NONLINEAR PREDICTIVE FUNCTIONAL CONTROL BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract: An Artificial Neural Network (ANN) is an adequate tool for modeling nonlinear systems and can be applied straightforward in the predictive functional control. New structure of ANN multi-step prediction that is different from cascade or parallel is presented, at the same time, the nonlinear predictive functional control using this ANN model has been developed in this paper. The useful of this control strategy is evaluated by applying it to a Continuous Stirred Tank Reactor (CSTR). The simulation results indicate that it is more effective than PID control.

Keywords: Artificial Neural Network, Nonlinear, Model Based Predictive Control, Predictive Functional Control

1. INTRODUCTION

Model Based Predictive Control (MBPC) refers to a class of algorithms that compute a sequence of manipulated variable in order to optimize the process performance. It is recognized as an efficient control strategy by the industrial control community. The first MBPC techniques were developed in 1970s. Model Predictive Heuristic Control (MPHC) based on finite impulse response has been successfully applied in PVC plant, a distillation column and power plant by Richalet, et al.(1978). Dynamic Matrix Control (DMC) based on finite step response was developed by Cutler, et al.(1980). Not only MPHC but also DMC belong to MBPC based on nonparametric model. In 1987, the Generalized Predictive Control (GPC) of Clarke, et al.(1987a,b) which absorbs the advantages of predictive control and adaptive control can turn the model parameter online. The Predictive Functional Control (PFC) which belongs to the third generation predictive control has been developed by Richalet, et al.(1988), which has been successfully used in the fast and accurate robot control.

Many processes are sufficiently nonlinear to preclude the successful application of linear model based predictive control technology. MBPC such as DMC and GPC developed initially for linear processes have been successfully extended to nonlinear processes by many researchers (Mutha, et al.(1998), Robit, et al.(1998)). Henson(1998) has published excellent technical reviews of Nonlinear Model Based Predictive Control (NMBPC). It has presented the current status of NMBPC technology, and meanwhile outlined myriads of directions for future research.

The purpose of this paper is to develop a Nonlinear Predictive Functional Control (NPFC) based on the Artificial Neural Network (ANN) model. The general principle of PFC is discussed in section 2. In section 3, the ANN model is developed. NPFC using ANN model is developed in section 4. Simulation results are elucidated in section 5 and conclusion is described in section 6.

2. GENERAL PRINCIPLE OF PREDICTIVE FUNCTIONAL CONTROL

PFC belongs to the classical family of MBPC. It is essentially based on the following three principles of MBPC: predictive model, receding horizon optimization, modeling error compensation.

2.1 Predictive model

PFC uses a model to predict future output. The output of the model $y_m(k+i)$ can be divided into two main components: free response $y_l(k+i)$ and forced response $y_f(k+i)$.

Free response has nothing to do with future inputs and thus just depends on the actual model output.

The other component of the model output is forced response that depends on the set of future manipulated variables and has nothing to do with the actual model output. The structure of manipulated variables is the key to the control performance in PFC. The future manipulated variable are structured by a linear combination of functions defined forehead that we refer to as base functions. The future manipulated variables u(k+i) and forced response are given by:

$$u(k+i)=\sum_{n=1}^{N}\mu_n u_{bn}(i), i=1,2,...,H \quad (1)$$

$$y_f(k+i)=\sum_{n=1}^{N}\mu_n y_{bn}(i) \quad (2)$$

Where μ_n stands for coefficients, $u_{bn}(i)$ the nth base function at $t=iT_s$, $y_{bn}(i)$ is the advance output of the nth base function at $t=iT_s$ and T_s is the sampling period. The selection of the base functions depends on the nature of the set point and on the process. Often the polynomial base function set is used.

2.2 Receding Horizon Optimization

Various types of reference trajectories can be used. The most elementary reference trajectory is a first-order exponential trajectory. The reference trajectory $y_r(k+i)$ can be given by:

$$y_r(k+i)=c(k+i)-\lambda(c(k)-y_P(k)) \quad (3)$$

Where c is the set point, $\lambda=e^{(-Ts/Tr)}$ and T_r is the 95% response time of the reference trajectory, y_P is the process output.

