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Neural Network Based on Nonlinear Smith Predictor *

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Abstract: An extension of the Smith predictor principle to the nonlinear case is proposed. This nonlinear predictor can be constructed using neural networks. This is very useful for the time-delay compensation of nonlinear processes.

The neural network based predictor has been applied to the prediction of nonlinear dynamic process. A comparison of the proposed strategy with the iterative and non-iterative d-step-ahead neural predictors for the prediction of the manifold pressure process in an automotive engine is illustrated. The predictive result of the corresponding first-principles model-based nonlinear predictor is also illustrated for the comparison.

Key words: neural networks; Smith predictor; nonlinear system; time-delay

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基于神经网络的非线性 Smith 预估器

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摘要:将 Smith 预估原理推广到非线性系统,并用神经网络予以实现以对非线性大滞后系统进行纯滞后补偿.并将所提出的神经网络非线性 Smith 预估器用于非线性动态系统即汽车发动机歧气管压力系统的预报,并与基于神经网络的迭代及非迭代 d 步超前预报器进行了比较.还给出了与基于机理模型的预报器的比较结果.

关键词:神经网络;Smith 预估器;非线性系统;时滞

1 Introduction

In industry, time-delays exist in many processes, such as chemical processes and thermal processes. If the time-delay is larger than or equal to the main time-constant, it may have a significant effect on the performance of the control system. So one should consider the time-delay compensation if the influence of the time-delay can not be ignored. A useful method to overcome the effect of a time-delay is to use prediction technique. The earliest prediction method used in control engineering was the Smith predictor[1,2]. However, this method was proposed on the basis of the assumption that the process is linear.

It is well known that most industrial systems involve nonlinear factors. The linear model-based prediction methods may fail to make for prediction if the non-linearity of the process is severe. Therefore, for the processes with severe non-linearity, it is worthwhile to develop corresponding nonlinear model based predictors. Wong and Seborg applied Smith's prediction method directly to an affine nonlinear system[3]. In this paper, a nonlinear Smith predictor implemented with neural networks is proposed for large time-delay compensation in nonlinear processes. This paper is organized as follows: in Section 2, a brief description of the neural network based d-step-ahead prediction strategies are presented. In order to handle the large time-delay compensation of nonlinear processes, a neural-network-based Smith pre-dictor is proposed in Section 3. After that, Section 4 illustrates the comparison among the neural predictors.

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Then, the experimental results for the manifold pressure process of an automotive engine are shown in Section 5. Finally, Section 6 gives the conclusion of this paper.

2 Neural network based iterative and non-iterative predictors

Without loss of generality, it is assumed that the process with time-delay is described by the following nonlinear discrete time equation:

$$y(t) = F[Y_{t-1}, U_{t-d}] \tag{1}$$

where $Y_{t-1} = [y_{t-1}, \cdots, y_{t-n}]^{\mathrm{T}}$ and $U_{t-d} = [u_{t-d}, \cdots, u_{t-d-m}]^{\mathrm{T}}$ are respectively the vectors of output and input of the process; d is the time-delay of the process; and $F(\cdot)$ is a continuous nonlinear function. Suppose the neural model to represent the process shown in (1) is

$$\hat{y}(t) = W^0 s[I^{\mathrm{T}}(t) W^i], \tag{2}$$

where $W^j (j = 0, i)$ are the synaptic weight vectors, $s(\cdot)$ is a sigmoid function, and $I^{\mathrm{T}}(t) = [y(t-1), \cdots, y(t-n), u(t-d), \cdots, u(t-d-m)]^{\mathrm{T}}$. In terms of the neural model, one can derive a neural-network-based iterative d-step-ahead predictor that is expressed as follows:

$$\hat{y}(t+d) = W^0 s[I_r^{\mathrm{T}}(t+d) W^i] \tag{3}$$

where $I_r^{\mathrm{T}}(t+d) = \{\hat{y}(t+d-1), \cdots, \hat{y}(t+d-n), u(t), \cdots u(t-m)\}$. Since (3) relies on the previous prediction output of the neural predictor, the computational effort within one sampling period is much expensive if the time-delay is large.

