots,m \text{ and}$$

$$P_{m+1}\overset{def}{=}z \tag{6}$$

To emphasize more recent predictions, an exponential factor λ is multiplied to the gradient term:

$$\Delta w_t=\alpha(P_{t+1}-P_t)\sum_{k=1}^{t}\lambda^{t-k}\nabla_w P_k \tag{7}$$

Where $0 \le \lambda \le 1$. This results in a family of learning rules, $TD(\lambda)$, with constant values of λ. But there are two special cases:

First, when $\lambda = 1$, equation (7) falls back to equation (6), which produces the same training result as the supervised learning in Equation (5).

Second, when $\lambda = 0$, equation (7) becomes

$$\Delta w_t = \alpha(P_{t+1} - P_t)\nabla_w P_k \qquad (8)$$

Which has a similar form as equation (5). So the same training algorithm for supervised learning can be used for $TD(0)$.

TDMLP Neural Network

Recently, computational intelligence systems and among 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 word. They can map from a set of patterns in the input space to a set of desired vales 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 which provide possibility of modeling any kind of nonlinear relations. 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 branches of sciences and industries, especially in power systems and design of the nonlinear control systems [8].

Multilayer perseptrons are an important class of neural networks that have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with some learning algorithms such as error correction learning rule, delta rule and etc.

The classical generalized delta rule for multi-layer feedforward network is [23]:

$$\Delta w_l = \alpha y_{l-1}^T \delta_l$$

Where w_l is a $m \times n$ weight matrix connecting layer $l-1$ and l, m is the size of layer $l-1$ and n is the size of layer l, α is the learning rate (a scalar), y_{l-1}^T is transpose of the column vector y_{l-1} which is the output in layer $l-1$, δ_l is a column vector of error propagated from layer l to $l-1$, $l=0$ for the input layer. For output layer and for hidden layer the vector of backpropagated error, δ_l, is deferent and defined as:

$$\delta_l = \begin{cases} (T-Z) * f_l'(net_l) & \text{if } l \text{ is an output layer} \\ f_l'(net_l) * w_{l+1}\delta_{l+1} & \text{if } l \text{ is a hidden layer} \end{cases}$$

Where $f_l'(.)$ is the derivative of transfer function, f_l, in layer l, net_l is the weighted sum in layer l, δ_{l+1} is the delta value backpropagated from the upper layer of layer l, * denotes the element-wise vector multiplication, T is the target vector, Z is the output vector. To applying TD learning to the multi-layer feedforward network, we extract the term $(T-Z)$ from the original δ_l and obtain the δ_l^* as a new delta rule. So we define δ_{k+1}^* as:

$$\delta_{k+1}^* = diag\left[f'_{k+l}(net_{k+l})\right] \qquad (11)$$

Where *diag* is the diagonal matrix and l is the output layer. If l is a hidden layer, equation (11) can be written as:

$$\delta_l^* = f_l'(net_l) * \omega_{l+1}.\delta_{l+1}^* \qquad (12)$$

With the new delta, equation for change of each weight is rewritten as:

$$[\Delta\omega_l]_{ij} = \alpha[y_{l-1}]_i[\delta_l]_j = \alpha(T-Z)^T.\left([y_{l-1}]_i[\delta_l^*]_j\right)$$

Where $[\delta_l^*]_j$ is the *jth* element in vector δ_l^* and $[y_{l-1}]_i$ is the *ith* element in vector y_{l-1}. Unlike the original delta which is a vector backpropagated from an upper to a lower layer, now the new delta, δ_l^* is a $m \times n$ matrix where m is the size of output layer and n is the size of layer l. The error term $(T-Z)$ is needed for calculation of every weight increment. Comparing gradient decent in supervised learning in equation (5) and the backpropagation with new delta in equation (11) $\nabla_w P(t)$, the gradient term at time t for weight w' is:

$$\nabla_{w'} P_t = \left([y_{l-1}]_i[\delta_l^*(t)]_j\right)^T \qquad (14)$$

Where $w' = [w_l(l)]_{ij}$ is the *ijth* element in the weight matrix w_l at the time t. By substituting this result to the formula of $TD(\lambda)$ learning in equation (7), we have:

$$[\Delta w_{lt}]_{ij} = \alpha(P_{t+1} - P_t)^T \sum_{k=1}^{t} \lambda^{t-k}\left([y_{l-1}(k)]_i [\delta_l^*(k)]_{j,:}\right)^T$$

Where Δw_{lt} is the matrix of increment of weight connecting layer l and $l-1$ for prediction P_t. The term inside summation is called the history vector, denoted by $[h_l(t)]_{ij}$. We now obtain updating rules of TD learning by backpropagation. The weight update is performed by equation (15) with the new delta.