The control objective of PFC is to minimize the sum of squared errors between the predicted output and the reference trajectory at all coincidence points. The objective function can be given by:

$$\min J_p=\sum_{i=H_1}^{H_2}(y_r(k+i)-\tilde{y}(k+i))^2 \quad (4)$$

$$\tilde{y}(k+i)=y_m(k+i)+e(k+i) \quad (5)$$

Where $\tilde{y}(k+i)$ is the predicted output at $t=(k+i)T_s$, $y_m(k+i)$ is the output of the model at $t=(k+i)T_s$, $e(k+i)$ is the predicted errors, H_1, H_2 are coincidence horizon.

2.3 Modelling error compensation

The output of the predictive model and the process in general differ due to model mismatches, secondary input and disturbances which are not taken into account by the predictive model. There are several procedures to eliminate a permanent off-set by compensating the reference trajectory with the predicted errors between model and process output at each time instant of the coincidence horizon. The predicted errors can be given by:

$$e(k+i)=y_P(k)-y_m(k) \quad (6)$$

Where $y_P(k)$ is the process output at $t=kT_s$, $y_m(k)$ is the model output at $t=kT_s$.

3. ARTIFICIAL NEURAL NETWORK MODEL

PFC uses a model to predict future outputs. Any type of predictive model such as transfer function, state equations and ANN model can be used. NPFC requires the availability of a suitable nonlinear dynamic model of the process. The NPFC controller may be based on a fundamental model or a combination of the fundamental and empirical model. First, it is difficult for us to construct sufficiently accurate comprehensive mathematical process models. On the other hand, the potential disadvantage of the fundamental modeling approach is that the resulting dynamic model may be too complex to be useful for NPFC. In this work, ANN model is employed as the predictive model in PFC.

During the last decade, there has been an increasing trend in the industry towards the use of ANN. It has been proven that a feed forward ANN which is comprised of a great number of interconnected neurons can approximate any continuous function to any desired accuracy. This makes feed forward ANN very suited to deal with complex nonlinear. A feed forward layered ANN is employed as the model of NPFC.

The structure of ANN is shown in Fig 1. It consists of a layer of input neurons, a layer of output neurons, and two hidden layers. The transfer function f1(x) of the first hidden layer neuron is given by:

$$f1(x)=(e^{x}-e^{-x})/(e^{x}+e^{-x}) \quad (7)$$

The activate function f2(x) of the second hidden layer neuron is shown by:

$$f2(x)=1/(1+e^{-x}) \quad (8)$$

The transfer function f3(x) of the output hidden layer neuron is given by:

$$f3(x)=x \quad (9)$$

The most important aspect of the ANN is learning the information about the system to be modeled. The most versatile learning algorithm for feed-forward layered network is back propagation (BP). Unfortunately, BP is very slow because it requires small learning rates for stable learning, on the other hand, it is possible for the network solution to become trapped in the local minimum. Levenberg_Marquardt(LM)(Matlab User's Guide, 1994) optimization algorithm is used in this investigation. This technique is more powerful than gradient descent, but requires more memory.

The L_M update rule is given by:

$$\triangle W=(J^{T}J+\mu I)^{-1}J^{T}E \quad (10)$$

Where J is the Jacobian matrix of derivation of each error to each weight, μ is a scalar, and e is an error vector. If the scalar μ is very large, the above expression approximates gradient, while if it is small the above expression becomes the Gauss-Newton method.

4. NONLINEAR PREDICTIVE FUNCTIONAL CONTROL

A NPFC strategy is developed in this section. The principle of the NPFC using ANN is shown in Fig. 2.