A non-iterative d-step-ahead predictor can also be used to predict the output of the process d step of the horizon in the future, but it does not depend upon the iterative technique. The characteristic of a non-iterative predictor is that it predicts $t + d$ steps of the future values of the process, based on the available information until time t. Compared with the iterative d-step-ahead predictor, the non-iterative version is simple for d-step ahead prediction since it does not require the iterative procedure that may cost much more computational effort. The corresponding neural predictor is obtained as:

$$\hat{y}(t+d) = W^0 s[W^i I_n(t+d)] \tag{4}$$

where $I_n(t+d) = [y(t), \cdots, y(t+1-n), u(t), \cdots, u(t+1-d-m)]^{\mathrm{T}}$. Obviously, although a non-iterative d-step-ahead predictor does not require any iterative claculation, the inputs and the corresponding connection weight will be greatly increased as the time-delay d is large[4].

3 Nonlinear Smith predictor using neural networks

In this section, the extension of the Smith prediction technique to the nonlinear process with time-delay will be given. It is assumed that the following nonlinear model, which can describe the nonlinear process with time-dealy, has been obtained:

$$y_d(t) = f[Y_{t-1}^d, U_{t-d_m}] \tag{5}$$

where $Y_{t-1}^d = [y_d(t-1), \cdots, y_d(t-n)]^{\mathrm{T}}$ and $U_{t-d_m} = [u(t-d_m), \cdots, u(t-d_m-m)]^{\mathrm{T}}$. Suppose $d_m = d$ and $f(\cdot) = F(\cdot)$, thus $y_d = y$. Then the same nonlinear function is used to construct the following time-delay-free model, i.e.

$$y_0(t) = f[Y_{t-1}^0, U_{t-1}] \tag{6}$$

Where $Y_{t-1}^0 = [y_0(t-1), \cdots, y_0(t-n)]^{\mathrm{T}}$ and $U_{t-1} = [u(t-1), \cdots, u(t-m-1)]^{\mathrm{T}}$. For the extension of the principle of the Smith predictor to a nonlinear process, it is not difficult to prove the following theorem:

Theorem Suppose

$$u(t) = 0, t \leqslant 0, \; y_d(t) = y_0(t) = 0, \; t \leqslant 0, \tag{7}$$

and the nonlinear function has the feature:

$$f(x) = 0, x = 0; f(x) \neq 0, x \neq 0, \tag{8}$$

Then, the output of (6) at time t is equal to the output of (5) at time $t + d$. It means that y_0 is d steps ahead of y_d in the time domain, i.e. $y_0(t) = y_d(t + d_m)$.

This also allows the straightforward construction of a Smith predictor for a nonlinear process. Fig.1 illustrates the structure of the nonlinear Smith predictor. In this structure, the input is fed to the true process, as well as the nonlinear model with or without time-delay, which are respectively represented by NMD and NM. Subtracting the output difference between the model with time-delay and the model free of time-delay from the response of the real process gives

$$y_p(t+1) = y(t+1) - [y_d(t+1) - y_0(t+1)]. \tag{9}$$

Provided that the nonlinear models are well modeled, this becomes

$$y_p(t+1) = y_0(t+1). \tag{10}$$

Thus, the effect of time-delay has been eliminated. The output of the predictor is equivalent to $y(t+d+1)$.

