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Nonlinear Process Identification using Neural Networks

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Abstract

In industry process control, the model identification of nonlinear systems are always difficult problems. The main aim of this paper is to establish a reliable model for the nonlinear process. In many applications, development of empirical nonlinear model from dynamic plant data. This process is known as 'Nonlinear System Identification'.

Artificial neural networks are the most popular frame-work for empirical model development .In order to obtain this reliable model for the process dynamics, the neural black-box identification by means of a Nonlinear Autoregressive exogenous input (NARMAX) model has been chosen in this study. The model is implemented by training a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) with input-output experimental data is found and results shown that the neural model successfully predicts the evolution of the product composition. The simulation result illustrates the validity and feasibility of the nonlinear model identification. Trained data obtained from nonlinear process identification, can be used to control the nonlinear system.

Keywords: Neural network, NARX model identification, MLP.

Introduction

NEURAL networks have been successfully applied to broad spectrum of data-intensive applications, such as: Process Modeling and Control, Character Recognition, Machine Diagnostics, Target Recognition, Medical Diagnosis, Credit Rating and Voice Recognition. In recent years, the requirements for the quality of automatic control in the process industries increased significantly due to the increased complexity of the plants and sharper specifications of product quality. At the same time, the available computing power is increased to a very high level.

In many applications, lack of process knowledge and/or a suitable dynamic simulator precludes the derivation of fundamental model. This necessitates the development of empirical nonlinear model from dynamic plant data. This process is known as nonlinear system identification [1],[2]. A fundamental difficulty associated with the empirical modeling approach is the selection of a suitable model form. Discrete-time models are most appropriate because plant data is available at discrete time instants. Artificial neural networks are the most popular frame-work for empirical model development. [6]

Nonlinear process identification

The use of neural networks offers some useful properties and capabilities such as: Nonlinearity, Input-Output mapping, Adaptivity, Fault tolerance. There are large numbers of neural network algorithms available. These algorithms include: multilayer perceptron (Backpropagation Networks), Radial Basis Functions (RBF) networks, Hopfield networks and adaptive resonance networks. Of all these networks, the backpropagation and Radial Basis Function networks have been applied in most process control applications. Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error backpropagation algorithm. This algorithm is based on error correction learning rule. [3],[4],[5]

In general, parameters in a dynamic model, regardless of the form of its mathematical representation, can be estimated by two different

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approaches: a series-parallel and a parallel identification method. In most of the neural network applications, a multilayer feedforward network is employed as a nonlinear autoregressive with exogenous input model (NARX), in which the network uses a number of past (delayed) plant inputs and outputs to predict the future system output. A NARX model is a subset of the general NARMAX model [1] in which additional moving average terms are present for modeling the stochastic components of a dynamic process. Neural Networks are typically over parameterized, an important training issue that arises involves when to stop the training. A simplified version of the statistical technique of cross validation, called test set validation is usually employed.[2]

Results and discussions

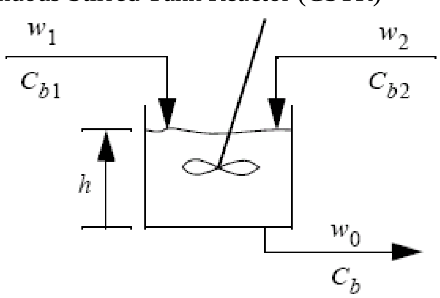
The Related work is based on implementation of nonlinear process identification.

A. Nonlinear Process Identification

The first phase of the work will be generation of empirical model using neural network. The critically important issue is to generate a more accurate nonlinear model for process prediction and optimization problem.
Model identification involves following tasks:

1. Structure selection

Continuous Stirred Tank Reactor (CSTR)



$$\frac{dh(t)}{dt} = w_1(t) + w_2(t) - 0.2\sqrt{h(t)}$$

$$\frac{dC_b(t)}{dt} = (C_{b1} - C_b(t))\frac{w_1(t)}{h(t)} + (C_{b2} - C_b(t))\frac{w_2(t)}{h(t)} - \frac{k_1(t)C_b(t)}{(1 + k_2 C_b(t))^2}$$

Where h (t) is the liquid level, Cb (t) is the product concentration at the output of the process, w_1 (t) is the flow rate of the concentrated feed Cb_1, and w_2 (t) is the flow rate of the diluted feed Cb_2.

2. Input sequence design

Determination of input sequence which is injected into the plant to generate the output sequence. The data set that is used is split into two parts, one for training and one for testing.

3. Parameter estimation

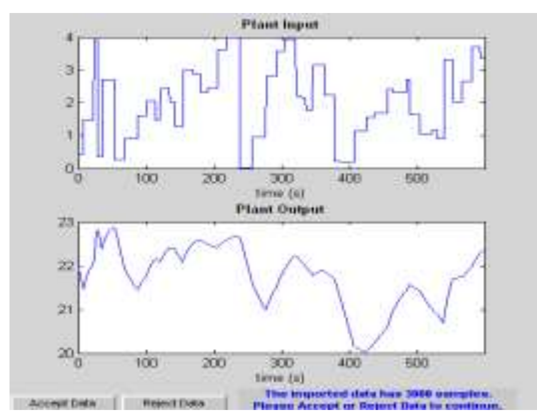
In this step estimation of model parameters is done by training the neural network. The initial training of neural network is typically done using backpropagation algorithm. Periodically, one stops training the network and calculates the error that the network with its current parameters produces on the testing data. Training is terminated when a minimum in the test set error is observed. By using this train-test approach, the fact that a network has too many parameters does not result in a problem and accurate models can be achieved. A backpropagation feedforward network is used to model a single-input-single-output (SISO) system in the series-parallel approach and an external recurrent network resulting from the parallel identification of a feedforward network for an SISO system [1].