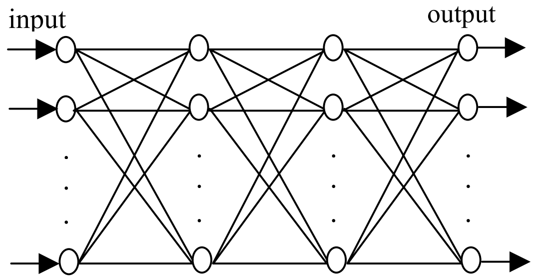

Fig. 1 Structure of ANN

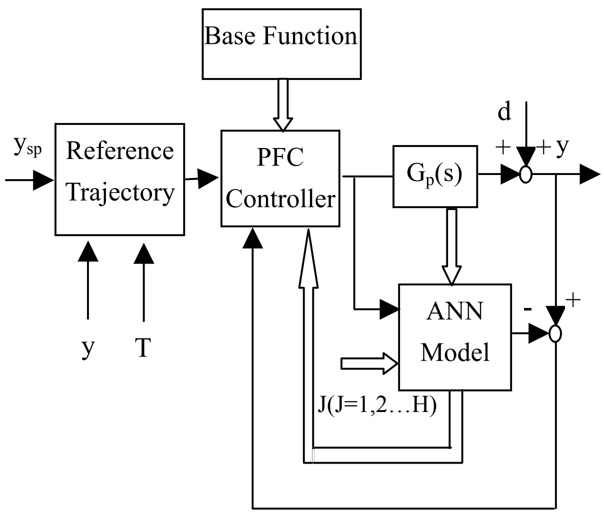

Fig. 2 Principle of the NPFC using ANN model

4.1 Artificial neural network model

Predictive model plays a key role in predictive functional control. It demands that certain precision must be attained, at the same time with multi-step prediction. Generally there are two kinds of structures which can fulfil multi-step prediction using ANN, one is cascade, the other is parallel. Cascade structure, in which the output of time k+1($y_m(k+1)$) can be achieved from the data of time k, and next time $y_m(k+1)$ as input to estimate the output of time k+2($y_m(k+2)$), and so on. The benefit of this structure is that only one ANN model is needed. But there also exists the accumulation of prediction error in such a structure. Parallel structure needs many ANNs to predict, with each ANN for a specific step. The benefit of parallel is that the prediction error is comparatively small, but the disadvantage is that the calculation is heavy for there are so many ANNs to be trained. In this paper, a new structure for multi-step prediction is proposed. Only an ANN is needed in such a structure. In order to fulfil multi-step prediction, an additional input J(J=1,2,…H) is employed, which distinguishes the ANN outputs $y_m(k+J)$. So the multi-step prediction is realized.

4.2 Nonlinear predictive functional control using artificial neural network model

The objective function of NPFC is similar to the other classical MBPC. With a certain optimization procedure we can determine a sequential manipulated variable that minimizes the objective function. The objective function of NPFC is given by equation 4. The method of Levenberg-Marquardt or Gauss-Newton which can be realized by MATLAB TOOLBOX is used as optimization algorithm.

The algorithm of NPFC can be summarized in the following steps:

1) Select the sample for training
2) Identify the ANN model with sample
3) Evaluate the extent of ANN model
4) Realize the NPFC strategy using ANN model and L_M optimization algorithm

① Calculate the error between the output of process $y_p(k)$ and actual model output $y_m(k)$

② Calculate the actual model output $y_m(k+i)$,i=1,2,…,H and the predictive output of the process $\tilde{y}(k+i)$

③ calculate for reference trajectory of $y_r(k+i)$, i=1,2,…,H

④ calculate the sequence manipulated variable u(k+i) i=1,2,…,H using the method of L_M optimization algorithm.

⑤ Perform u(k) and go to ① at the next sample time.

5. SIMULATION

In order to evaluate the performance of the NPFC, a Continuous Stirred Tank Reactor (CSTR) is chosen as an application example.

5.1 Reactor

The dynamic equations describing the CSTR systems can be written as:

$$V\frac{dC_A}{dt} = F(C_{Af} - C_A) - Vk_0 e^{(-\frac{ET_r}{R_g})} C_A \qquad (11)$$

$$V_\rho C_p \frac{dT_r}{dt} = \rho C_p F(T_f - T_r)$$

$$-V(-\Delta H)k_0 \exp(-\frac{ET_r}{R_g})C_A - UA_h(T_r - T_c) \qquad (12)$$

The dynamic equations can be written in dimensionless from Venkateswarlu(1997) as:

$$\dot{x}_1 = -x_1 + D_a(1-x_1)\exp(\frac{x_2}{1+x_2/\varphi})$$

$$\dot{x}_2 = -x_2 + B_h D_a(1-x_1)\exp(\frac{x_2}{1+x_2/\varphi}) + \beta(u-x_2) \qquad (13)$$

$$y = x_1$$

Where x_1 and x_2 are the dimensionless reactant concentration and temperature, respectively. The input u is the cooling jacket temperature. The physical parameters are chosen as:

$$D_a = 0.072,\ \ \Phi = 20.0,\ \ B_h = 8.0,\ \ \beta = 0.3 \qquad (14)$$

Here the task is to control the reactant concentration x_1, and the manipulated variable is the input u of the cooling water temperature.

5.2 Predictive model of artificial neural network

Given the $x_1(k)$, $x_2(k)$,$u(k)$ at the $t=(k)T_s$ and J, the $x_1(k+J)$ at the $t=(k+J)T_s$ can be obtained. The number of neurons in the two hidden layers is 10, respectively. In order to evaluate the performance of the ANN model, 30 groups input data are created at random to compare the output of the ANN and process. The output of ANN model (+) and the output of the process (o) are shown in the Fig 3(a). The errors between the output of ANN model and process are shown in Fig 3(b). We can obtain that the accuracy of ANN model is enough for NPFC.

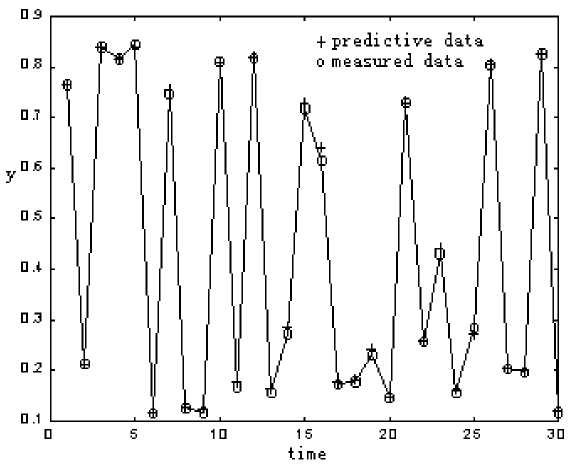

Fig. 3(a) Results of process output and ANN output

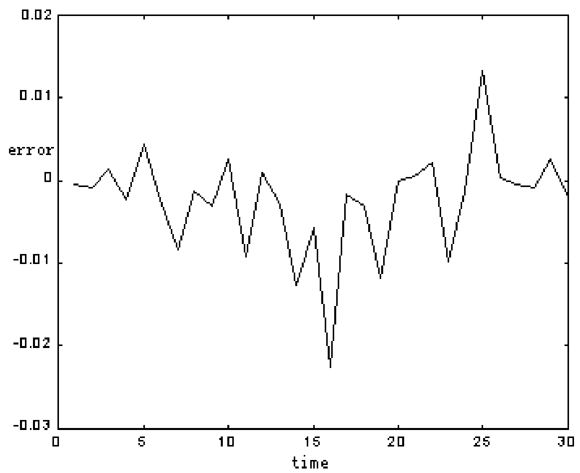

Fig. 3(b) Errors between process output and ANN output

5.3 Simulation of nonlinear predictive functional control and PID control for CSTR

Simulation studies are carried out in order to evaluate the performance of the NPFC, the results of PID are also presented as a reference. The parameters of PID are P=0.2, I=30 seconds and D=0. The NPFC selects one base function. The parameters of NPFC are given by H=5, Tr=10 seconds.

The setpoint of concentration is changed from x1=0.2 to x1=0.6 at t=20, at the same time, a step disturbance 0.1 has been applied to the system at t=200. The results of PID control are shown in the Fig 4(a). The manipulated variable of PID is shown in Fig 4(b). The results of NPFC are shown in the Fig 5(a). The manipulated variable of NPFC is shown in Fig 5(b).