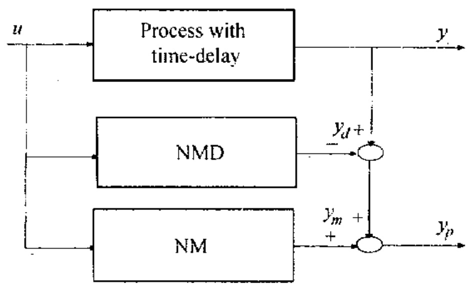

Fig. 1 Structure of neural Smith predictor

Considering the universal approximation property of neural networks, it seems promising to use them to build a nonlinear Smith predictor for the compensation of large time-delays in nonlinear processes. In the following, neural networks are used for the implementation of a nonlinear Smith predictor. The neural model with time-delay (NMD) can be described by

$$y_d(t+1) = X^{\mathrm{T}}(t+1)W^0,\ x_j(t+1) = s(I_d^{\mathrm{T}}(t+1)W_j^i) \tag{11}$$

where $I_d^{\mathrm{T}}(t+1) = [y_d(t),\cdots,y_d(t+1-n),u(t-d+1),\cdots,u(t+1-d-m)]$ and the mathematical description of the neural model without time-delay (NM) is:

$$y_0(t+1) = \hat{X}^{\mathrm{T}}(t+1)W^0,\ \hat{x}_j(t+1) = s(I_0^{\mathrm{T}}(t+1)W_j^i) \tag{12}$$

where $I_0^{\mathrm{T}}(t+1) = [y_0(t),\cdots,y_0(t+1-n),u(t),\cdots,u(t-m)]$. The corresponding output of the neural Smith predictor is

$$y_p(t+1) = y(t+1) - [y_d(t+1) - y_0(t+1)]. \tag{13}$$

If the neural model can accurately describe the true process, this immediately gives

$$y_p(t+1) = y_0(t+1). \tag{14}$$

In this case, it is obvious that the neural model without time-delay has a dominant effect on the output of the predictor.

4 Comparison of the computational efforts of the neural predictors

In this section, an evaluation of the neural-network-based predictors in terms of their computational effort is presented. Suppose a process with order n for $\{y(t)\}$, order m for $\{u(t)\}$, and time-delay d, is considered. The feedforward neural model has one output neuron and H hidden neurons. Table 1 presents a comparison of these neural predictors in terms of their computation requirements. Column 1 in Table 1 shows that the computational effort of the neural Smith predictor bears no relation to the time-delay d, while the computational effort of the other two neural predictors depends upon the time-delay. Therefore, if the time-delay exceeds a certain value, i.e. $d > n+m+2$, both the iterative and non-iterative neural predictors are much more expensive in terms of computation.

Table 1 Computational efforts of neural predictors

Smith	Iterative	Non-iterative
Add: $2H(n+m)-2$	$dH(n+m)-d$	$H(n+m+d-1)-1$
Multip: $2H(n+m+1)$	$dH(n+m+1)$	$H(n+m+d)$
Nonlinear: $2H$	dH	H

From Table 1, it can be seen that the computational effort of the neural Smith predictor is the most efficient when dealing with a large time-delay if $d > n+m+2$. Although the Smith predictor requires two neural networks for the prediction, it is still simpler in terms of computation than the other two mentioned predictors in the cases where the time-delay is larger than $n+m+2$.

5 Application to automotive engine

Manifold pressure (MP) is one of the main outputs of an automotive engine. The time-delay due to the sensor's characteristics may have an effect on the control performance[5,6] so that the prediction is expected to be made for time-delay compensation. The manifold pressure of an engine is a rather complex system, which is a nonlinear dynamic function of throttle angle (TA), mass flow (MF), engine speed (ES), as well as the exhaust gas re-circulation (EGR), which is also a nonlinear function of mass flow, manifold pressure and throttle angle. The EGR is described by a table look-up method.