4. Model Validation

Second part of data set is used for validation of the model.After application of input signal generated output from process and model are compared here. If the comparison is good then we can replace process by its equivalent model in control process.

Plant Input and Output Data

The program generates training data by applying a series of random step inputs to the Simulink plant model. The potential training data is then displayed in a figure similar to the following.



Training with TRAINGD

The training proceeds according to the training algorithm (traingd in this case) selected. This is a straightforward application of training, as

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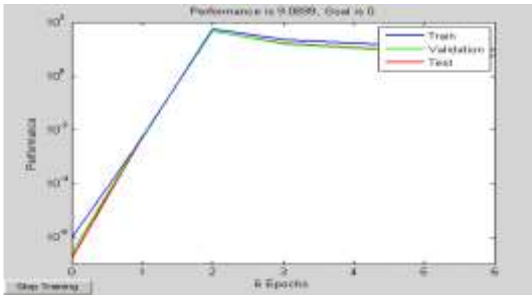
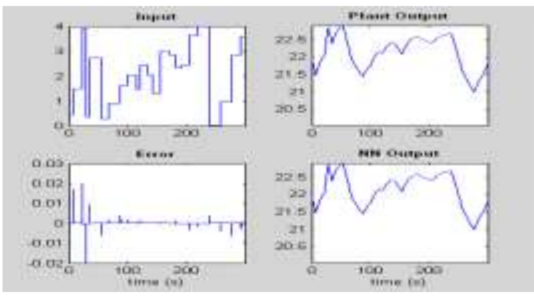
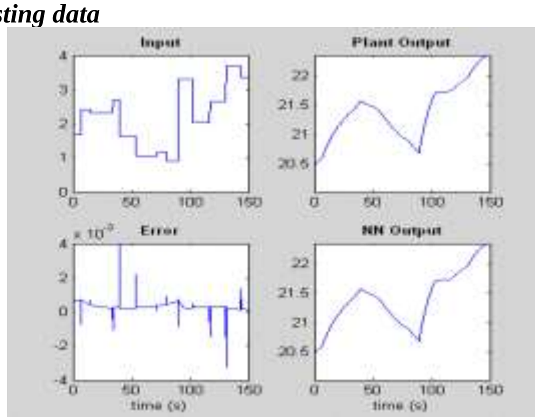
described in Backpropagation. After the training is complete, the response of the resulting plant model is displayed, as in the following figure.



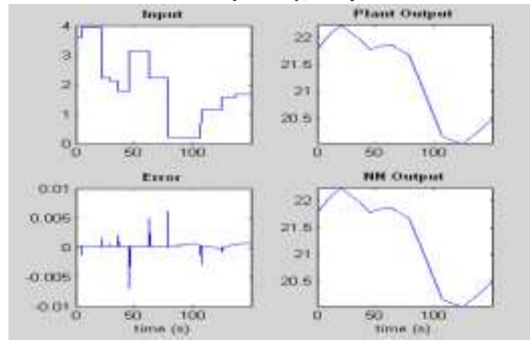


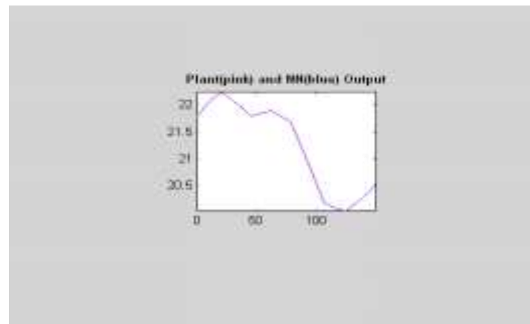
Testing data



Validation Data

Input signal generated and output from process ,model are compared here. If the comparison is good then we can replace process by its equivalent model in control process.





Conclusion

This paper has explored in depth the use of multilayer perceptron networks for dynamic modeling. The simulation result illustrates the validity and feasibility of the nonlinear model identification. Valid data obtained from nonlinear process identification, can be used to control the nonlinear system.

Future scope

Nonlinear process identification, can be used to control the nonlinear system for this use "Nonlinear Model Predictive Control" (NMPC).

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References

1. *Su.H.T. and McAvoy.T.J. (1997). Artificial Neural Networks for nonlinear Process Identification and control. In Henson, M.A., & Seborg, D .E. (Eds).*
2. *Michael A. Henson (1998).Nonlinear model predictive control: current status and future directions.*
3. *Martin T.Hagan, Howar B.Demuth.Neural Networks for Control*
4. *J.C.Hokins and D.M.Himmelblau.Artificial neural network models of knowledge*

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representation in chemical engineering. Computers & Chemical Engineering.12:881-890.1988.

5. *K.Hornik, M.Stinchcombe, and H.White.Multilayer feedforward networks are universal approximatros.Neural Networks, 2(5):359-366, 1989.*
6. *M.Pottmann and D.Seborg.A radial basis function control strategy and its application to a ph neutralization process. Proceedings of Second European Control Conf.ECC'93, 1993.Groningen, Netherlands.*