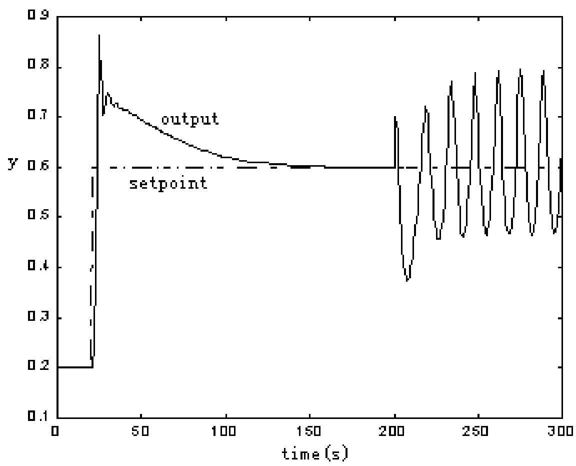

Fig. 4(a) Results of PID control

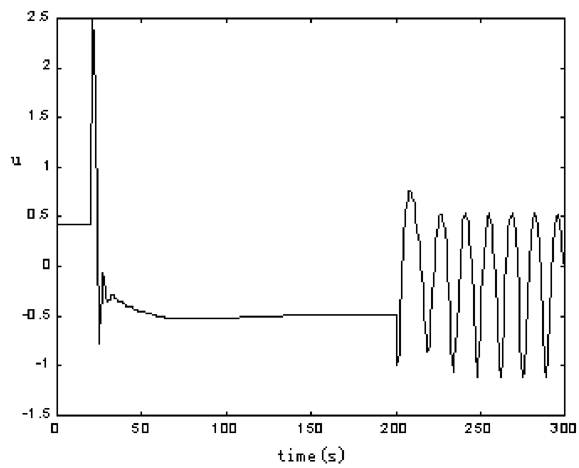

Fig. 4(b) Manipulated variable of PID control

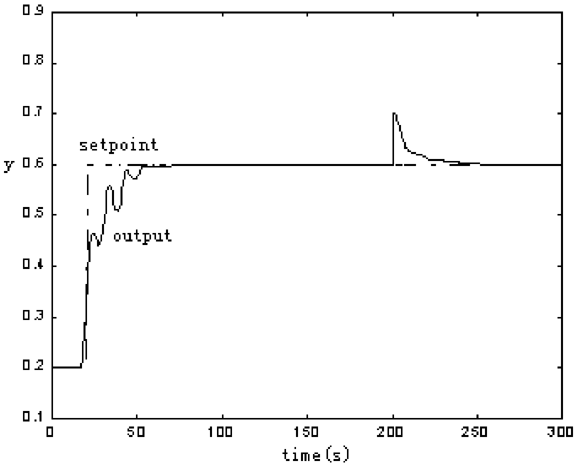

Fig. 5(a) Result of NPFC control

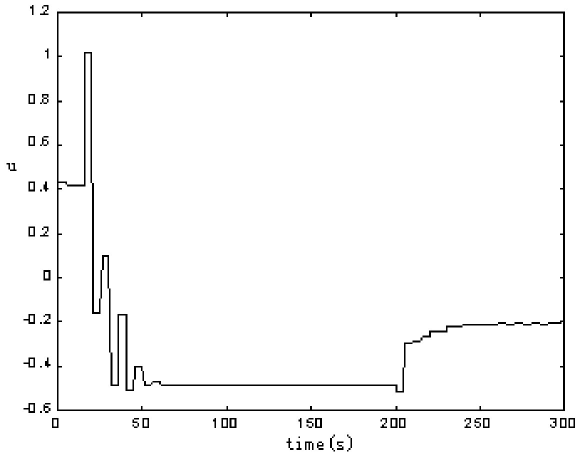

Fig. 5(b) Manipulated variable of NPFC control

As can be seen from the figure, PID control has fast response but has large overshoot. NPFC using ANN has slow response but no overshoot. Compared with PID control, NPFC can reject the disturbance more effectively.

6. CONCLUSION

An NPFC using ANN model strategy is presented for control of high-nonlinear system. The performance of this strategy is evaluated by applying it to a CSTR for controlling them at the desired state operating point. The results illustrate that the NPFC is more effective for control nonlinear system than PID control.

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