In this paper, the multilayer feedforward neural network with external recurrent connections is employed to describe the process. Based on the knowledge obtained about the system, the orders of the system are chosen as: $n_p = 2$, $n_{maf} = 1$, $n_e = 1$, $n_v = 1$, and $n_\theta = 1$, where n_p, n_{maf}, n_e, n_v, and n_θ are respectively the orders of the MP, MF, EGR, ES, and TA. The number of the

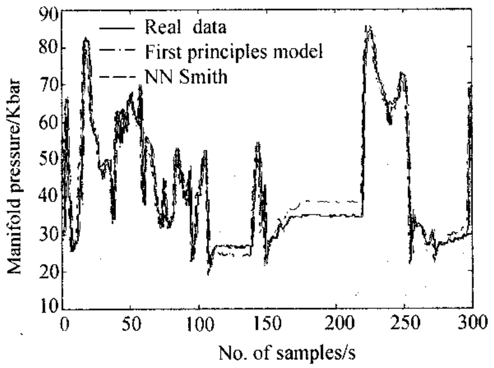

Fig.2 Comparison between NN Smith presicator and first – principles model based predictor

hidden nodes is chosen as 4. Fig.2 shows the prediction results. In Fig. 2, the first-principles model-based prediction[6] is illustrated to allow a comparison with the neural-network model-based Smith predictor. Fig. 3illustrates the prediction errors of the NN Smith, NN iterative, NN non-iterative as well as the first principles approaches. Table 2 presents the corresponding evaluation of the MSPE (mean squared prediction error) of these methods.

Note that the neural Smith predictor has the best performance in prediction. The non-iterative neural predictor won the second place. The prediction error of the iterative method was the worst among three neural-network-based approaches, due to the accumulation of the prediction error in the iteration, but it was still better than the strategy of the first principles.

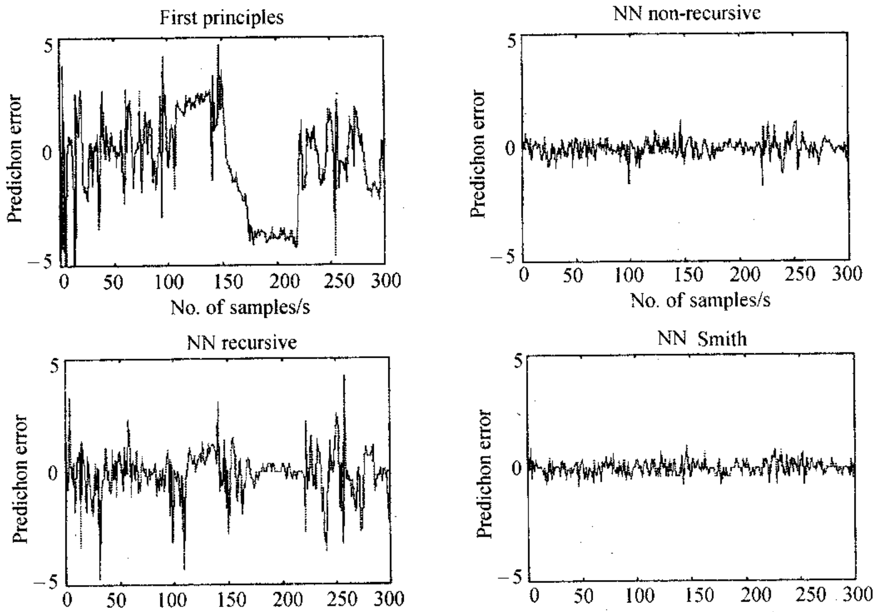

Fig.3 Comparison of the prediction errors

Table 2 MSPE of the prediction

Prediction methods	MSPE
NN Smith	0.1173
NN Iterative	2.8927
NN Non-iterative	0.3661
First-principles	4.7357

6 Conclusion

This paper has proposed a nonlinear Smith prediction strategy, which is realized via neural network. Both the iterative and non-iterative d-step-ahead neural predictors have been presented for comparison. It notes that the computational effort of the neural Smith predictor bears no relation to the time-delay, therefore, it is simple and promising for large time-delay compensation for nonlinear processes in industry. For large time-delay compensation, both the long-range neural prediction method and the neural Smith predictor can be used. However, the neural Smith predictor is much simpler to implement in this case, even though it consists of two neural networks.

This paper finally illustrates an application of the proposed neural-network-based method to the manifold pressure system in an automotive engine. In this practical example, the neural network based prediction methods obtained better performance in prediction than the first-principles-based method.

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