Training Procedure

Compared to the original backpropagation algorithm, the new procedures for $TD(\lambda)$ learning requires some more storage for keeping the following values:

1. The previous output vector, P_{t-1}, at time t, which is used in computing every weight change.
2. The history vector, $h_l(t,i,j) = \sum \lambda^{t-k}[\delta_l^*(k)]_j [y_{l-1}(k)]_i$ for each weight-connecting *ith* node in layer $l-1$ to *jth* node in layer l. It has the same size as the output vector. Each weight shall have its own history vector. The training procedure involves 3 stages (at time t):

1. Feedforward: calculation of new prediction P_t.
2. Weight update: calculation of weight increments by equation. (15) using the history terms at time $t-1$.
3. Backprop: calculation of the new deltas at time $t+1$; $\delta^*_{l(t+1)}$, for each layer l, starting from the output layer. The history term is updated by:

$$h_l(t,i,j) = [\delta_l^*(t+1)]_j [y_{l-1}(t+1)]_i + \lambda h_l(t-1,i,j)_i$$

Design of TDMLP Neural Network for Power System LFC

The objective of the controller design in interconnected power system is damping of the frequency and tie-line power deviations oscillations, stability of the overall system for all admissible uncertainties and load disturbances. Fig.2 shows the block diagram of the closed-loop system, consists of TDMLP controller. The simulation results on a single machine power system show that the performance of MLP neural network is much better than conventional PID controllers. Therefore, for the design of the nonlinear LFC controller in two areas power systems the MLP neural network is being used. Since the objective of LFC controller design in interconnected power system are damping the frequency and tie-line power deviations with minimizing transient oscillation under the different load conditions. Thus, frequency deviations, tie-line power deviations and the load perturbation are chosen as MLP neural network inputs. Moreover, in order to evaluate the control signal (u), the MLP neural network controller makes use of a piece of information which is not used in the conventional and modern controller (an estimate of the load perturbation $\Delta\hat{P}D_i$). In general, the load perturbation of the large system is not directly measurable. Therefore, it must be estimated by a linear estimator or by a nonlinear neural network estimator, if the nonlinearities in the system justify it. Such an estimator takes as inputs a series of k samples of the frequency fluctuations at the output of the generator $[\Delta F(n) \quad \Delta F(n-1) \quad ... \quad \Delta F(n-k+1)]T$, and estimates the instantaneous value of the load perturbation based on this input vector. The implementation of such an estimator is beyond the scope of this paper. Here, we assume that the load estimate $\Delta\hat{P}D_i$ is available, i.e. $\Delta\hat{P}D(n) = \Delta PD(n)$ .Thus, frequency deviations, tie-line power deviations and the load perturbation are chosen as the MLP neural network inputs. The outputs of the neural network are the control signals, which are applied to the governors. The data required for the MLP neural network training is obtained from the TDL design in different operating conditions and under various load disturbances.

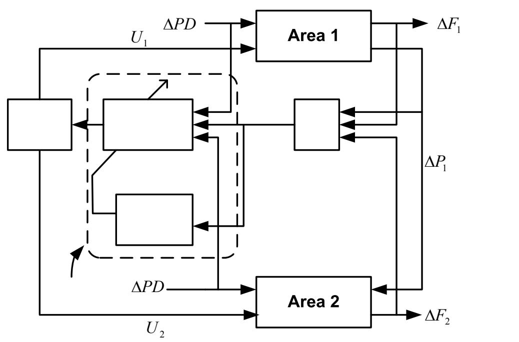

Figure 2. Block-Diagram of the TDMLP neural network applied to LFC

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 software using continuous-time domain functions. In this study, the application of TDMLP neural controller for LFC in two areas power system is investigated. The performance of this method is compared with the RBF neural controller and PID controller, which has been widely used in power system. Fig. 3 to 5 depicts performances of the TDMLP, RBF and PID controllers when different load step disturbances in two areas are applied to the system. Fig.3 shows the tie-line power deviations when a 2% and 0.5% load step disturbances are applied in areas 1 and 2, respectively. Fig.4 shows the performances of controllers with applying a 0.5% and 1.5% load step disturbances to 1 and 2 areas, respectively, whereas the parameters are decreased from their nominal values to the minimum values. Fig.5 shows the responses of the controllers when the parameters are increased from their nominal values to their maximum values and a 2% and 0.8% load step disturbance are applied to 1 and 2 areas, respectively. To show the performance of the proposed controller, we run several tests, not shown here.

The simulation results obtained show that the proposed TDMLP neural network 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. From these figure, it is seen that the proposed method is superior compared to other controllers against to increasing of the step load disturbances in the areas of power systems, especially when the system parameters are changing.

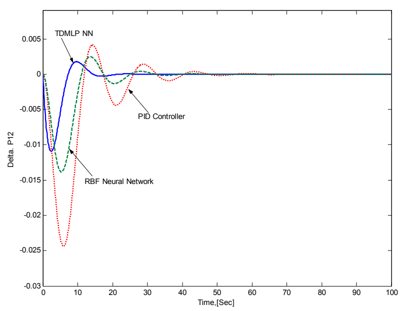

Fig. 3- The performance of controllers with nominal parameters

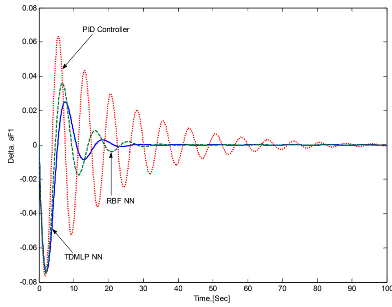

Fig. 4a- The performance of the controllers for frequency deviations with minimum parameters

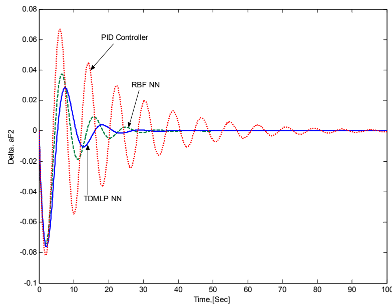

Fig. 4b- The performance of the controllers for frequency deviations with minimum parameters

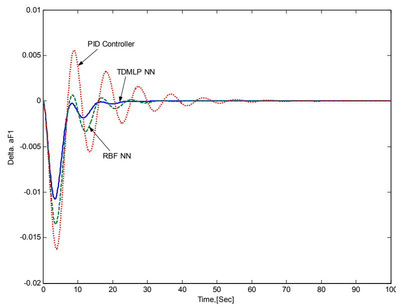

Fig. 5a- The performance of the controllers for frequency deviations with maximum parameters

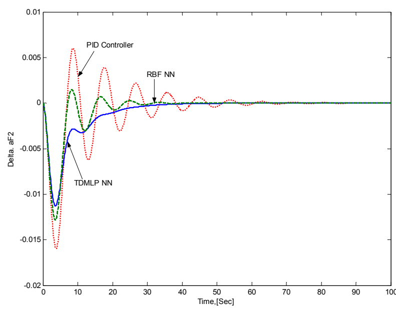

Fig. 5b- The performance of the controllers for frequency deviations with maximum parameters

Conclusion

This study shows an application of the neural network to automatic generation control in the power system. In this paper, a TDMLP neural network load frequency control has been proposed to improve the performance and stability of the power system. This control strategy was chosen because the power systems involve many parametric uncertainties with varying operating conditions. In this work, transient behavior of the frequency of each area and tie-line power deviations in the power system with two areas is considered under any load perturbations in any area. The simulation results show that proposed controller is effective and can ensure that the overall system will be stable for all admissible uncertainties and load disturbances, also The TDMLP controller can achieve good performance even in the presence of GRC, especially when the system parameters are changing. And the performance of the proposed controller is better than RBF neural network and PID controller to the load disturbances at any area in the interconnected power system.

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